Intersectional Disparities in Benefit Receipt: A Capital-Based Examination

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Intersectional Disparities in Benefit Receipt: A Capital-Based Approach

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Synthesis

This chapter benefitted from valuable feedback provided by Ineke Maas, Cok Vrooman and Joey Tang

Jos Slabbekoorn: is the sole author of this chapter.

1.1 Introduction

The welfare state and the social security it offers are integral elements of contemporary societies. In a narrower sense, it encompasses various social insurance programs and tax-funded benefits designed to ensure a basic level of income and provide financial security against risks such as unemployment, illness, disability, and aging (Béland et al., 2021; Esping-Andersen, 1990). A broader view of the welfare state goes beyond income protection to include measures aimed at prevention, reintegration, and fostering social participation (Vrooman, 2009b, pp. 111–126), specifically policies that reduce dependency on benefits, promote public health, and encourage labor market and societal engagement. From a fiscal standpoint, maintaining high labor market participation and minimizing long-term benefit reliance are essential for controlling public expenditures. This dissertation focuses on benefit receipt within the core-workforce (25-60) population in the Netherlands and Norway, in particular social assistance and unemployment insurance benefits.

Studying benefit receipt is relevant for society and policy, due to its profound economic, social, and psychological consequences (Brady & Bostic, 2015; van Oorschot, 2006). Social benefits serve as a vital safety net, providing income security and alleviating poverty during periods of unemployment, illness, or economic hardship, thus enabling individuals to maintain their standard of living while transitioning back into the labor market (Barr, 2001; Béland et al., 2021; OECD, 2019a). However, benefit receipt is not unproblematic from a collective point of view; research highlights its recurrent nature, with significant proportions of recipients returning to or remaining dependent on benefits over time, raising concerns about state dependence, intergenerational transfer, and long-term health consequences (Arranz & García-Serrano, 2014; Boschman et al., 2019; Brady & Bostic, 2015; van Oorschot, 2006). These dynamics underscore the need to understand social inequalities in benefit and its structural determinants to design welfare policies targeted at combating the root causes of these inequalities.

Welfare systems, grounded in principles of social solidarity, reflect a collective commitment to mutual support, aiming to balance equity, efficiency, and effectiveness in resource allocation (Durkheim, 1893 (2014); Pierson, 1996). Insights into the patterns of inequality in benefit receipt, as well as the underlying processes driving it, can inform policy that strengthens both the protective and enabling roles of welfare, particularly as welfare states confront mounting economic and demographic pressures (Béland et al., 2021; C. A. Larsen, 2016). By studying who is the most vulnerable and the inequality-generating processes underlying benefit receipt, researchers can contribute to reducing these disparities by informing public policy (Clasen & Siegel, 2007).

A prominent topic in public discussions about the welfare state is the increase in immigration, particularly from non-Western countries. A major policy issue lies in the lower labor market integration of immigrants, reflected in lower participation rates and higher dependency on social benefits. Across EU countries, immigrants with non-Western or non-EU/OECD backgrounds generally exhibit weaker labor market attachment compared to native populations, although these disparities vary by country and national-origin group (Eurostat, 2024). In the Netherlands, individuals with a non-Western immigrant background are more likely to receive social benefits than native Dutch citizens. In 2019, among the four largest non-Western groups in the Netherlands, 8 percent (Surinamese and Turkish) to 13 percent (Moroccan) received social assistance benefits, compared to 2 percent among those with a Dutch background (CBS, 2020, p. 89). Additionally, recent findings from Statistics Netherlands (CBS, 2024) showed that women had a 2 percent higher social assistance incidence than men.

In this dissertation I focus on intersectional inequalities in benefit receipt. While traditional research has advanced our understanding of how singular social categories like gender, age, and migration background influence benefit receipt, these categories are often treated independently, oversimplifying the complexity of inequalities. Building on Crenshaw's (1989) concept of intersectionality, traditionally applied to race and gender, in this dissertation I study how overlapping social categories create compounded inequalities. For example, the combined effects of a migration background and gender may amplify economic vulnerability and barriers to welfare access for migrant women. Traditional single-axis analyses often fail to capture these complexities, under- or overestimating the actual benefit receipt at some intersections. My quantitative intersectional analysis provides a more granular view on the patterns of inequality in benefit receipt, revealing who are disproportionately more relying on social benefits.

Furthermore, I study potential mechanisms driving intersectional inequalities in benefit receipt. This furthers the current state of the quantitative intersectional literature (K. Yang, 2023) as it tests potential root causes of inequalities – in this dissertation in terms of benefit receipt. Specifically, the mechanisms explored include: (1) capital disparities, which refer to the mediating role of capitals (i.e. economic, social, cultural, and person capital) in explaining intersectional inequalities in benefit receipt, (2) differential returns on capital (i.e. the moderated effect of capitals on benefit receipt), highlighting how some groups benefit more or less from the same levels of capital, and, (3) persistency feedback loops (i.e. Matthew effects) addressing how prolonged or intermittent reliance on benefits can reinforce benefit receipt inequality. By studying these mechanisms, this research not only deepens the understanding of intersectional disparities but also highlights how inequality patterns of benefit receipt are brought about. These insights aim to inform more effective and equitable welfare policies that address the root causes of social inequality.

Importantly, we need to acknowledge the potential risk of perpetuating stereotypes and stigmas against disadvantaged groups – particularly those facing multiple layers of disadvantage – when presenting detailed findings on benefit receipt. In some cases, such reporting could inadvertently reinforce or worsen the marginalized position of these groups. This tension is a persistent challenge in any account of disadvantaged populations; and although not unique to this study, the level of detail in its analyses could amplify this concern. Yet it is also crucial to acknowledge that the use of social assistance or unemployment insurance may point to broader structural issues, such as systemic inequality and discrimination. On the one hand, benefit receipt highlights economic and social vulnerabilities, which can disproportionately affect people who are disadvantaged in several respects. Conversely, the benefit system was designed to address such problems, by offering support in times of unemployment and hardship. The most critical issue is to determine whether and how these purposes are achieved, and if there are any blind spots in the benefit system, particularly with regard to groups facing multiple disadvantages. Addressing these questions quantitatively requires detailed data and complex statistical modeling. The insights gained from these analysis can contribute to the development of more targeted policies that will strengthen support for vulnerable groups and communities, rather than perpetuating stigma or stereotypes.

1.2 Benefit receipts and the Dutch welfare state

This dissertation examines benefit receipt in the Netherlands and Norway, two countries with comprehensive welfare systems and high-quality register data that enable reliable, longitudinal analyses. In the following section I will provide a more detailed description of the Dutch welfare state, which I conclude with how Norway serves as a complementary context to study intersectional inequalities in benefit receipt.

Within the welfare state typology, the Dutch welfare state is often described as 'hybrid' (Ferragina & Seeleib-Kaiser, 2011; Vrooman, 2012) with elements of corporatist, liberal, and social-democratic regimes. In recent years, the Netherlands has shown increasing liberalization within its social security system (Ferragina & Filetti, 2022; Vrooman, 2012). Historically, the Netherlands exhibited characteristics of both social-democratic and corporatist regimes, but in recent years, the balance has shifted toward more liberal elements. This shift is characterized by reduced decommodification and adjustments in benefit generosity, aligning more closely with liberal welfare traits. Furthermore, Vrooman (2012) highlights the growing alignment between formal welfare institutions and evolving cultural attitudes toward individual responsibility and labor market participation, indicative of a broader cultural shift toward liberal welfare ideologies. The liberalization process involved recalibrating unemployment benefits and shifting toward policies emphasizing workforce activation rather than passive income maintenance.

In the Netherlands, several social benefit programs either supplement individual income in specific instances – such as housing or health insurance benefits – or provide income security. This dissertation focuses on the latter programs, specifically those related to the working-age population. Specifically, we study two major benefit programs: Unemployment insurance ('werkloosheidsuitkering') and social assistance benefits ('bijstandsuitkering'). The benefit programs analyzed here reflect characteristics from all three types of welfare regimes to varying degrees. Unemployment insurance is organized as a contribution-based social insurance scheme, a characteristic typical of corporatist welfare states. Employees are required to contribute, and the benefits are managed centrally by the Employee Insurance Agency ('Uitvoeringsinstituut Werknemersverzekeringen' or UWV). Eligibility for unemployment insurance is contingent on previous contributions as well as job loss. The duration of unemployment benefits is linked to the number of months employed and contributed in the past, up to 38 months, while the amount of benefits is based on prior earnings. Unemployment benefits can also be received partially if an individual experiences a reduction in work hours.

Social assistance, by contrast, is a means-tested, household-level benefit, reflecting both social-democratic (universal) and liberal (means-tested) elements of the Dutch welfare system. Administered by municipal authorities, social assistance is available to anyone whose income falls below a legally defined minimum level, taking into account wealth and other possessions in addition to income. To qualify, the combined income of the household must fall below the statutory social minimum. The statutory minimum depends on household composition, and, in the absence of other sources of income, the benefit amount matches this minimum. Specifically, in 2023 the household's assets must not exceed €7,575 for single-person households or €15,150 for households with more than one adult. When assessing eligibility, housing property is also considered, but the first €63,900 of equity in the property is exempted from the asset calculation (Rijksoverheid, 2024). This means that individuals or households with property equity below this threshold may still qualify for assistance, provided they meet the income and remaining asset criteria. Social assistance can also be received partially to supplement income that falls below the statutory minimum, such as from a part-time job or other social benefits. Individuals who have exhausted their unemployment insurance (i.e., have used unemployment insurance for the full duration) may apply for social assistance if they meet all the eligibility requirements. The Participation Act ('Participatiewet'), enacted in 2015, introduced further liberalization of social assistance in the Netherlands, requiring recipients to actively participate in society, apply for jobs, or risk being fined. Specifically, recipients are obligated to accept and retain offered employment, register with employment agencies upon request, actively seek work, be willing to commute up to three hours daily for employment, and, if necessary, relocate to secure a job. They must also acquire and maintain necessary skills, cooperate with municipal support aimed at employment integration, and ensure that their appearance and behavior do not hinder job acquisition. Non-compliance with these obligations can result in a reduction of benefits.

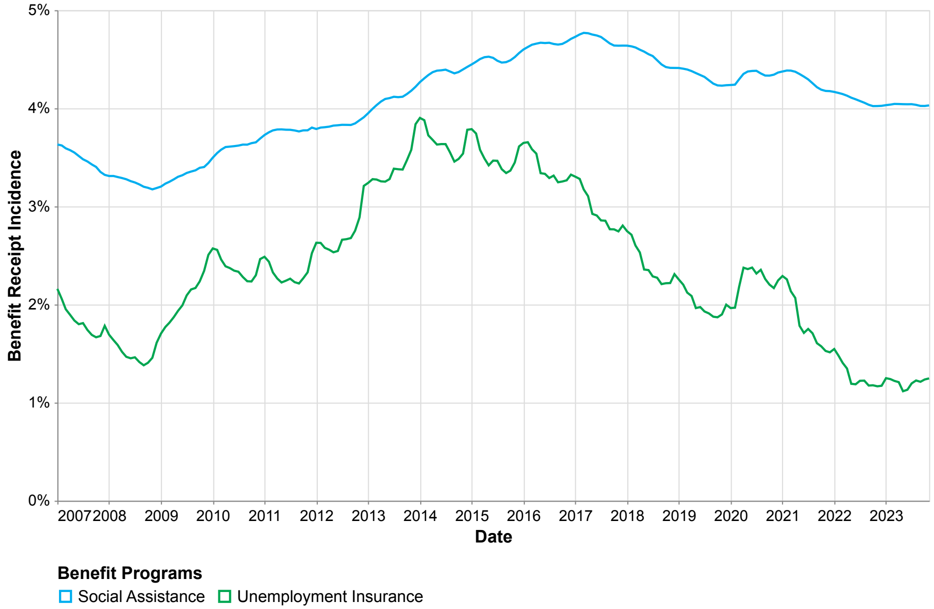
At the local level, municipalities have enacted the Participation Act in diverse ways, shaping the obligations imposed on benefit recipients. Nearly all municipalities require recipients to actively engage in tailored employment plans, seek work, and accept and retain offered employment (van Echtelt et al., 2019). Many have also introduced the requirement of quid pro quo activities, whereby recipients must contribute through unpaid activities – such as providing informal care – in return for their benefits. 57.4 percent of municipalities indicated that such quid pro quo activities were required, and later findings show that 55 percent of municipalities continue to enforce this measure – with 60 percent increasing its frequency since the Act's introduction (Cuelenaere et al., 2017, 2019). Additionally, the language requirement has become more prominent, with 66 percent of municipalities more frequently imposing it to ensure recipients possess the necessary communication skills for the labor market. Despite these common measures, enforcement practices vary significantly across municipalities, suggesting that while the overarching goals of the Participation Act are consistent, the specific obligations and their enforcement are tailored locally. This variation raises concerns regarding the equitable treatment of recipients, as differences in local implementation may lead to unequal outcomes for comparable groups of citizens (Inspectie SZW, 2017; van Echtelt et al., 2019).

Figure 1.1 shows the incidence of social assistance and unemployment insurance benefits as a percentage of the population aged 18 to 67 years in the Netherlands from 2007 to 2024. The chart uses separate line plots to represent the incidence of these two benefit programs over time. The trendline for social assistance shows a relatively stable incidence throughout the period, fluctuating between approximately 3.2% and 4.8%. In contrast, the incidence of unemployment insurance benefit receipt exhibits more pronounced variability. Unemployment insurance incidence rose sharply during the economic crisis period from 2008 to 2014, peaking around 2014 at nearly 4%, followed by a steady decline until 2019. This decline aligns with economic recovery and improvements in the labor market during that period. During the COVID-19 pandemic (2020-2021), there is a slight uptick in the incidence of unemployment insurance, reflecting economic disruptions caused by the pandemic. However, the increase is not as sharp as during the earlier financial crisis, likely due to government interventions to maintain employment. Following 2021, the incidence of unemployment insurance stabilized at around 1.2%, suggesting economic recovery. To exclude potential COVID-19-related influences, in this dissertation the observation period is limited to exclude this period in the empirical chapters of this dissertation.

Norwegian social assistance – known locally as *sosialhjelp* – shares with the Dutch system the goal of ensuring a minimum standard of living for all citizens, and is similarly administered at the municipal level through the Norwegian Labour and Welfare Administration (NAV). Like in the Netherlands, eligibility in Norway is determined via a means test that considers income, assets, and household circumstances. However, Norway's approach is rooted in the Nordic model, which places a strong emphasis on universal social rights and egalitarianism. Consequently, while both systems offer income support as a safety net, Norwegian policies tend to be less punitive in their activation requirements. In Norway, recipients are encouraged to engage in labor market activities through supportive, rather than strictly enforced, measures, reflecting a broader cultural commitment to social inclusion and comprehensive welfare protection (Lorentzen & Dahl, 2021; OECD, 2021). This contrasts with the Netherlands, where increasing liberalization has led to stricter obligations and financial penalties for non-compliance, underscoring divergent policy priorities despite underlying similarities in benefit design.

1.3 Theoretical background and research questions

This dissertation builds on a well-established tradition of investigating benefit receipt and social welfare. In this section, I will provide a brief summary of the current state of research on benefit



Note: Social assistance and unemployment insurance incidence calculated as the number of benefit recipients divided by the number of individuals aged between 18 and 67 years old. **Source**: Author's own calculation based on publicly available CBS StatLine Data.

Figure 1.1: Social assistance and unemployment insurance incidence between 2007 and 2024

receipt, followed by an introduction to an intersectional perspective, underscoring its relevance to social welfare studies. Then, I will present the capital typology used in this work and argue how capital-based mechanisms may drive intersectional inequalities in benefit receipt. Finally, I will present the research questions that form the basis of this dissertation.

1.3.1 Current state of research on inequalities in benefit receipt

Research on social welfare has consistently emphasized key factors like gender, age, and migration background as significant determinants of disparities in benefit receipt. While each of these factors has been well-studied, much of the existing work remains fragmented, often siloed within specific disciplines or focused on isolated aspects of inequality (i.e. focusing either on gender, migration background or age).

Migrants, for instance, face unique challenges that significantly increase their likelihood of receiving benefits. First-generation migrants, particularly those from less socio-economically developed countries, are more likely to encounter language barriers, resource deficiencies, and systemic discrimination in the labor market (Blommaert et al., 2012; Connor & Koenig, 2015; Jongen et al., 2020). These challenges hinder employment chances and increase dependence on social assistance (Strockmeijer et al., 2020). Even second-generation migrants, despite improved language skills and educational attainment compared to their parents, continue to experience disadvantages in employment due to discriminatory practices, resulting in higher rates of benefit receipt compared to native populations (Sevinç, 2016).

Gender inequalities also prevail in benefit receipt. Although the educational gap between men and women has been closed – and women now on average exceed men with regard to educational attainment, women are still more likely to occupy lower-status, less secure jobs, partly due to societal expectations around family responsibilities (Jansen et al., 2021; van den Brakel et al., 2020). Women often choose part-time or flexible work arrangements to balance work and family, leading to increased employment insecurity and a greater risk of dependence on social assistance (Gati & Perez, 2014; Morgan et al., 2013). Gender discrimination in hiring, especially related to pregnancy and childcare, further limits women's access to stable employment (S. O. Becker et al., 2019; Correll et al., 2007).

Age, too, plays a crucial role in benefit receipt: older individuals, especially those in their 50s and 60s, often face challenges such as skill obsolescence, age-related health issues, and discrimination, leading to higher unemployment rates and prolonged reliance on benefits (Levinsky & Schiff, 2021; Lössbroek et al., 2021), while younger individuals, despite high unemployment, typically benefit from targeted labor market policies that help them re-enter the workforce more quickly, thereby reducing the duration of their benefit dependency (Quintini & Martin, 2006; Shahidi et al., 2019).

1.3.2 The need for an intersectional perspective

While research on inequalities in benefit receipt has made significant progress in identifying how social categories like gender, age, and migration background affect outcomes, these categories are often treated as independent factors. This approach risks oversimplifying the complexity of inequalities by overlooking how multiple social characteristics intersect to create unique experiences of disadvantage.

Intersectionality, introduced by Crenshaw (1989), provides an analytical framework for understanding how overlapping social categories – such as gender, race, age, and educational attainment – combine to shape specific outcomes in benefit receipt. Crenshaw's critique of the "single-axis framework" highlighted that treating categories like race and gender as separate often fails to capture the compounded forms of disadvantage experienced by marginalized groups. This insight has been expanded beyond race and gender to encompass a wider range of intersecting social characteristics, including class, nationality, and age (Collins & Bilge, 2020).

Intersectionality emphasizes that social categories are interrelated and should be understood in relationship to each other, creating compounded disadvantages that cannot be fully understood by studying each category in isolation (Settles & Buchanan, 2014). For example, the experience of employment discrimination faced by a Black woman cannot be fully captured by studying either race or gender independently. Instead, it is the intersection of these social characteristics that shapes her unique position in the labor market.

Quantitative approaches to intersectionality provide an important means of empirically assessing how overlapping social categories interact to produce unique outcomes. While intersectionality has traditionally been rooted in qualitative methods, recent theoretical advancements highlight the merit of quantitative approaches in capturing the complexity of intersecting social characteristics (Cole, 2009; Dubrow, 2008). Methods such as multilevel models, interaction effects, and mixed methods allow researchers to systematically explore disparities across different social groups, thereby providing empirical evidence for the compounded effects of overlapping social characteristics (K. Yang, 2023). By quantifying intersectional inequalities, scholars can advance intersectional theory and provide concrete insights into the social inequalities that shape benefit receipt (Bauer et al., 2021; Fehrenbacher & Patel, 2020; Spierings, 2022), which enhances the generalizability of intersectional findings (Else-Quest & Hyde, 2016).

Quantitative intersectional research has emerged relatively recently (K. Yang, 2023) and has been applied to a broad range of outcomes, including health (Axelsson Fisk et al., 2018; Evans et al., 2018, 2020; Gkiouleka & Huijts, 2020), well-being (Bixby, 2024; Kern et al., 2020), education (Gross et al., 2020; Keller et al., 2023), and hiring discrimination (Di Stasio & Larsen, 2020). These studies highlight the value of studying intersecting social characteristics – such as ethnicity, gender, and socioeconomic status – to uncover the complex mechanisms driving disparities in these outcomes. Benefit receipt has rarely been studied using quantitative intersectional methods, with only one other study focusing on social assistance in Sweden (Hussénius, 2021). By also analyzing unemployment insurance and exploring different national contexts, this dissertation adds significantly to the scarce academic literature on this topic.

In conclusion, while traditional research has provided valuable insights into the key factors influencing benefit receipt, an intersectional approach is necessary to fully understand the complexities of social inequalities. By moving beyond single-axis analyses and acknowledging the interplay of multiple social characteristics, we can better capture the subtle and compounded disadvantages that shape individuals' experiences with social welfare.

1.3.3 Capitals

In this dissertation, I conceptualize social inequality as being shaped by multiple forms of capital – economic, cultural, social, and person capital. This approach is informed by the work of Savage (2015), Friedman & Laurison (2019), and Vrooman et al. (2024), who emphasize that inequalities are not just rooted in economic disparities but also in how individuals navigate different social contexts (cultural capital) and the support they receive from their networks (social capital), as well as an individual's health and appearance (person capital). This multidimensional perspective on inequality aims to account for "what people have," "how they fit in," "who they know," and "who they are." Table 1.1 helps clarify how these types of capital are theorized, drawing on

Table 1.1: Theories of capital.

	Economic Capital	Cultural Capital	Social Capital	Person Capital
Theorist	Schultz, Becker	Bourdieu	Lin, Burt, Marsden, Flap	Bourdieu, Pareto
Locus	”What people possess”	”How people fit in”	”Who people know”	”Who they are”
Capital	Investment in technical skills, knowledge and wealth	Internalization or recognition of dominant values signals	Investments in social networks	Investments in health and appearance
Development	Accumulation of surplus value by labor and assets	Reproduction of dominant symbols and meanings (values)	Access to and use of resources embedded in social networks	Advantages of bodily and mental state

Note: Adaptation of Lin’s (2011) overview of capitals, using the capital typology of Vrooman et. al. (2024)

influential scholars like Schultz, Becker, Bourdieu, Lin, and Pareto. It provides an overview of the key theorists, and descriptions for each type of capital, guiding how these resources are conceptualized and applied in the empirical chapters.

The concept of *capital* refers to resources that individuals can draw upon to improve their life chances and social position. These capitals are often categorized into different types, each contributing to social inequality in unique ways. Below, I provide definitions for the various forms of capital considered in this research and explain how they help to understand differences in benefit receipt.

The first type of resource considered is *economic capital*, which includes educational attainment, professional skills, labor market position, and income or wealth. These resources reflect traditional economic inequality, such as income disparities and labor market position, as well as other phenomena like wealth gaps and cognitive stratification. In this context, educational attainment is treated as an economic resource, as it reflects the knowledge, skills, and qualifications individuals have gained, in line with Becker’s ([1963] 1993) human capital theory. Educational differences may translate into disparities in income, wealth, health, social relations, and cultural capital. Although formal education can reinforce social class structures, it is also a means for upward social mobility, particularly in modern education systems with goals of equal opportunity (van de Werfhorst, 2014). Economic capital may considerably affect an individual’s risk of benefit receipt. Higher levels of economic capital provide better job opportunities and a stronger position in the labor market, reducing reliance on benefits. Conversely, individuals with lower educational attainment or limited wealth are at a greater risk of benefit receipt due to their weaker competitive position in the labor market and fewer accumulated assets.

Cultural capital refers to behaviors, attributes, and predispositions that signal social position. This includes language skills, preferences for cultural activities, and symbolic markers like titles or reputations. Building on Bourdieu’s (1986) work, cultural capital can manifest in various forms, such as fluency in languages, or appreciation of different art forms. It is important to note that cultural capital is context-dependent, shaped by the social circles individuals move in. Those who possess the "right" cultural capital can use it to gain higher social positions, while newcomers lacking it may struggle to integrate into elite social groups (Friedman & Laurison, 2019). Hence, cultural capital can affect the likelihood of benefit receipt. Those with higher levels of cultural capital are better equipped to navigate the labor market and secure employment, as employers often favor candidates who exhibit competence through cultural signals.

Social capital consists of the resources individuals derive from their social networks. This includes both the size of one's network and quality of one's connections, which can offer financial, informational, emotional, or reputational support (Burt, 1982; Flap & Boxman, 2001; Granovetter, 2018; Lin, 2000, 2001; Marsden, 2001). An ego-centered approach is used here, viewing social capital as an individual asset rather than a characteristic of larger communities or groups. Research shows that social capital plays a key role in social hierarchies, with individuals at the top having larger, more powerful networks from early in life (Martin, 2013). These networks can provide advantages in education, employment, and overall well-being. Social stratification is often reinforced by homophily and resource hoarding, as people tend to associate with those similar to themselves, and powerful networks may limit access to resources for others. Social capital can significantly improve employment prospects and lower the likelihood of benefit receipt. Individuals with more extensive and resourceful networks are better positioned to receive job information, recommendations, and support during the job search process.

Person capital refers to the physical and mental characteristics that contribute to an individual's life chances. This concept, partly derived from Bourdieu's (1986) notion of "embodied" cultural capital, emphasizes the importance of health and other personal attributes in social inequality. Unlike other forms of capital, person capital highlights individual heterogeneity, aligning with Pareto's (Nielsen, 2007; 1935) idea that life chances are influenced by competition among individuals rather than solely by group characteristics. Thus, person capital is considered an independent dimension of social inequality, recognizing that two individuals with similar economic, cultural, and social resources can still experience different outcomes based on their physical or mental condition. Person capital directly impacts individuals' employability and, consequently, their likelihood of benefit receipt. Poor health or mental health issues can reduce job performance or prevent individuals from securing stable employment, increasing their reliance on benefits.

1.3.4 Explaining differences in benefit receipt through capitals

Capitals can help to explain differences in benefit receipt in three key ways: through capital deficits, return deficits, and feedback loops.

1. **Capital Deficits**: Some social groups possess fewer resources compared to others, which influences their likelihood of benefit receipt. A lack of economic, social, cultural, or person

capital reduces individuals' opportunities, making them more dependent on social benefits. The distribution of these forms of capital may help explain differences in benefit receipt, as migrants, women, and individuals at different life stages often have varying levels of capital. Migrants, for instance, may encounter difficulties in adapting to the dominant cultural norms or language in their host country, limiting their cultural capital and their ability to access employment or navigate social systems effectively (Castronova et al., 2001; Renema & Lubbers, 2019; Strockmeijer et al., 2020). Women, particularly those balancing caregiving responsibilities, may experience interruptions in their career trajectories, limiting their accumulation of economic capital over time (S. O. Becker et al., 2019; Correll et al., 2007). Similarly, capitals can vary with age; younger individuals may have smaller social networks that provide fewer professional opportunities (Quintini & Martin, 2006).

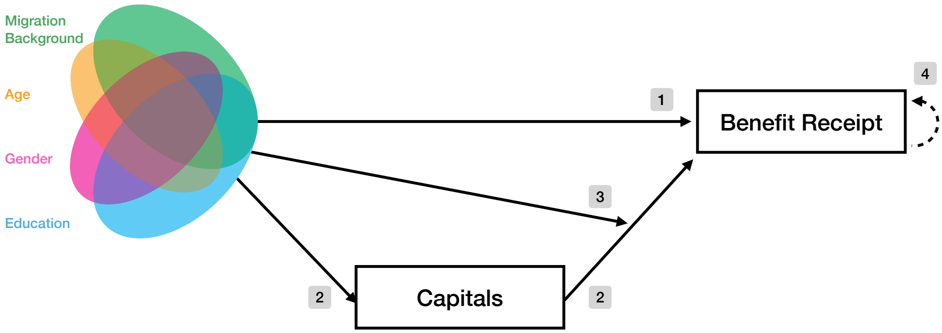
2. **Return Deficits**: Even when individuals possess similar levels of capital, some groups may be able to make more or less use of these resources. For example, women, migrants, or older individuals may face systemic barriers (e.g., discrimination) that limit the returns they receive from their economic, social, cultural, or person capital. This means that despite having comparable qualifications or networks, these groups may experience less favorable employment outcomes, leading to a greater reliance on benefits. Return deficits illustrate how structural factors and discrimination can affect how effectively individuals can convert their capitals into desirable social and economic outcomes.

3. **Feedback Loops**: Prior receipt of benefits can lead to a higher incidence of future benefit reliance – a phenomenon often referred to as Matthew effects (Merton, 1968, 1988). In other words, initial dependence on benefits can create self-reinforcing cycles, where early benefit receipt undermines employment opportunities, further increasing the likelihood of future benefit dependence. This mechanism is particularly useful for understanding intersectional differences in benefit receipt. For instance, disadvantaged individuals – such as migrants, women, or older individuals – may be more susceptible to these feedback loops. Their early reliance on benefits, compounded by structural barriers, can lead to a cumulative disadvantage over time, thereby reinforcing and deepening existing social and economic inequalities.

1.3.5 Research questions

Figure 1.2 presents the conceptual model for the empirical chapters this dissertation. In the first part of this dissertation, I aim to establish whether intersectional inequalities exist in benefit receipt, with a key contribution being the integration of social welfare and intersectionality literatures. Chapter 2 addresses the first overarching research question:

> *Are there intersectional differences in benefit receipt, and which intersections have disproportionately high or low incidences?*



Note: The numbered labels in this figure highlight key aspects of benefit receipt dynamics. (1) Represents intersectional differences in the incidence of benefit receipt. (2) Indicates the extent to which capital deficits may mediate intersectional disparities in benefit receipt. (3) Depicts return deficits, focusing on whether the effects of capitals vary intersectionally. (4) Illustrates persistency loops, referring to the extent to which prior benefit receipt increases the likelihood of benefit receipt in subsequent years.

Figure 1.2: Conceptual model for the empirical chapters

Chapter 2 moves beyond additive assumptions and studies how education, gender, age, and migration background interact to shape unique and complex inequalities in benefit receipt through an intersectional framework. In essence, by using an intersectional framework, we study how social characteristics overlap, creating unique social positions, which are visualized as a Venn diagram in Figure 1.2. When multiple disadvantaged identities overlap, their effects can compound to create greater inequality than expected, while intersecting privileges can either amplify benefits or be diminished by accompanying disadvantages. Through this approach, I explore how combinations of disadvantages can lead to aggravating effects, where intersecting disadvantages intensify one another, creating heightened barriers or inequalities. Alternatively, combinations of social characteristics may result in partial compensation, where certain advantages mitigate but do not fully counteract disadvantages. In some cases, these dynamics can result in diminutive advantage, where an otherwise privileged characteristic is weakened or undermined by the presence of intersecting disadvantages, creating a less pronounced benefit.

The second part of the dissertation moves beyond identifying disparities and focuses on understanding the mechanisms driving these intersectional differences. The second overarching research question is:

> *To what extent can we explain intersectional differences in benefit receipt through capital deficits, return deficits, or persistency loops?*

Chapter 3, through 5 investigate these mechanisms in a more detailed manner. In Chapter 3, I explore a capital-based mediation mechanism to understand whether disparities in economic, social, cultural, and person capital can explain intersectional differences in benefit receipt. These resources – essential for securing employment and avoiding benefit receipt – often differ significantly across social groups, with marginalized groups such as women, migrants, and older adults facing greater disadvantages. For instance, first-generation non-Western migrant women in the Netherlands typically have lower proficiency in Dutch compared to their male counterparts (Bernhard & Bernhard, 2022), partly due to traditional gender roles that limit their participation in language-learning opportunities. This lower level of cultural capital can hinder their access to the labor market, increasing their likelihood of benefit receipt.

Chapter 4 builds on this by investigating a capital-based moderation mechanism. Here, I study whether disadvantaged groups may experience lower returns on these various forms of capital due to factors like discrimination or stigmatization, which limit their ability to fully utilize their resources. For instance, disadvantaged individuals (e.g., migrant men) may face challenges converting their economic or social capital into stable employment, which increases their reliance on social benefits. This chapter challenges the notion of homogenous capital returns and seeks to uncover how returns differ across different intersections, such as of gender, migration background, and age.

Chapter 5 turns to the persistence of social assistance receipt, often referred to as the 'Matthew effect,' where individuals who receive benefits in one period are more likely to continue receiving them in subsequent periods. This is visualized in Figure 1.2 as the recursive arrow on benefit receipt. This chapter explores the mechanisms of persistence, such as the direct impact of prior social assistance on further reliance. I then study how the combination of gender, migration background, and generation can exacerbate or mitigate the persistence of benefit receipt. This contributes to our understanding of why some individuals remain trapped in cycles of benefit receipt, while others are able to exit.

By combining these different mechanisms—capital deficits, return deficits, and persistency loops – I aim to identify the root causes of intersectional inequalities in benefit receipt. This approach ultimately provides insights into the structural barriers faced by disadvantaged groups and sheds light on who is most vulnerable to benefit receipt, based on the intersection of multiple social characteristics.

1.4 Methodological approach

In this dissertation, I use a quantitative intersectional approach, building on recent advances in modeling intersectional inequalities through multilevel models (Evans et al., 2018; Merlo, 2018). Multilevel Analysis of Individual Heterogeneity and Discriminatory Accuracy (MAIHDA) provide an innovative framework for this purpose, addressing the limitations of traditional regression-based approaches that rely heavily on interaction terms (Merlo, 2018; K. Yang, 2023). MAIHDA represents a significant advancement in capturing intersectional inequalities, which often involve a large number of categories, making single-level modeling impractical (Evans et al., 2018).

1.4.1 Conceptualizing intersectional groups as higher-level units

One of the core innovations of MAIHDA is the conceptualization of intersectional groups as higher-level units in a multilevel model. This approach allows researchers to manage the complexity of intersectional data without relying on numerous interaction terms, making the analysis more efficient and interpretable. Traditional approaches, such as regression models with interaction terms, struggle with the complexity introduced by a large number of socio-demographic attributes, each with multiple categories. For instance, if five attributes each have three categories, this results in 243 intersectional groups, leading to an unmanageable number of interaction terms and coefficients (K. Yang, 2023). Such models become inefficient and statistically unreliable, particularly for groups with few data points. MAIHDA addresses this challenge by treating individuals as nested within intersectional categories, effectively simplifying the model while retaining the ability to explore intersectional effects (Evans et al., 2018; Green et al., 2017; Merlo et al., 2006).

Unlike natural higher-level units like schools or neighborhoods, intersectional groups are analytical constructs formed by combining selected attributes of interest, such as gender, age, race, and class. These constructs are exhaustive by definition, encompassing all possible combinations of the selected attributes, which differentiates them from natural clusters typically sampled to represent broader populations (Evans et al., 2018). Instead of focusing on traditional statistical inference, MAIHDA emphasizes exploring overall clustering effects among intersectional groups, thus, providing insights into which combinations are most vulnerable.

1.4.2 Addressing small sample sizes and statistical challenges

MAIHDA offers significant advantages, such as mitigating instability and improving robustness, in addressing the statistical challenges associated with small intersectional group sizes. In traditional regression models, small group sizes can lead to unstable estimates due to high variability and the influence of outliers. MAIHDA incorporates weights that adjust the influence of small groups on coefficient estimation, ensuring a more balanced estimation process. This means that smaller groups have less influence on the overall model, thereby reducing instability and improving robustness (Evans et al., 2018). For example, studies like those by Evans et al. (2018), which analyzed hundreds of intersectional groups, demonstrate how MAIHDA can mitigate the impact of small group sizes by applying weights inversely related to group size.

The use of Bayesian methods in MAIHDA enhances its capacity to handle uncertainty. This is particularly useful in cases involving small or sparse data. Bayesian analyses allow researchers to derive posterior distributions of parameters, providing credible intervals instead of relying solely on point estimates or p-values, as is common in frequentist approaches. This is especially advantageous for small intersectional groups, which are prone to unstable estimates in traditional models (Evans et al., 2024; Keller et al., 2023). By offering full distributions for random intercepts and effects, Bayesian methods intrinsically model variability and uncertainty, making them a powerful tool for studying intersectional inequalities (Evans et al., 2024; Keller et al., 2023).

1.4.3 Additive and non-additive effects in intersectional analysis

An important aspect of intersectional analysis with MAIHDA is distinguishing between additive and non-additive (or interactive) effects. Additive effects assume that the influence of different social categories simply accumulates, whereas non-additive effects occur when the intersection of multiple categories leads to a level of disadvantage that is greater (or less) than the sum of individual effects. For example, the combined effect of being a woman and belonging to a lower socioeconomic class may lead to a greater level of disadvantage than would be expected if these two effects simply added up, highlighting how intersecting social characteristics can amplify inequalities. MAIHDA identifies these non-additive effects by distinguishing between the contributions of each social category and the emergent effects arising from their intersection. For instance, the interaction between gender and race may produce health outcomes that cannot be fully explained by additive effects alone, highlighting the importance of considering these complex interactions.

1.4.4 A versatile framework

MAIHDA has primarily been used to study differences in intercepts, which represent differences in the outcome variable across different intersectional groups (e.g., Evans et al., 2018). However, it can also be expanded to explore mediation and moderation effects, which allows researchers to study the mechanisms underlying intersectional inequalities. This makes it a powerful tool for understanding how intersectional inequalities arise and how different factors distinctly influence inequalities across intersectional groups. By leveraging MAIHDA's ability to explore mediation and moderation effects, one can test mechanisms that shape intersectional inequalities (K. Yang, 2023).

1.5 Research design and data

In this section, I provide an overview of the analytical approach used in the empirical chapters of this dissertation. This approach advances the study of benefit receipt inequalities in several key ways by leveraging a combination of high-quality data sources and sophisticated quantitative methods. This research utilizes administrative data, which offers highly reliable information on benefit receipt for all registered inhabitants of the Netherlands (Bakker et al., 2014). This data source allows for comprehensive coverage, including populations that are often harder to reach through survey-based data collection, thus enhancing the generalizability of the findings. Additionally, the administrative data in certain analyses is complemented by longitudinal survey data from the Longitudinal Internet Studies for the Social Sciences (LISS: Scherpenzeel & Das, 2010). This dataset provides rich and detailed information about various forms of capital – economic, social, cultural, and person – on a nationally representative sample of the Netherlands, tracked over time. Moreover, the LISS data is supplemented by an additional data collection, conducted by ourselves, that includes retrospective questions on health-related absenteeism from

Table 1.2: Overview of the data and methods employed in each chapter.

Ch.	Data Source	Data Structure	Sample Selection	Method	Response Variable
2	Administrative Data (Statistics Netherlands)	Longitudinal	Stratified sample, 25 - 60 year olds	MAIHDA	SA and UI (seperately) = major source of income for 3 consecutive months
3	LISS enriched with Administrative Data (Statistics Netherlands)	Longitudinal – Explanatory variables measured at $t-1$ predict benefit receipt at t	Nationally respresentative sample, 20 - 60 year olds	Bayesian Multilevel Structural Equation Models (BMSEM)(1)	SA and UI (combined) = major source of income for at least one month
4	LISS enriched with Administrative Data (Statistics Netherlands)	Longitudinal – Explanatory variables measured at $t-1$ predict benefit receipt at t	Nationally respresentative sample, 20 - 60 year olds	MAIHDA, including random slopes	SA and UI (combined) = major source of income for at least one month
5	Administrative Data (Statistics Norway)	Longitudinal – Explanatory variables measured at $t-1$ predict benefit receipt at t	Stratified sample, 25 - 60 year olds	MAIHDA, including random slopes	SA = individual has received in calendar year

Note: LISS = Longitudinal Internet Studies for the Social sciences, MAIHDA = multilevel analysis of individual heterogeneity and discriminatory accuracy, SA = Social Assistance, UI = Unemployment Insurance. **1.** This methodological approach closely mimics MAIHDA framework models

work, offering further insight into the interplay between health and benefit receipt (Vrooman et al., 2022). Table 1.2 provides an overview of data sources used in this dissertation's empirical work, including key charactersics of the analytical approach.

1.5.1 Data sources

The empirical chapters of this dissertation primarily rely on three data sources. A common feature across all chapters is the use of individual-level longitudinal administrative data to measure the response variables. The administrative data come from various linked registers, including the Social Statistical Database (SSD)[1] used in Chapters 2-4, and the FD-trygd database[2] used in Chapter 5. By using objective administrative data to measure benefit receipt, we eliminate the bias that can result from misreporting in surveys (Bruckmeier et al., 2018). In surveys, respondents

[1]Under certain conditions, these microdata are accessible for scientific research. For further information: microdata@cbs.nl

[2]For more information about accessing these data, see: https://www.ssb.no/data-til-forskning/utlan-av-data-til-forskere

may unintentionally misreport their benefit receipt due to recall errors, misunderstanding of the questions, or even social desirability bias, where individuals might underreport their reliance on benefits due to stigma associated with welfare use. Administrative data, however, are collected directly from official records, ensuring a high level of accuracy and completeness. This data captures actual benefit receipt without relying on respondents' perceptions or memories, leading to more reliable estimates. As noted by Bruckmeier et al. (2018), such objectivity is crucial for studying sensitive topics like welfare participation, where misreporting can skew the understanding of benefit utilization patterns and the analysis of social inequality. In Chapter 3 and 4 these registers are linked through unique individual identifiers and provide detailed information on socioeconomic characteristics and basic demographics, such as individuals' primary sources of income, annual income, place of residence, and household composition.

Another aspect as to why register data is uniquely suitable to study intersectional inequalities in benefit receipt, is that it readily contains information about populations which might be small or harder to reach in survey-based research (Tourangeau et al., 2014), such as older migrant women with an university degree that have received social benefits. This allows us to draw a stratified sample with sufficient cases at each intersection. In Chapter 5 I used administrative data from FD-trygd database, provided by Statistics Norway. Based on data availability, I used information from 2004 to 2019 on individuals who are part of the core workforce (aged 25 to 60 years). In set-up these are very similar to the infrastructure provided in the SSD, and using these data therefore comes with similar advantages as I mentioned for Chapter 2.

Survey data generally offer richer information than administrative data, covering a broader range of topics in greater detail. Administrative registers are maintained for practical, administrative purposes and may lack the tailored information that surveys can provide. For example, surveys can be used to measure the network ties between individuals in a precise way, while administrative data cannot do so. For explaining intersectional differences, I make use of the LISS (Longitudinal Internet Survey for the Social Sciences) panel, administered by CentERdata at Tilburg University in the Netherlands. This panel covers a wide range of topics relevant to the social sciences and began in 2007 with a national probability sample of 4,500 Dutch households, including 7,000 individuals. For my analysis, I utilize data from the period 2008 to 2019, focusing on respondents' economic, social, cultural and person capital. To construct the capital variables, I also used additional information about health related absenteeism which was assed retrospectively in an additional data collection, which we commenced in the LISS-panel ourselves in 2021. The survey data were linked to individual-level longitudinal administrative data. Combining survey and administrative data also enables the use of time-lagged measurements, where explanatory and response variables are recorded at different time points –an approach used in Chapter 3 and 4.

1.6 Overview of empirical chapters

1.6.1 Intersectionality and benefit receipt: The interplay between education, gender, age and migration background (Chapter 2)

Chapter 2 focuses on studying disparities in social assistance and unemployment insurance receipt at the intersection of migration background, age, gender, and education. The results indicate that intersectional disparities are more pronounced for social assistance than for unemployment insurance. Consistent with previous research, the findings reveal significant differences based on additive effects of migration background, age, and education for both types of benefits. However, I do not find gender differences for social assistance, while small gender disparities are evident for unemployment insurance. The variation in social assistance receipt among intersectional groups is largely explained by additive effects, suggesting that non-additive effects have a limited role. In contrast, the variation in unemployment insurance receipt is more influenced by the complex interaction of gender, migration background, age, and education. Overall, the findings underscore that disparities in benefit receipt are primarily driven by the additive effects of gender, migration background, age, and education. Nonetheless, for some intersections, the interconnectedness of these factors plays an important role in producing relative (dis-)advantages.

1.6.2 The mediating role of resources in shaping intersectional inequalities in benefit receipt (Chapter 3)

Chapter 3 studies the role of various resources – economic, social, cultural, and person capital – in mediating intersectional inequalities in benefit receipt. I explore how disparities in these resources explain differences in benefit receipt (i.e. social assistance and unemployment insurance jointly), focusing on the intersection of gender, migration background, and age. Thereto, this chapter aims to study a potential mechanism underlying benefit receipt. I find that disparities in benefit receipt, particularly among ethnic minorities and age groups, are largely explained by differences in economic resources, mental health, and to a lesser extent, cultural capital. Gender differences were minimal, with men exhibiting better mental health than women in an additive sense. Other resources (i.e. physical health, social resources, and educational attainment) did not independently explain differences in benefit receipt. Additionally, the study highlighted non-additive indirect effects, particularly among migrant groups, indicating that some intersectional groups face disproportionate resource deficits, which increases their likelihood of receiving benefits. Economic resources played a significant role in these deficits. For example, young men with a first-generation Western migration background and older women with a second-generation migration background were found to have high benefit receipt due to economic vulnerability.

1.6.3 Heterogeneous returns of capital in terms of benefit receipt: An empirical study of intersectional inequalities (Chapter 4)

In Chapter 4, I studied the heterogeneous effects of the same four types of capital on benefit receipt. I focused on intersectional inequalities across gender, migration background, and age to determine whether disadvantaged groups can derive lesser, equal or greater returns from these forms of capital. I find that economic and person capital significantly reduce benefit receipt. These findings largely corroborate our findings in Chapter 3, but differ slightly as capitals were operationalized differently for theoretical reasons. Economic capital had a lesser impact in advantaged groups, while person capital consistently lowered benefit receipt across all groups. This finding challenges the traditional understanding of privilege, where advantaged groups are expected to benefit more from their resources. Instead, advantaged groups appear to be less affected by having less economic capital.

1.6.4 Social assistance persistence at the intersection of gender and migration background (Chapter 5)

Chapter 5 focuses on the persistence of social assistance receipt, investigating how intersecting social characteristics – gender, migration background, and migration generation – shape the likelihood of prolonged benefit receipt in Norway. I analyze whether previous social assistance receipt influences future benefit receipt differently across intersectional groups. I find considerable variation in social assistance receipt, primarily driven by a few vulnerable groups, particularly individuals with migration backgrounds from African or Middle East and North Africa (i.e. MENA) countries, especially men of these migrant groups. Potentially, these groups face severe hiring discrimination, contributing to their higher reliance on social assistance. While much of the variation in social assistance receipt is explained by additive factors, there are exceptions where certain groups, such as first- and second-generation African migrants, experience compounded disadvantages that increase their risk of receiving assistance. Persistency effects, where social assistance receipt leads to subsequent reliance, show more heterogeneity, with some groups, such as first-generation Western European and second-generation Polish men, showing lower persistency, while others, like first-generation Pakistani, Bangladeshi, and Indian men, experience disproportionately higher persistency. At other intersections the persistency effects did not diverge from additive expectations.

The most influential factor in both incidence and persistency of social assistance is migration background and country of origin, with gender playing a less significant role. Some migrant groups not only rely more heavily on social assistance but also make more persistent use of it. In a few cases, disadvantages compound multiplicatively, especially among first-generation African and MENA migrants who make more persistent use of social assistance. The chapter highlights the importance of understanding both additive and multiplicative effects in social assistance receipt and persistency and suggests further research to disentangle the mechanisms behind these patterns, such as true state dependency versus selection processes.

1.7 Conclusions, limitations and implications

1.7.1 Conclusion and discussion

This dissertation investigated intersectional inequalities in benefit receipt. Additionally, I studied potential underlying mechanisms of intersectional inequalities in benefit receipt, focusing on capital deficits, return deficits, and persistency loops.

The first overall conclusion to emerge from this dissertation is that benefit receipt is influenced by both additive and non-additive effects of intersectional factors. Historically, disparities in benefit receipt have often been studied additively, where each dimension of inequality – has been analyzed in isolation, without considering how these factors interact. Social assistance receipt shows larger disparities compared to unemployment insurance, primarily driven by migration background, age, and education. Gender plays a minor role overall but is more pronounced in unemployment insurance receipt. Importantly, the findings suggest that social assistance disparities are largely explained by additive effects, meaning that the intersectional attributes of individuals do not necessarily interact in complex ways to create unique vulnerabilities in this context. This contrasts with unemployment insurance, where the interplay of gender, age, migration background, and education produces a more intricate pattern of disparities.

In sum, our analysis challenges the conventional notion that belonging to multiple marginalized groups necessarily results in cumulative disadvantages that exceed the sum of their individual effects (King, 1988; Settles & Buchanan, 2014). Instead, the data reveal that even highly educated groups with a migration background experience a form of diminished benefit from their academic credentials – consistent with findings from the classic study by Blau and Duncan (1967) – suggesting that advantages on one dimension can be curtailed by disadvantages on another. Furthermore, while the expected pattern of multiple jeopardy was largely absent, we do observe specific cases where relative advantage is also constrained. For instance, women with a migration background often fare better than anticipated in unemployment insurance outcomes (Arai et al., 2016; Di Stasio & Larsen, 2020), potentially due to lower levels of labor market discrimination or alternative role choices, whereas even multiply advantaged groups, such as young native Dutch men with academic education, do not fully capitalize on their favorable attributes.

These findings underscore the importance of quantitative intersectional analyses, as they allow for the precise measurement of disparities and reveal exactly which groups are most disadvantaged and by how much (K. Yang, 2023). While qualitative research has often emphasized the compounded disadvantages experienced by multiply marginalized groups, this quantitative approach exposes a more intricate landscape where both unexpected disadvantages and mitigated disadvantages emerge across different intersections.

The second focus of this dissertation was to explore the underlying mechanisms driving these intersectional differences, specifically to what extent these differences can be explained by capital deficits, disparities in returns from available resources, or persistency loops. Chapter 3, 4, and 5 provide an in-depth examination of these mechanisms.

Economic resources, mental health, and, to a lesser extent, cultural capital explain inequalities across intersectional groups. Intersectional groups having less of these resources are found to have a higher incidence of benefit receipt. Additionally, some intersectional groups face compounded resource inequalities – particularly among migrant groups – which increase their likelihood of receiving benefits. Economic resources, in particular, play a non-additive role in shaping these patterns. For example, young men with a first-generation Western migration background and older women with a second-generation migration background exhibited higher levels of benefit receipt, primarily driven by a severe lack of economic resources. While intersectional capital deficits help explain benefit receipt inequalities, this finding applies to only a few specific intersectional groups. This suggests that for most groups, capital disparities – particularly economic resource disparities – do not fully explain the non-additive differences in benefit receipt.

Disparities in returns to capitals in terms of benefit receipt partially explain intersectional inequalities in benefit receipt. Specifically, I find that the effect of economic capital varies between intersectional groups, whereas other capital effects do not exhibit such variation. Notably, the analysis tested two theoretical perspectives: exacerbating effects, where disadvantaged intersections derive lower returns on capital due to systemic barriers that limit their ability to leverage these resources, and buffering effects, where disadvantaged intersections derive higher returns on capital because they use these resources more strategically to overcome systemic barriers. I find supportive evidence for the latter. However, the theoretical reasoning suggests that economic capital serves as a buffering resource for some disadvantaged intersection, enabling them to navigate systemic labor market obstacles such as discrimination and precarious employment conditions (Anderson et al., 2010; Bernardi, 2012). My analysis shows that privileged intersections often experience low returns to economic capital. These findings have important implications for understanding the role of privilege and the differential utilization of capital, as this reliance reflects broader structural inequalities where privileged individuals are less reliant on their resources to avoid benefit receipt, whereas disadvantaged intersections depend more heavily on the limited resources available to them. This dynamic underscores the importance of addressing structural barriers (e.g. discrimination) that constrain access to and the utility of capital for marginalized populations.

Persistency in benefit receipt explains inequalities across intersectional groups. Groups receiving benefits in one period are more likely to continue receiving them in subsequent periods, a dynamic often referred to as the 'Matthew effect' (Merton, 1968, 1988). Vulnerable groups, such as those with African or MENA migration backgrounds, face persistency loops that prolong dependence on social assistance. These loops result from structural barriers and ongoing economic vulnerabilities that hinder exit from benefit receipt. In contrast, other groups experience lower persistence, reflecting differences in resilience and risk of prolonged dependence across intersectional strata. At three intersections we find disproportionately high or low persistence of social assistance. First-generation men from Western Europe and second-generation Polish men exhibit a lower persistence of social assistance receipt than would be expected on the basis of additive factors. For individuals at these intersections, social assistance receipt may not convey as negative a signal, thereby minimally affecting their employment prospects and consequently reducing the probability of subsequent social assistance receipt. Alternatively, as these groups have generally migrated to Norway for employment purposes, they may have a different work ethic and different cultural or personal attitudes towards work and social assistance than other groups. A strong work ethic or a cultural stigma against receiving benefits could lead people to seek employment more intensively, implying that they leave social assistance sooner. On the other hand, first-generation Pakistani, Bangladeshi, and Indian men showed a disproportionately higher persistence, indicating that previous social assistance receipt may adversely affect their likelihood of re-employment and consequently subsequent social assistance receipt.

This dissertation investigated intersectional inequalities in benefit receipt, emphasizing the additive and non-additive effects of intersectional factors, as well as the mechanisms driving these inequalities. While social assistance disparities are largely additive, unemployment insurance receipt exhibits non-additive disparities driven by the interplay of gender, age, migration background, and education. This more granular understanding challenges conventional implicit additive assumption underlying studies about benefit receipt and highlights the importance of intersectionality in welfare research.

1.7.2 Limitations and future research

This study has several limitations that should be acknowledged. First, while the use of register and survey data provided valuable insights, it also imposed constraints on the operationalization of key variables. Certain dimensions of economic (e.g., work experience, Azambuja et al., 2024), social (e.g., relationship quality, Chaker, 2020), cultural (e.g., digital literacy, Ragnedda et al., 2022), and person capital (e.g. appearance, Vrooman et al., 2022), were not captured, limiting our understanding of how these factors might influence benefit receipt. For example, work experience and employment stability, key components of economic capital, can significantly impact an individual's likelihood of needing social assistance, especially in precarious job markets (Heggebø et al., 2020). Similarly, the quality of social relationships, a part of social capital, may affect the availability of support during times of financial hardship, which could influence whether someone applies for benefits (Lin, 2000). Future research could benefit from more comprehensive data collection that includes these aspects to deepen our understanding of the dynamics of benefit reliance.

Second, the use of time-lagged data, while helpful in reducing reverse causality concerns, does not establish definitive causal relationships between the variables (Falkenström, 2024; Gangl, 2010). Although time-lagged data allows for a temporal ordering of events, it does not fully capture the dynamic and potentially reciprocal nature of the relationships between variables (Pearl, 2015). For instance, changes in economic capital, such as losing a job, may influence benefit receipt, but receiving benefits may also impact an individual's economic opportunities and stability over time. The complexity of these interactions requires more sophisticated analytical techniques to draw causal conclusions. Future studies should use robust causal inference methods, such as fixed effects models to better understand the link between resources and benefit receipt, and to more accurately determine the causal pathways involved (Angrist & Pischke, 2008; Gangl, 2010). Employing fixed effects regression would offer a more robust method for drawing causal inferences, as it accounts for unobserved individual traits that remain constant over time (Angrist & Pischke, 2008) and specifically examines how changes in capital influence benefit receipt. To this end, future research with larger sample sizes would be better positioned to investigate these causal links and provide stronger evidence for causal interpretations (Falkenström, 2024).

Third, the study faced challenges related to representation and identity. Official records, such as gender and country of origin, may not fully align with individuals' self-identification, leading to potential inaccuracies in capturing the diversity of experiences. For instance, individuals whose gender identity does not conform to the male/female dichotomy may be misrepresented in the data, which could obscure important differences in benefit receipt patterns across gender-diverse populations (Nelson, 2020). This limitation is particularly pertinent in intersectional research, where particular identity factors may be crucial for understanding inequalities. Incorporating qualitative approaches, such as interviews or focus groups, could offer a richer understanding of marginalized groups' experiences and characteristics in future studies, allowing researchers to better capture the complex realities of these individuals. Furthermore, survey-based studies should aim to measure gender more accurately by including a broader range of gender categories and employing self-identification measures rather than relying solely on administrative records. Enhanced survey design with more inclusive response options would provide a more comprehensive picture of gender diversity, helping to refine our understanding of how intersecting identities influence benefit receipt patterns.

Finally, the study did not account for individuals' eligibility for benefits, which limits the interpretation of the observed patterns in benefit receipt. Eligibility is a complex process influenced by multiple factors, including both individual circumstances and administrative rules (Bennett, 2024). Some individuals who appear eligible may not receive benefits due to barriers such as non-application, lack of awareness, perceived stigma, or administrative hurdles (Janssens & Van Mechelen, 2022). Individuals might avoid applying for benefits because of the stigma associated with welfare or because they lack the necessary information about their entitlements. Conversely, some ineligible individuals might still receive benefits due to errors in the administrative process or because of special considerations, such as discretionary decisions made by caseworkers. Future research should aim to incorporate more detailed data on eligibility criteria and application processes to better capture these complexities and provide a clearer picture of the factors influencing benefit receipt.

Despite these limitations, this dissertation demonstrates the value of quantitative intersectional analyses in uncovering the complexity of social inequalities. While the focus has been on intersectional inequalities in benefit receipt, I strongly advocate for extending quantitative intersectional research to other critical social outcomes. These include income, education, wealth, and socioeconomic status. However, compounded disadvantages may be more pronounced in other domains, such as income or wealth, where intersecting factors like gender and migration background could exacerbate inequalities. Expanding research into these areas could offer a more comprehensive and granular understanding of social inequalities.

1.7.3 Policy implications

The findings of this dissertation have implications for social policy concerning benefit receipt, particularly with regard to addressing the intersectional inequalities revealed in this research. To effectively reduce disparities in benefit receipt, social policies must acknowledge both the additive (the individual contributions of each social characteristic) and non-additive (the interactions between social characteristics) effects of intersecting social factors, such as gender, migration background, age, and education (Crenshaw, 1989; Hankivsky, 2014). Historically, benefit policies have often adopted a one-size-fits-all approach that fails to consider how these intersecting dimensions interact to shape unique vulnerabilities (Hancock, 2007), adopted a so-called "doelgroepbeleid" that mostly focussed on one social characteristic. This research indicates that such an approach is adequate for a large number of intersections, but risks overlooking the compounded challenges faced by certain groups, ultimately worsening inequitable access to social benefits.

One major policy implication is the need for a differentiated approach to social assistance and unemployment insurance programs. Social assistance recipients often experience greater disparities compared to those receiving unemployment insurance, primarily due to factors such as gender, migration background, and age. Policies designed to better target these disparities – for example, through culturally responsive support for migrants, including language-specific job counseling programs, or tailored employment initiatives for older individuals with lower educational attainment, such as specialized retraining courses – could help bridge the gaps in benefit receipt. Moreover, in the context of unemployment insurance, targeted interventions that address gender-specific barriers – such as those affecting migrant women – could ensure that benefits are both more accessible and more adequate. Therefore, social policy must consider not only broad social categories but also the complex ways in which intersecting factors influence individual outcomes, enabling more tailored and effective interventions (Lister, 2021).

Policies addressing benefit receipt disparities should tackle both capital deficits and the unequal returns on capital to effectively reduce inequalities. Disparities in economic resources, mental health, and cultural capital were identified as significant mediators of benefit receipt inequalities, highlighting the need for targeted interventions. Addressing economic capital disparities might involve providing financial support to marginalized communities and improving access to quality education. Similarly, expanding mental health services is crucial, particularly for vulnerable groups such as migrants, who face unique socio-economic pressures and migration-related stress (Bhugra, 2004). By focusing on these capital deficits, particularly economic resources and mental health, social policies can help mitigate structural factors driving persistent inequalities (Marmot et al., 2008).

However, our findings on return deficits underscore that ensuring equal access to resources is insufficient; it is equally important to ensure that different groups can effectively benefit from these resources (Darity et al., 2017). For less privileged groups, the stronger association between economic capital and benefit receipt suggests a need to enhance the returns on capital through tailored interventions. Strengthening community support systems, improving access to resource utilization programs, and designing job training and economic empowerment initiatives that address the specific needs of disadvantaged communities can help bridge this gap (Wilson, 1996). Moreover, the mechanisms underlying benefit receipt disparities vary across specific intersections, indicating that blanket policy solutions are unlikely to be effective. Fine-grained, intersectional approaches are necessary to address these disparities comprehensively.

Persistency loops, which refer to the repeated and prolonged dependence on benefits once initiated, highlight the importance of breaking the cycle of prolonged benefit receipt among vulnerable groups (Shildrick & MacDonald, 2012). To combat these persistency loops, social policies should focus on creating pathways for sustained exit from benefit receipt, particularly for groups with a high risk of prolonged dependence, such as those with African or MENA migration backgrounds (Shutes, 2011). Strategies could include more robust re-employment programs, individualized case management, and supportive follow-up services for those transitioning out of social assistance (OECD, 2023). Addressing structural barriers that contribute to benefit persistency, such as discrimination in the labor market or limited access to stable housing, is also crucial for ensuring that once individuals leave the benefit system, they have the resources and stability to remain independent.

Moreover, these findings underline the added value of adopting an intersectional lens in designing social policies. Social assistance policies that take into account the non-additive effects of intersectional attributes, such as the compounded disadvantages faced by specific migrant groups, are more likely to create equitable outcomes (Bentley et al., 2023). For instance, targeted initiatives aimed at specific subgroups – such as young men with a first-generation Western migration background or older women with a second-generation migration background – could more effectively address the specific ways in which capital deficits and return disparities occur (Hancock, 2007). By moving away from a one-size-fits-all approach and instead implementing data-driven, intersectionally informed policies, social assistance programs can better meet the diverse needs of recipients (Hankivsky, 2014).

In conclusion, the findings of this dissertation suggest that a shift in social policy from generic, broad-stroke interventions to more intersection-based strategies could be useful to some extent. In doing so policies that specifically target capital disparities, ensure equitable returns from resources, and focus on breaking the cycles of persistency in benefit receipt could be instrumental in mitigating intersectional inequalities in benefit receipt (Crenshaw, 1989). An intersectional policy framework not only acknowledges the diversity of experiences among benefit recipients, but also seeks to create conditions for equitable support and opportunities for all, by addressing key components such as targeted resource allocation, culturally responsive services, and specific support mechanisms for compounded disadvantages.

Chapter 2

Intersectionality and benefit receipt: The interplay between education, gender, age and migration background

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Jos Slabbekoorn: Conceptualization, Methodology, Formal analysis, Writing – Original Draft, Visualization. **Ineke Maas:** Conceptualization, Writing – Review & Editing. **J. Cok Vrooman:** Conceptualization, Writing – Review & Editing, Funding acquisition.

ABSTRACT

This chapter examines differences in benefit receipt using an intersectional approach. Intersectionality theory emphasizes the importance of the interplay of multiple social dimensions. Taking this as a starting point, the chapter investigates how different combinations of three demographic variables plus education buffer or amplify benefit receipt and thereby create relatively advantaged and disadvantaged groups. Administrative data were used, sourced from Dutch registers that provide accurate and detailed information on benefit receipt for the entire Dutch population, including small and hard-to-reach segments. Multilevel Analyses of Individual Heterogeneity and Discriminatory Accuracy (MAIHDA) are performed to assess which intersectional groups are relatively advantaged or disadvantaged with respect to benefit receipt. Intersectional group differences are more pronounced for social assistance than for unemployment insurance. Complex combinations of education, gender, age and migration background are required to better understand differences in benefit receipt, especially for unemployment insurance.

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2.1 Introduction

As in most affluent welfare states, in the Netherlands benefit schemes have been created to reduce the consequences of unemployment among the labor force. These benefits (i.e., social assistance and unemployment insurance) aim to help individuals and households to meet their needs and sustain their standard of living to a certain degree (Vrooman, 2009a). In some social groups, the incidence of benefit receipt is elevated due to systemic inequities and discrimination mechanisms (Hoff et al., 2019). Various studies consistently find women, older people, people who followed vocational training and people with a migration background to be more dependent upon benefits (Cappellari & Jenkins, 2014; J. Hansen & Lofstrom, 2009; Hoff et al., 2019; Königs, 2014b, 2018). These social groups might be at greater risk to experience negative consequences because – in spite of the monetary support provided by these schemes – benefit periods tend to increase the risk of poverty and to lower people's wellbeing (Huber et al., 2011; McKee-Ryan et al., 2005).

Prior research on benefit receipt has typically relied on the implicit assumption that the advantages and disadvantages from various social dimensions are independent of one another. There are a few notable exceptions, which considered non-additive accumulation of disadvantage by running separate models for men and women or migrants and natives (Bergmark, 2004; Smedsvik et al., 2022). However, a growing body of intersectional literature argues that social dimensions constitute overlapping co-determinants of (dis)advantages (Choo & Ferree, 2010). From that perspective, previous studies may have under- or overestimated the (dis-)advantages faced by certain people, if they ignored the interdependence of multiple social characteristics and an intersectional approach to studying benefit receipt seems warranted.

Intersectional approaches (Cole, 2008; McCall, 2005) comprise a theoretical and analytical framework that considers multiple social dimensions simultaneously (e.g., gender, race, class and age). It is argued that the combination of such characteristics creates a unique social landscape that shapes the social identity and reality of individuals. The key idea behind intersectional approaches is that (dis-)advantages from multiple social dimensions do not simply add up but can influence each other. The multiple jeopardy hypothesis argues that being a member of multiple marginalized social groups can have larger negative effects than the simple combination of negative effects from all social group memberships (King, 1988; Settles & Buchanan, 2014). This amplification implies an added penalty for combining disadvantage from multiple marginalized group memberships, resulting in higher relative disadvantage and an increased risk of benefit receipt. Likewise, it is possible that membership of multiple marginalized social groups compensates part of the disadvantage that a specific social dimension might bring. For instance, women with a migration background seem to be able to partially buffer their disadvantage (Arai et al., 2016), and this indicates that certain groups can experience a relative advantage through specific combinations of risk factors.

Intersectional quantitative studies are scientifically relevant because they provide a more detailed understanding of social inequality that accounts for the ways in which multiple forms of disadvantage intersect and interact. Recently, quantitative approaches in the analysis of intersectional inequalities are becoming increasingly popular. Thus far, these studies have mainly focused on labor market discrimination at the intersection of gender and migration background (Arai et al., 2016; Di Stasio & Larsen, 2020), or people's health at the intersection of age, migration background and SES (Axelsson Fisk et al., 2018; Evans et al., 2018; Kern et al., 2020). Intersectional insights may also be relevant for policy makers. Rather than focusing on broader population groups (e.g., young people, older people or people with a migration background) which is currently common practice, intersectional insights may help to focus efforts of social policy on specific subgroups (e.g. older people with a migration background) with an especially high incidence of benefit receipt.

The first contribution of this chapter is theoretical. It adds to the literature by developing a typology of six combinations of disadvantages and advantages, which identify patterns of social inequality that are often overlooked in traditional quantitative approaches. By using an intersectional and mechanism-based approach, we theorize how different forms of disadvantage and advantage might combine to shape social outcomes. Hereby, we move beyond simple descriptions of patterns of inequality and towards a more sophisticated understanding of the underlying mechanisms that drive these patterns. Secondly, we introduce a new and efficient way of analyzing the many interactions implied by intersectional research to mainstream sociological research. Multilevel Analyses of Individual Heterogeneity and Discriminatory Accuracy (MAIHDA) has – with very few exceptions – only been used in medical studies (Bauer et al., 2021). As we will show, it is a parsimonious method to estimate the advantages and disadvantages of the 163 intersectional groups that we distinguish. Third, we use register data covering the complete population of the Netherlands, that include small and hard to reach population segments (e.g., older low-educated women with a migration background), that may be especially disadvantaged. We will therefore also provide descriptive results that can guide policy interventions. By identifying the specific ways in which different groups experience inequality, policymakers can more effectively target interventions to address the root causes of social inequality and promote greater equity.

Therefore, this chapter explores the complexities of inequality in social benefit receipt by answering two questions: (1) *to what extent do intersectional differences (i.e., unique combinations of education, gender, age and migration background) occur in benefit receipt in the Netherlands?* And (2) *which intersections are relatively disadvantaged or advantaged (i.e., show non-additive negative or positive effects on benefit receipt)?*

In this chapter, register data from the System of Social Statistical Datasets (SSD) were used, which are made available by Statistics Netherlands (CBS). This database consists of interlinked datasets on the entire population of the Netherlands. These data contain reliable and detailed information on benefit receipt. Multilevel Analyses of Individual Heterogeneity and Discriminatory Accuracy (MAIHDA, Axelsson Fisk et al., 2018) are used to analyze the intersectional nature of benefit receipt. This chapter focuses on two programs that provide financial support to people who have experienced a partial or complete loss of employment: benefits based on the Unemployment Insurance Act (Werkloosheidswet, or WW) and general Social Assistance (Bijstand). Dutch unemployment insurance is available to individuals who involuntarily lost paid employment. Its duration is limited and in order to be eligible, people must have worked 26 weeks out of the previous 39; if they are entitled, the benefit lasts between 3 and 38 months, depending on their employment history. Unemployment insurance benefits levels are 70-75% of a person's previous earnings from waged employment (up to a maximum amount) and entitlements are not means-tested. Social assistance provides financial support to adults in households whose combined income is below the statutory social minimum and whose assets do not exceed 7,575 euro for single person households and 15,150 euro for household with more than one adult person. This includes housing property of which the first 63,900 euros of equity on the house is exempted. In line with the European Union directive for non-discriminatory social policies, the entry requirements for social assistance and unemployment insurance are not dependent upon nationality and these benefits are accessible to all (previously employed) individuals legally residing in the Netherlands. The only exceptions pertain to immigrants with a short-term residence permit who recently came to the Netherlands. Together, these benefit schemes serve as an integrated social welfare system that covers the risk of unemployment due to economic factors. Individuals can transition from unemployment insurance to social assistance when they have surpassed the maximum period of unemployment insurance and meet the eligibility criteria for social assistance. Since the determinants for receipt of these benefits may be vastly different, they are analyzed separately in our main analyses.

2.2 Theoretical background

In the subsequent section, we will first present theoretical arguments on disparities in benefit receipt related to education, gender, migration background and age separately. This gives an overview of the current state of social welfare research and explicates which social groups have a generally higher incidence of benefit receipt. Following this, we will present an intersectional theoretical argument, offering an overview of six pathways through which (dis-)advantages stemming from multiple social identities may intersect and subsequently influence the relative advantage or disadvantage with respect to the likelihood of benefit receipt for intersectional groups.

2.2.1 Education

A substantial sociological and economic literature analyses the effect of educational attainment on employment (G. S. Becker, [1963] 1993). While the knowledge gained during education can be considered a valuable resource in itself (Bernstrøm et al., 2018) educational systems also form an important locus for the (re-)production of social class (Bourdieu, 1986; Thompson, 2019). Educational qualifications serve not only as an indicator of knowledge, skills and competences, but also as an indicator for the composite value of embodied cultural capital. This implies a poorer competitive position on the labor market for lower educated individuals, who consequently are less likely to find secure and stable employment. Social segregation further strengthens those dynamics. Individuals establish long-lasting relationships and accumulate social capital at school. Later in life on the labor market, jobseekers can receive job referrals, support and recommendations from their contacts which improve their employment chances (Kristiansen, 2021; Munasib, 2007). Lower educated individuals may have fewer valuable contacts who could help them find a secure and stable job. Furthermore, lower educated people have less healthy lifestyles, since they experience poorer life and work circumstances (i.e., living in unhealthy neighborhoods and physically demanding jobs), have more limited opportunities for healthy behavior (Brunello et al., 2016). This puts them at higher risk to be without a job due to health reasons. Based on the reasoning above, it is expected that lower educated people are generally more likely to receive a benefit than higher educated people.

2.2.2 Gender

Although the gap in educational attainment between men and women has recently closed, women consistently hold lower status and less secure jobs than men (van den Brakel et al., 2020). Living up to gendered expectations of society at large and their own social circles, women might make different career and study choices, as they anticipate motherhood-related changes in employment later in life (Gati & Perez, 2014; Jansen et al., 2021; Morgan et al., 2013). Many women seek employment in sectors that are motherhood-friendly (Aisenbrey et al., 2009). In addition, women may be more willing to take-up lower status and less secure jobs in order to combine family and work commitments (e.g., through part-time or zero-hour contracts: van den Brakel et al., 2020). Some women are voluntarily jobless and live in a traditional household where the man is the sole breadwinner. In the case of divorce or a deceased partner, these women in particular are prone to be on social assistance, as their inactivity on the labor market makes them ineligible for other benefits. Additionally, this labor market status and childcare responsibilities can reduce their opportunities to find stable employment. Lastly, women face discrimination on the labor market contingent on the risk of work absence during pregnancy and periods of maternal leave (S. O. Becker et al., 2019; Correll et al., 2007), combined with gendered expectations of employers (Di Stasio & Larsen, 2020). In turn, this can make it more difficult to find stable and secure employment (González et al., 2019). All in all, women face several disadvantages that increase their likelihood of unemployment and the risk of benefit receipt. Therefore, it is expected that women are, in general, more likely to receive a benefit than men.

2.2.3 Age

At the end of their professional careers, people have accumulated (work-specific) experience, knowledge, skills, contacts and status. However, some knowledge and skills of people in their 50s and 60s may have become obsolete or less valuable on the labor market (Victor, 2013). For instance, some older people may experience greater difficulty in acquiring skills that are essential in the increasingly digitalizing labor market (Hargittai et al., 2019). Additionally, older people may face age discrimination, which affects employers' hiring decisions (Lössbroek et al., 2021). This may, in particular, reduce their chances of re-entering the labor market after losing their jobs (Birkelund, 2016; Ng & Feldman, 2012), thus increasing the likelihood for long-term unemployment. Lastly, since health tends to deteriorate with age (Levinsky & Schiff, 2021), older people are more likely to lose employment due to health reasons. All in all, it is expected that older people are generally more likely to receive a benefit than less senior people.

Young people are at the start of their professional careers and often are still in the process of acquiring (work-specific) skills, knowledge, and contacts. Therefore, they typically hold unstable, short-term, lower status jobs, such as traineeships (Quintini & Martin, 2006). Therefore, the risk for young people to become unemployed is greater; but due to their limited work experience, they are less likely to be eligible for Dutch unemployment insurance benefits. If they are entitled, young people can rely on unemployment insurance benefit for a shorter period of time, since its duration is based on the individual employment history. Additionally, young people who enter into benefit receipt are more likely to obtain help from regional employment offices. Active Labor Market Policies in the Netherlands, as in other EU countries, specifically target younger age groups, as they are deemed easier to help to work (Spies, 2017). Therefore, young people can get out of benefit receipt more easily. In sum and despite their position in the labor market, it is expected that younger people are generally less likely to receive a benefit than mid-aged and older people.

2.2.4 Migration background

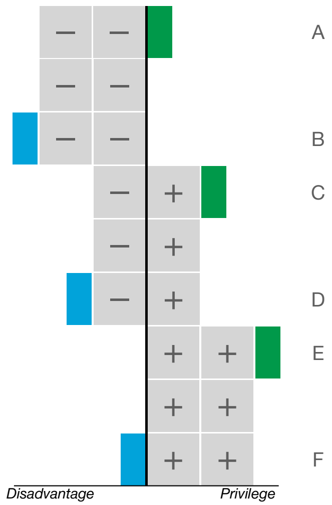
There are considerable differences between migrant groups and natives, which may translate into diverging incidence rates of benefit receipt (Connor & Koenig, 2015; Jongen et al., 2020). On the one hand, poorer language proficiency of some groups of first generation migrants may on average lead to a lower take- up of benefits when eligible. However, findings regarding the take-up of benefits are mixed; where some studies find comparable take-up of benefits between migrants and natives (Castronova et al., 2001; Strockmeijer et al., 2020), others find lower take-up of benefits (Renema & Lubbers, 2019). Recent migrants may also have a too short employment history to be eligible for unemployment benefits, but with the exception of those who are in the Netherlands shorter than 3 months, all legal migrants are eligible for social assistance. We do not expect that eligibility and differential take-up will lead to a substantial lower incidence of benefit receipt for migrants compared to natives.

On the other hand, migrants are more likely to have deficiencies in resources, leading to poorer labor market outcomes (Siebers & van Gastel, 2015). There is a substantial gap in Dutch language proficiency between several migrant groups and natives, although this is less among second generation migrants (Sevinç, 2016). Since proficiency in the Dutch language is required for many jobs, the employment chances for people with a migration background are likely to be reduced and consequently it might be expected that they have a higher likelihood of benefit receipt. Studies also consistently find that – even when the levels of resources are equal – people with a migration background face additional forms of disadvantage on the labor market (Blommaert et al., 2012; Gracia et al., 2016). Research shows that they are less likely to be invited for job interviews, probably because the prevailing ethnic stereotypes inform the choices that employers make (Thijssen et al., 2021). It is found that ethnic discrimination particularly affects individuals with a migration background from countries that are less socio-economically developed than the Netherlands, such as Turkey and Morocco. On these grounds, it is expected that people with a migration background are more likely to receive a benefit than people without a migration background. In addition, we expect the incidence of benefit receipt to depend on country of origin and to be highest among first generation migrants, and lower among second generation migrants.

2.2.5 Intersectionality and benefit receipt

Intersectionality theory argues that memberships of multiple social groups (e.g., gender, migration background, education, age) are interconnected and should be understood in relationship to each other (Cole, 2008). Thus, the meaning and implications of being a member of a certain social group (e.g., being a migrant) is conditional on other social dimensions (e.g., people's age, education, or gender). From an overarching perspective, the intersectional literature provides a framework through which the combination of disadvantages and advantages can be studied (Settles & Buchanan, 2014). The core idea behind this strand of literature is that the combination of advantages and disadvantages stemming from various social dimensions can be more complex than a simple sum of parts. In academic fields like gender studies, an intersectional lens is commonly used to study multiply disadvantaged groups (Crenshaw, 1989). However, theoretically, there are six possible non-additive ways in which disadvantages and advantages from two social identities can be interconnected (numbered A – F in Figure 2.1). The remainder of our theoretical argument will further elaborate upon the ways disadvantages and advantages could combine and mutually influence each other. First, three cases where people are relatively disadvantaged (shaded orange in Figure 2.1) will be discussed. At these intersections, people are worse off than would be expected based on a simple combination of advantages and/or disadvantages (Bask & Bask, 2015). In essence, people face an extra penalty for their multiple group membership. Second, a discussion of three cases that could lead to a relative advantage (shaded blue in Figure 2.1) follows. These cases are better off than expected based on the simple combination of advantages and/or disadvantages.

Inherently, relative (dis)advantages stem from comparisons between intersections. This implies that a relative disadvantage for one intersection might be resulting from a relative advantage of another intersection. For example, the multiple jeopardy for black women in the US (Crenshaw, 1989) can only arise in a social context where another group holds privileged positions – in this case white men. This double-edged sword principle always applies when comparing dichotomous cases, such as those that are discussed in the remainder of our theoretical argument. However,



Note: Gray squares with a [—] denote disadvantageous social characteristics. Gray squares with a [+] denote advantageous social characteristics. Green rectangles denote the extra rewards for relatively advantaged groups. Blue rectangles denote the extra penalties for relatively disadvantaged groups. In addition to the six interconnected combinations of advantages and disadvantages (number A through F), the additive combinations (i.e., those that do not comprise extra rewards or penalties) are included as a baseline.

Figure 2.1: Intersectional combinations of advantages and disadvantages

in higher dimensional intersectional comparisons – as is the case in our analysis – one relative disadvantage is not necessarily opposed to a specific advantaged group but could be caused by factors that particularly burden a specific intersectional group.

2.2.5.1 Relative disadvantage

King's (1988) famous multiple jeopardy hypothesis comes to mind first when thinking of relatively disadvantaged groups. The multiple jeopardy hypothesis posits that simultaneously being a member of more than one marginalized group exceeds the negative effects of a simple addition of disadvantages. Disadvantages from multiple sources could amplify each other and result in an additional penalty that increases the risk of negative experiences (case B in Figure 2.1). The multiple jeopardy hypothesis (Beal, 2008; King, 1988) was developed to study the marginalized position of black women in the United States. However, other intersectional groups might face a multiple jeopardy in similar ways, such as: lower educated migrants. Lower educated migrants are for example less fluent in Dutch than higher educated migrants. This could further aggravate the ethnic disadvantage on the labor market, which could make them more vulnerable for benefit receipt.

Furthermore, intersectional groups that combine an advantage and disadvantage could still be relatively disadvantaged (case D in Figure 2.1). These intersectional groups might not completely compensate their disadvantage with their advantage, since they might not be able to fully benefit from their advantaged position. A first example of such a case can be found in the classic work of Blau & Duncan (1967), who show that black men benefitted less from having a higher educational attainment than their white counterparts. Due to factors like discrimination, black higher educated men were less likely to be employed and if they had found employment, they did so in lower status jobs than white men with the same education. A second example concerns lower educated men who benefit from gender privilege but are disadvantaged due to their educational attainment. For men, having a lower education might pose a relatively bigger disadvantage, since jobs that are typically held by lower educated men are more susceptible to being crowded out, than jobs typically held by lower educated women (Gesthuizen & Wolbers, 2010; Sum et al., 2011). Additionally, lower educated men work in more physically demanding jobs than lower educated women, which increases their risk of benefit receipt (Lund et al., 2001).

In a similar vein, multiply advantaged groups might not be fully able to benefit from their advantaged position (case F in Figure 2.1). Where multiple privileges can help to acquire positions of power and higher income, they might not help to provide additional protection against benefit receipt. And especially regarding benefit receipt, there might be diminishing returns to advantages. Once a social group is sufficiently advantaged to reduce the risk of benefit receipt (e.g., by being likely to hold a secure job), advantages from another social identity might only marginally lower the risk of benefit receipt. For example, the risk of benefit receipt of higher educated individuals is probably affected less by privilege from their gender- or native background-identity than the risk of lower educated individuals.

2.2.5.2 Relative advantage

Quantitative research on labor market discrimination that studied the intersection of gender and migration background found a reverse gender gap , case A in 2.1. Although women with a migration background combine two disadvantaged social characteristics, these studies show that they have a relative advantage compared to men with a migration background on the labor market. It is argued that discrimination based on ethnic stereotypes particularly impacts men, since their profile is more in line with the prevailing ethnic stereotypical prototypes (e.g., higher likelihood of having a criminal past, aggression, female unfriendly, see Eagly & Kite, 1987; in Bursell, 2014). Since women with a migration background fit these ethnic stereotypes less well, their ethnic penalty might be partially buffered (Purdie-Vaughns & Eibach, 2008). Therefore, women with a migration background might be less vulnerable for benefit receipt compared to men with a migration background.

Similarly, intersectional groups that combine an advantage and disadvantage, might be able to overcome some of the disadvantage they experience. As such, these groups do better than expected based on the simple combination of their advantage and disadvantage (case C in Figure 2.1). For instance, higher educated older men might be able to turn their age disadvantage into an advantage. Older men may have profited from Matthew effects and have accumulated career success (Damian et al., 2015). This career success consolidates in having increased job security (i.e., having a tenured job position, see: Chkalova et al., 2017). In turn, their age effect is more positive than for women; older women less often hold tenured job positions, since many women reduced working hours after childbirth.

Lastly, having multiple advantaged identities could be considered an advantage in itself (case E in Figure 2.1). And just as disadvantages may strengthen each other and thereby create an additional punishment, two advantages can be mutually reinforcing and bolster one's position even further (Cole, 2008; Settles & Buchanan, 2014; Shields, 2008). White men in particular may experience mutually reinforcing advantages on the labor market. Since powerful people who make hiring decisions are (and traditionally have been) male with a native background, the labor market is an environment that may favor white men in two ways. First, employers may make homophily-based choices and prefer to hire candidates that are most similar to them (white men prefer to hire white men). Second, employers may prefer to hire candidates that are most similar to people that have formerly held similar positions. Since a large share of high-status jobs is held by men, this makes it disproportionately likely that they will be hired in high status jobs (Kim, 2006; Settles & Buchanan, 2014), in turn lowering their risk for benefit receipt.

In the section above, six examples of complex combinations of advantaged and disadvantaged social characteristics that could lead to a relative advantage or a relative disadvantage for certain intersectional groups were discussed. These examples mainly comprised intersections of two social characteristics and illustrated how these can be mutually influential. The focus on dyadic intersection was made intentionally to provide a simple overview of the general theoretical mechanisms that could illustrate the potential impact of different intersections on social outcomes. Additionally, not all possible combinations of age, gender, migration background and educational attainment were discussed because there is currently little theoretical work available for the intersections of concern in this chapter. A detailed discussion of all possible combinations of age, gender, migration background and educational attainment would forgo the exploratory aims of this chapter, which is to numerically identify relatively disadvantaged and advantaged groups.

2.3 Data and methods

2.3.1 Data

For this chapter, register data from the Social Statistical Datasets (SSD) were used (under certain conditions, these data are accessible for statistical and scientific research. For further information: microdata@cbs.nl). This database comprises over forty standardized and interlinked administrative datasets, sourced from various Dutch registers (Bakker et al., 2014). In this chapter we sourced data from PERSOONSTAB, SECMBUS and HOOGSTEOPLTAB which contain information that is provided by Dutch Municipalities (Person Population Register, Administration of Employee Insurance Schemes) and Governmental Administrations (Administrations of Employee Insurance Schemes and the Social Security Bank) as well as individual tax and education data. These data provide a unique opportunity for quantitative intersectional analyses of benefit receipt because it contains detailed and reliable data on benefit receipt for all registered inhabitants of the Netherlands, including harder to reach populations.

The observation period was limited to start at 01-01-2006 and end at 31-12-2019 because data for some benefits were only included in the SSD as of 2006 and to exclude potential COVID19-related biases. Our sample was limited to employable individuals of working age using the following criteria: (a) they should be at least 25 years of age in 2019, (b) they should be younger than 60 years of age in 2006, (c) they should not be a student or pensioner (since these groups may not be eligible due to other social provisions they receive) and (d) they should at least have 3 years of observations. This resulted in a sample of approximately 6.5 million employable individuals of working age. Then, a stratified sample per intersectional group was drawn to facilitate the estimation of our analytical models. For privacy reasons, 17 intersectional groups were excluded, since they consisted of fewer than 100 individuals. From strata with fewer than 600 individuals half of the individuals were selected and from strata comprising 600 or more individuals 300 individuals were. This resulted in at an analytical sample of 41,599 individuals. This sampling procedure was repeated twice (not including the same individuals) to create a comparable training-sample, which was used for model calibration purposes.

2.3.2 Operationalization

2.3.2.1 Dependent variables

Two dependent variables were constructed: *social assistance benefit receipt* and *unemployment insurance benefit receipt*, using information from the national income register. This register contains information about individuals' major source of income per month. This information was aggregated such that the variables indicate whether an individual had received a benefit (i.e., social assistance or unemployment insurance benefit) as a main source of income for at least three consecutive months during the observation period. Unlike many econometric studies on benefit receipt that analyze entry and exit rates (Cappellari & Jenkins, 2014; J. Hansen & Lofstrom, 2009; Hoff et al., 2019; Königs, 2014b, 2018), our operationalization focuses on the incidence of benefit use. This captures the net effect of entry and exit rates, reflecting who ultimately utilizes these programs. While acknowledging that social assistance typically targets households, we analyze individual data of social assistance receipt because all household members have to be eligible for social assistance in order to receive it and we assume the household members will share the benefit.

2.3.2.2 Independent variables

Gender was operationalized as the registered gender in the 2019 register. Information from the 2019 register was used to include all potential changes in registered gender. In 2014 restrictions were lifted that prohibited changes in registered gender in the Netherlands. Therefore, the most recent record in the person registration is more likely to reflect the gender expression of an individual.

Age groups: the following three age groups were constructed: young [25-34], middle [35-49] and old [50-59]. Observations of individuals were censored if they were younger or older than the outer range of their age group. For example, observations between 2006 and 2011 were excluded for individuals who turned 25 in 2012.

Education was operationalized to indicate whether an individual holds a university degree. Information from HOOGSTOPLTAB was used, which is a microdata source from Statistics Netherlands based on administrative and survey data. Per individual, the first available record in the education register after they turned 25 years old was used. This data source suffers from systemic incompleteness in the registration of non-academic levels of education due to the gradual roll-out of the registration. In the past three decades the registration of education was implemented in the following chronological order: universities (1983), universities for applied science (in Dutch HBO, 1986), high schools (2003/04), schools for vocational training (in Dutch MBO, 2004/05). Some missing information was imputed by Statistics Netherlands using information from the Labour Force Survey. Therefore, no distinction was made between other levels of educational attainment. People with an academic degree have the lowest incidence of benefit receipt (Saarela, 2004).

Migration background was constructed using the registered country of birth of individuals and their parents from the person register. Eight origin groups were constructed: Dutch, Dutch Antillean, Moroccan, Surinamese, Turkish, Central and Eastern European, Other European and a miscellaneous group. These origin groups were chosen to provide more detailed information for the largest migration groups in the Netherlands, while retaining information on all people with a migration background from other countries. For all non-Dutch origin groups, it was distinguished whether an individual was a first-generation immigrant (foreign-born) or second-generation migrant (native-born with at least one foreign-born parent). For first-generation migrants, the individuals' country of birth was used to infer migration background. For second generation migrants, the birth country of the mother was used, except when the mother was born in the Netherlands, then the country of birth of the father was used to infer migration background. Individuals who were born in the Netherlands and whose parents were both born in the Netherlands were classified as Dutch natives. For the descriptive statistics of the variables used in our analyses, see Table 2.1.

Table 2.1: Descriptive statistics of the employable population and analytical sample

	Core Workforce (%)	Analytical Sample (%)
Gender		
Female	0.500	0.502
Male	0.500	0.498
Age		
Young	0.461	0.387
Middle	0.355	0.357
Old	0.184	0.256
Migration Background		
Dutch	0.733	0.080
Dutch Antilles 1st gen.	0.010	0.063
Dutch Antilles 2nd gen.	0.003	0.052
Moroccan 1st gen.	0.017	0.065
Moroccan 2nd gen.	0.009	0.042
Surinamese 1st gen.	0.017	0.074
Surinamese 2nd gen.	0.011	0.065
Turkish 1st gen.	0.019	0.068
Turkish 2nd gen.	0.011	0.044
Eastern European 1st gen.	0.017	0.072
Eastern European 2nd gen.	0.002	0.057
Other European 1st gen.	0.024	0.080
Other European 2nd gen.	0.022	0.080
Other 1st gen.	0.071	0.080
Other 2nd gen.	0.036	0.080
Education		
Academic	0.125	0.442
Non-Academic	0.875	0.558
Benefit Receipt		
Social Assistance	0.100	0.168
Unemployment Insurance	0.192	0.301

Note: For categorical or binary variables, the mean reflects the proportion. Due to rounding, the proportions of some categorical variables may not add up to exactly 100 percent. N(Analytical Sample) = 45,119, N(Core-Workforce) = 6,555,549. **Source**: Authors' own calculation based on non-public individual level register data from the Social Statistical Datasets (SSD) of Statistics Netherlands (CBS).

2.3.3 Analytical Strategy

In this chapter Multilevel Analysis of Individual Heterogeneity and Discriminatory Accuracy (MAIHDA) (Axelsson Fisk et al., 2018) were used, for which Bayesian logistic multilevel regression models were estimated in Stata 16.1 (for a more detailed and technical description of our analytical procedure see Section A.1). MAIHDA has rapidly become the state-of-the-art method for intersectional quantitative research, as it overcomes some of the key challenges that quantitative intersectional analyses pose (Evans et al., 2020): (a) Traditional models risk inflating false positives, especially for small groups. MAIHDA employs "shrinkage" to pull interaction effect estimates towards the mean, reducing this risk and ensuring reliable findings. (b) Explicitly modeling every interaction between all social dimensions can be cumbersome. MAIHDA treats "multiplicative" effects as random intercept variations, leading to a simpler and more efficient model. (c) Theoretically, situating individuals within intersectional social strata, as MAIHDA does, reflects the focus on group level processes of inequality, which aligns well with the existing intersectional and social stratification literature.

In our models, individuals were nested in intersectional strata. These intersectional strata comprise all unique combination of gender, age groups, migration background groups (including first and second generation) and educational attainment (respectively: $2 \times 3 \times 15 \times 2$). In our sampling procedure, 17 intersectional strata that had fewer than 100 members in the employable population were excluded, which resulted in 163 intersectional strata. Social assistance and unemployment insurance were modelled separately.

First, baseline models (indexed: 0) were estimated. These models only include the intercept (denoting the overall average incidence), as well as random intercepts (denoting the differences between the predicted incidence per intersectional stratum and the overall average incidence). These models were used to estimate the incidence of benefit receipt for all intersectional strata. The baseline models were also used to calculate the intraclass correlation (ICC). The ICC serves as a measure for discriminatory accuracy and tells how much of the variation in benefit receipt can be attributed to differences between intersectional groups.

Second, so called partially adjusted models were estimated, one for each social dimension that was used to construct the intersectional strata (indexed: $1-4$). In these models, dummy variables for each social group per dimension were included. These models were used to calculate how much of the between strata variance can be explained by the respective social dimension, for which the proportional change of variance is calculated (PCVs, see Section A.2).

Third, fully adjusted models were estimated, in which all additive effects of all social dimensions were included simultaneously (indexed: 5). These models were used to calculated how much of the between strata variation in benefit receipt can be explained. The remaining stratum level variation in benefit receipt can be attributed to the complex combinations of social dimensions, which could lead to relative (dis-)advantages. The estimated random intercepts of this model denote the difference between the actual incidence per stratum and the predicted incidence based on the additive effects per stratum. In other words, the random intercepts of the fully adjusted model capture the relative (dis-)advantage per intersectional stratum. These are often referred to as the intersectional effect or multiplicative effect.

A possible further step in modelling intersectional differences in benefit receipt would be to add control, mediating or moderating variables. However, we refrain from doing so, because we first want to establish to what extent intersectional effects exist. In light of recent discussion of MAIHDA models regarding the interpretation of model estimates, we would like to repeat Evans and colleagues' (2020) counterarguments. First, the fixed effect predictions are weighted for sample size and provide conservative estimates of grand means per social dimension. This is one of the advantages of MAIHDA – as it reduces the influence of the majority group in the sample in the estimates of the fixed effect – which prevents that the majority group is used as a default with which other strata are compared. Second, the critique against interpretation of the fixed effect predictions in MAIHDA (Lizotte et al., 2020) focuses on specific simulated conditions, where group level variation is unrealistically high. In conditions with minor to moderate group level variation – like in the case of this chapter – grand means fall within the credible intervals of the fixed effect predictions.

We ran additional analyses to assess the relation between the length of the observation likelihood and benefit receipt incidence (see Section A.3). We do not find an association between duration and social assistance incidence. We do find a weak positive association with the incidence of unemployment insurance, however, this association disappears when we take age group into account. This suggests that the initial association with unemployment insurance was driven by age related difference in the duration of the observation period.

2.4 Results

2.4.1 Explained variances

Table 2.2 shows the results for Model 5, including the calculated ICCs and PCVs for social assistance and unemployment insurance benefit receipt (see Section A.2 for the "PCVs" of the partially adjusted models 1–4). For social assistance benefit receipt, it is found that group differences can explain 11.3% of the variation in incidence (ICC = 0.113, calculated using Model 0). This shows that there are substantial differences in social assistance receipt between intersectional groups; however, social group membership is by no means the sole contributing factor. The differences between intersectional groups can be largely explained in additive terms. 79.3% of the differences between intersectional groups are due to differences by gender, migration background, age and education (PCV = 0.793). The remaining 20.7% of intersectional group differences can be attributed to the complex combinations of social dimension associated (dis-)advantages. Men have a 1.6%pt lower social assistance benefit receipt incidence of social assistance than women. People aged between 35 and 49 have a 1.3%pt higher incidence than young people, but note that this might be due to the longer observation period for the middle-aged-group. People with an academic degree have a 14.3%pt lower incidence than people without an academic degree. Regarding migration background, notable differences emerge compared to the reference category of native Dutch individuals. A lower social assistance incidence was found among first and second generation Dutch Antileans, Eastern and other Europeans, second generation Moroccans, Surinamese, Turkish and migrants with another origin. First generation Surinamese had a similar incidence as Dutch Natives. A higher social assistance incidence was found among first generation Moroccans, and migrants with another origin. Compared to the overall incidence of social assistance receipt in or sample of 12.1%, these differences are moderate to substantial.

For unemployment insurance benefit receipt, 4.1% of the variation in incidence can be explained by intersectional group differences. Compared to social assistance a smaller fraction can be attributed to differences between intersectional strata and other contributing factors play a more important role in unemployment benefit receipt. Conversely, although differences between intersectional groups in terms of unemployment insurance benefit incidence are smaller compared to social assistance, the complex combinations of gender, migration background, age and education play a relatively larger role. A considerable fraction of the intersectional group differences (100–51.7 = 48.3) is attributable to non-additive effects. Still we found the following additive effects. Men have a 2.4%pt higher incidence of unemployment insurance benefit. Young people have an 8.9%pt lower incidence compared to people of middle age and a 4.8%pt lower incidence compared to older people. Older people have a 4.1%pt lower incidence compared to people of middle-aged. Academically educated people have a 10.4%pt lower incidence compared to people without an academic degree. Regarding migration background, credible differences arise when compared to native Dutch individuals. Specifically, both first- and second-generation Dutch Antilleans, Moroccans, and Turkish, as well as second-generation Surinamese, Eastern and Other Europeans, and migrants of other origins, experienced a lower incidence of unemployment insurance receipt. In contrast, first-generation Surinamese and Other European migrants had incidences similar to those of native Dutch, while first-generation Eastern Europeans and migrants of another origin exhibited higher incidences. These differences range from moderate to substantial relative to the baseline unemployment benefit recipiency rate of 29.2%.

2.4.2 Predicted incidences

Figure 2.2 shows the predicted incidence of social assistance and unemployment insurance benefit receipt for all strata (numerical values are available in Section A.2). Distinct patterns in social assistance utilization across demographic groups become apparent. Individuals with a migration background display a higher incidence of receiving social assistance compared to native strata. There are two exceptions: immigrants of European origin and second-generation immigrants with academic qualifications. They exhibit incidence rates similar to native strata. For social

Table 2.2: MAIHDA results for social assistance and unemployment insurance receipt

	Social Assistance	Unemployment Insurance
Intercept	0.312	0.414
	(0.286;0.342)	(0.404;0.427)
Gender (Ref. female)		
Male	-0.016	0.024
	(-0.022;-0.009)	(0.015;0.031)
Migration Background (Ref. Dutch)		
Dutch Antilles 1st gen.	-0.075	-0.071
	(-0.087;-0.062)	(-0.089;-0.053)
Dutch Antilles 2nd gen.	-0.125	-0.096
	(-0.132;-0.118)	(-0.117;-0.072)
Moroccan 1st gen.	0.085	-0.024
	(0.044;0.115)	(-0.045;-0.002)
Moroccan 2nd gen.	-0.095	-0.102
	(-0.105;-0.084)	(-0.115;-0.088)
Surinamese 1st gen.	-0.011	0.006
	(-0.029;0.017)	(-0.012;0.022)
Suriname 2nd gen.	-0.077	-0.045
	(-0.096;-0.057)	(-0.055;-0.037)
Turkish 1st gen.	0.001	-0.032
	(-0.026;0.029)	(-0.047;-0.012)
Turkish 2nd gen.	-0.142	-0.083
	(-0.153;-0.132)	(-0.095;-0.072)
Eastern European 1st gen.	-0.084	0.046
	(-0.103;-0.068)	(0.026;0.064)
Eastern European, 2nd gen.	-0.112	-0.116
	(-0.129;-0.089)	(-0.131;-0.100)
Other European 1st gen.	-0.083	0.012
	(-0.094;-0.070)	(-0.011;0.033)
Other European 2nd gen.	-0.124	-0.061
	(-0.148;-0.101)	(-0.074;-0.044)
Other 1st gen.	0.081	0.002
	(0.037;0.123)	(-0.011;0.012)
Other 2nd gen.	-0.105	-0.076
	(-0.125;-0.082)	(-0.087;-0.066)
Age (ref. Young)		
Middle	0.013	0.089
	(0.003;0.024)	(0.076;0.105)
Old	0.003	0.048
	(-0.007;0.014)	(0.034;0.064)
Education (ref. Academic)		
Non-Academic	-0.143	-0.104
	(-0.158;-0.131)	(-0.114;-0.093)
Log Likelihood	-17478.227	-26582.606
	(-17497.368;-17460.117)	(-26602.325;-26565.723)
ICC	0.113	0.041
	(0.090;0.140)	(0.032;0.052)
PCV	0.793	0.517
	(0.743;0.838)	(0.317;0.670)

Note: Averages of the fixed effects (AME) posterior distributions, 95% credible interval between parentheses. N(individuals) = 45,119. ICC is calculated using Model 0. **Source**: Authors' own calculation based on non-public individual level register data from the Social Statistical Database (SSD) of Statistics Netherlands (CBS).

assistance benefit receipt, the lowest incidence is found among Dutch middle-aged women with an academic degree ($\widehat{P}$ = 0.014; 1.4%). People with a Dutch or European background with an academic degree generally have the lowest incidence of social assistance. The highest incidence of social assistance benefit receipt is found among older women with a first-generation Moroccan migration background who did not have an academic degree ($\widehat{P}$ = 0.595; 59.5%). Among the groups with the highest incidence of social assistance an over-representation of people with a migration background that have not had an academic education is found.

Figure 2.2 shows that there is less variation in unemployment insurance incidence compared to social assistance incidence. The lowest incidence of unemployment insurance benefit receipt is found among older aged women with a first-generation Moroccan migration background who did not have an academic degree ($\widehat{P}$ = 0.121; 12.1%). This group, as well as middle aged women with a Moroccan origin, show considerably lower incidences than other lower educated women with a first generation migration background. Among intersectional groups with the lowest incidence of unemployment insurance benefit young people with an academic degree are overrepresented. The highest incidence is found among older aged men with a first generation easter European migration background who did not have an academic degree ($\widehat{P}$ = 0.530; 53%). Among the groups with the highest incidence of unemployment insurance, lower educated men with a European migration background are overrepresented. Additionally, the groups with an academic degree that had a high incidence of unemployment insurance all had an Eastern European background.

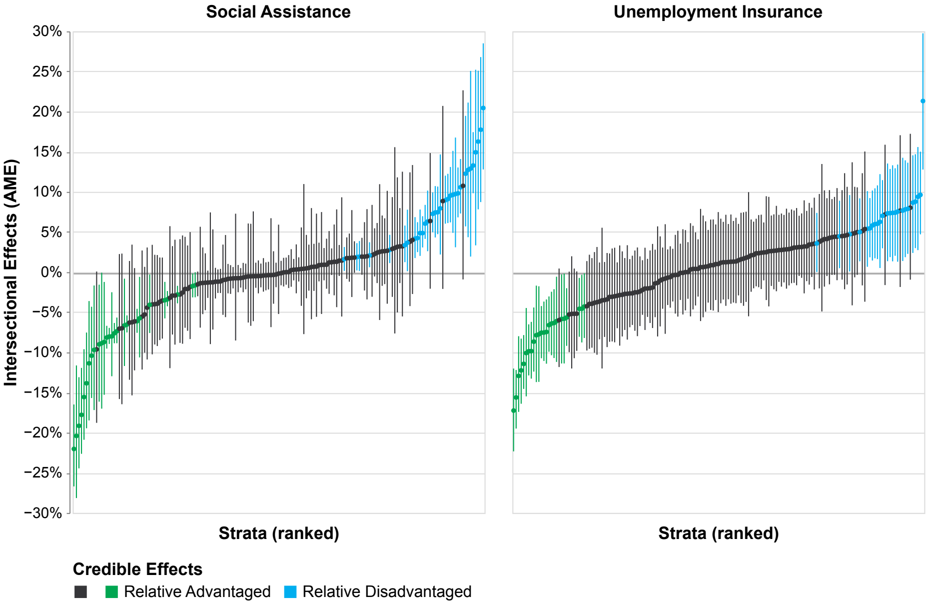
2.4.3 Intersectional effects

The intersectional effects (i.e., the random intercept per intersectional stratum) are visualized in Figure 2.3 (for a numerical summary of the results see Table A.3). The intersectional effect for most strata is not statistically different from 0. This means that the incidence of benefit receipt (of social assistance and unemployment insurance) for most strata is adequately explained using additive effects. However, for a considerable number of groups a significant intersectional effect is found. In these strata, the incidence of benefit receipt is lower or higher than would be predicted under additive assumptions. Thus, at these intersections social dimensions are mutually influential co-determinants of benefit receipt, leading to a relatively higher or lower incidence of benefit receipt.

For social assistance, 65 out of 164 strata had an intersectional effect that was statistically distinct from 0, of which 27 had a negative intersectional effect (i.e., were relatively advantaged) and 32 had a positive intersectional effect (i.e., were relatively disadvantage), see Figure 2.3 and Table 2.3. For a complete overview see Table A.3. Among the relatively advantaged groups, the following groups are overrepresented: academically educated Dutch individuals, academically educated women with a migration background and young people with a migration background. These groups have a lower incidence of social assistance than was expected using the additive model. It appears that all academically educated Dutch, irrespective of gender and age, are more likely to be

Note: Estimated incidence per stratum of baseline models (Model 0) based on burn-in depth of 10,000 iterations and posterior distributions 10,000 iterations. 95% credible intervals are displayed as error bars. N(individuals) = 45,119. **Source**: Authors' own calculation based on non-public individual level register data from the Social Statistical Database (SSD) of Statistics Netherlands (CBS)

Figure 2.2: Estimated incidence per stratum of social assistance and unemployment insurance receipt.



Note: Estimated posterior distributions of the random intercept terms of fully adjusted models (Model 5) based on burn-in depth of 10,000 iterations and posterior distributions 10,000 iterations. 95% credible intervals are displayed as error bars. The strata are ranked by the predicted intersectional effect for each respective benefit. N(individuals) = 45,119. **Source**: Authors' own calculation based on non-public individual level register data from the Social Statistical Database (SSD) of Statistics Netherlands (CBS)

Figure 2.3: Estimated intersectional effects (as average marginal effects) of social assistance and unemployment insurance benefit receipt.

Table 2.3: Predicted incidences of social assistance and unemployment insurance receipt

Background	Sex	Age	Education	AME	95%CI	Prop. a
			Social Assistance			
Dutch	Female	Old	Academic	-0.191	(-0.244;-0.131)	0.368
Dutch	Male	Middle	Academic	-0.178	(-0.226;-0.119)	1.897
Dutch	Male	Old	Academic	-0.156	(-0.209;-0.096)	0.752
Dutch	Female	Young	Academic	-0.138	(-0.195;-0.075)	2.331
Turkish 1st Gen.	Female	Young	Academic	-0.114	(-0.185;-0.036)	0.013
Dutch	Male	Young	Academic	-0.104	(-0.157;-0.043)	1.807
Surinamese 1st Gen.	Female	Middle	Academic	-0.097	(-0.172;-0.017)	0.022
Turkish 1st Gen.	Male	Young	Academic	-0.090	(-0.161;-0.016)	0.015
Turkish 1st Gen.	Female	Middle	Academic	-0.089	(-0.170;-0.001)	0.009
Surinamese 1st Gen.	Male	Young	Academic	-0.087	(-0.153;-0.012)	0.007
Dutch Antillean 1st Gen.	Male	Young	Non-Academic	0.098	(0.068;0.130)	0.200
Dutch Antillean 1st Gen.	Male	Middle	Non-Academic	0.106	(0.073;0.141)	0.160
Turkish 2nd Gen.	Female	Young	Academic	0.123	(0.057;0.195)	0.024
Marrocan 1st Gen.	Female	Middle	Academic	0.127	(0.044;0.211)	0.008
East EU 1st Gen.	Male	Old	Academic	0.129	(0.019;0.251)	0.003
Dutch Antillean 1st Gen.	Female	Middle	Non-Academic	0.133	(0.098;0.174)	0.159
Marrocan 1st Gen.	Male	Old	Academic	0.149	(0.033;0.252)	0.003
Other 1st Gen.	Male	Middle	Academic	0.163	(0.078;0.251)	0.115
East EU 1st Gen.	Female	Old	Academic	0.177	(0.087;0.268)	0.007
Other 1st Gen.	Male	Old	Academic	0.204	(0.128;0.285)	0.058
			Unemployment Insurance			
Dutch	Male	Middle	Academic	-0.172	(-0.223;-0.120)	1.897
Marrocan 1st Gen.	Female	Old	Non-Academic	-0.156	(-0.195;-0.122)	0.116
Dutch	Male	Young	Academic	-0.129	(-0.174;-0.080)	1.807
Marrocan 1st Gen.	Female	Middle	Non-Academic	-0.122	(-0.164;-0.083)	0.376
Other 1st Gen.	Female	Old	Non-Academic	-0.114	(-0.145;-0.078)	0.536
Dutch	Female	Middle	Academic	-0.101	(-0.155;-0.045)	1.570
Dutch	Male	Young	Non-Academic	-0.099	(-0.129;-0.065)	13.688
Turkish 1st Gen.	Female	Old	Non-Academic	-0.098	(-0.133;-0.062)	0.130
Other 1st Gen.	Female	Middle	Non-Academic	-0.087	(-0.124;-0.044)	1.171
Surinamese 1st Gen.	Male	Young	Academic	-0.079	(-0.137;-0.017)	0.007
Surinamese 2nd Gen.	Female	Young	Academic	0.074	(0.019;0.129)	0.037
East EU 1st Gen.	Male	Middle	Academic	0.075	(0.013;0.134)	0.008
Marrocan 1st Gen.	Male	Young	Academic	0.077	(0.014;0.142)	0.008
EU 1st Gen.	Male	Old	Academic	0.078	(0.019;0.139)	0.018
Other 2nd Gen.	Male	Old	Academic	0.079	(0.023;0.136)	0.041
EU 1st Gen.	Male	Middle	Academic	0.087	(0.024;0.146)	0.059
Marrocan 1st Gen.	Male	Middle	Academic	0.088	(0.030;0.147)	0.017
Marrocan 1st Gen.	Female	Middle	Academic	0.094	(0.027;0.156)	0.008
Other 2nd Gen.	Male	Old	Non-Academic	0.096	(0.047;0.150)	0.251
Turkish 1st Gen.	Male	Old	Academic	0.213	(0.128;0.298)	0.003

Note: Averages of the fixed effects (as average marginal effects) posterior distributions, 95% credible interval between parentheses. N(individuals) = 45,119. In this table, only the intersectional effects are presented for the top and bottom 10 strata that were substantially different from zero. **Source**: Authors' own calculation based on non-public individual level register data from the Social Statistical Database (SSD) of Statistics Netherlands (CBS). **a**: This column gives the proportional size of the respective stratum in the full Dutch employable population.

able to avoid social assistance than could be predicted using the characteristics of their strata. The same is true for young higher educated first generation migrants from 'traditional' countries of origin (Suriname and Turkey). It seems that they benefit more from their educational attainment than other groups. Conversely, when looking at the relatively disadvantaged groups, generally older academically educated people with a migration background and younger lower educated people with a migration background were found. This seems to suggest that older migrant groups have benefited less from education-related advantage.

For unemployment insurance, fewer intersectional effects were found. Namely, 48 out of 164 strata had a statistically distinct intersectional effect, of which 24 were relatively advantaged and 24 relatively disadvantaged. Among relatively advantaged groups, again academically educated Dutch people were found. Also, groups of non-academically educated women with a migration background less often receive unemployment benefits than expected. These results suggest that Dutch individuals with an academic degree might experience an amplification of their advantage that yields an extra relative advantage. Migrant women might be able to buffer some of the ethnic penalty they experience, resulting in a relatively advantaged position compared to migrant men. In correspondence with the results for social assistance, mainly academically educated men with a first-generation migration background were found among the relatively disadvantaged groups for unemployment insurance. Ethnic discrimination might explain why they are less able to fully benefit from their academic qualifications.

2.5 Conclusion

This chapter examined group differences in benefit receipt in the Netherlands and identified notable disparities at the intersection of gender, age, education and migration background. The variation among intersectional groups in receiving social assistance benefits is more pronounced than for unemployment insurance benefits. However, the differences in social assistance benefit receipt could be largely explained by the combined additive effects of migration background and education level. In contrast, the variation in unemployment insurance incidence was more intricate and required complex combinations of gender, migration background, age and education to explain group-level variation more accurately. We find the highest incidence of social assistance among older women with a first-generation Moroccan migration background and the lowest among Dutch middle-aged women with an academic degree. For unemployment insurance the highest incidence is found among older aged men with a first generation Eastern European migration background who did not have an academic degree and the lowest among older aged women with a first-generation Moroccan migration background who did not have an academic degree. The main aim of this chapter was to develop a theoretical schema of six different types of intersectional effects and to describe the extent of intersectional inequalities in benefit receipt. We discuss our findings against the light of the theoretically distinguished types of intersectional advantage and disadvantage.

Intersectional differences are most often associated with the idea that membership of more than one marginalized group leads to disadvantages that exceed those expected when simply summing up the disadvantage of each group. We find very little evidence for this multiple jeopardy hypothesis (King, 1988; Settles & Buchanan, 2014). The intersectional groups that show most relative disadvantage almost all have academic education. This means that they are not generally disadvantaged, but they are less advantaged than one would expect based on their high level of education. All these groups have a migration background and most of them are men. These findings are consistent with findings from the classic study by Blau and Duncan (1967) and suggest that migrants may not fully benefit from academic qualifications, illustrating cases of diminished education related advantage for these subpopulations. They showcase our second type of intersectional effects in which a group that is disadvantaged in one respect cannot fully benefit from an advantaged position on another dimension. We also find some indications for the existence of our third type of intersectional relative disadvantage: the case that multiply advantaged groups are not fully able to benefit from all their privileges. First generation male immigrants from EU countries with academic education (often called expats) are more likely to receive unemployment benefits than one would expect based on their characteristics.

We also distinguished three types of intersectional relative advantage. According to the reverse gender gap hypothesis women with a migration background are less disadvantaged than to be expected based on these two disadvantageous characteristics (Arai et al., 2016; Di Stasio & Larsen, 2020). In line with this hypothesis, we find that strata of women with a migration background are often found in the relatively advantaged groups with regards to having a low likelihood of receiving unemployment insurance benefits. This can be explained by women with a migration background being able to mitigate some of their ethnic disadvantage. They experience less discrimination on the labor market and are less likely to lose their job, in line with findings from previous research (Arai et al., 2016; Di Stasio & Larsen, 2020). However, it is also possible that at these intersections women are more likely to take on the role of stay-at-home mother. As a result, a larger proportion of women in these groups may not qualify for unemployment insurance benefits due to their limited work experience. Our finding that young native Dutch men with academic education are even more likely to avoid social assistance and unemployment benefits than expected based on their favorable characteristics, supports our expectation that multiple advantages can strengthen each other. We also find this for middle aged and older men, and for women of all age groups. These are examples of the last type of intersectional effects in which advantageous characteristics (being native Dutch and higher educated) compensate for the (smaller) disadvantages of being older and female.

In conclusion, our findings suggest that previous studies on benefit receipt, that assumed that disadvantage or advantage accumulates in an additive manner, have underestimated or overestimated benefit receipt for certain intersectional groups. Our results demonstrate that age, gender, migration background and education are interconnected factors that co-determine benefit receipt and should be considered together. However, intersectionality is not a simple cumulation of advantages or disadvantages, but more often comprises that groups that are disadvantaged in one respect are not able to fully benefit from some advantageous characteristic.

We did not study how intersectional effects in benefit receipt can be explained, but the most probable explanations are lack of resources and discrimination. Higher educated first generation migrants may, for example, lack social capital needed to find a (new) job. But it is also possible that they have no difficulties in identifying interesting vacancies, but that they are discriminated when applying for jobs. Research has shown that both types of explanations are needed to explain additive effects, but it is still largely unclear how to explain intersectional effects. Future research is also needed to explore entry and exit dynamics of benefit receipt to better understand the intersectional inequalities underlying benefit dependency. Some groups might have more difficulty accessing benefits, others might experience a harder time to find re-employment and have a longer duration of benefit receipt.

Although the use of register data is one of the strengths of this chapter, it comes with several drawbacks regarding the operationalization of certain independent variables. First, due to systemic missingness resulting from the gradual roll-out of the education register across all levels of education, the operationalization of educational attainment was limited. Ideally, we would have distinguished within the group without tertiary education, since groups that have a lower secondary education might be especially vulnerable to benefit receipt. In this light, the intersectional effects might be slightly underestimated for individuals having a primary or lower secondary education, as they are now grouped together with higher educated individuals. Second, the sociodemographic information contained in the person register might not perfectly reflect the self-identification of individuals. Individuals might not identify with their registered gender because their gender identity might not fit within the male/female dichotomy, or they might not have had the opportunity to change their registered gender. In a similar vein, individuals might not identify themselves with the country of origin (of their parents). Qualitative methods to study intersectional inequalities in benefit receipt are more suited to study such anti-categorical self-identification of individuals. Additionally, other aspects that concern migration, such as reasons for leaving the country of origin and the duration of residence after migration could provide valuable insights as to which migrant groups have a higher incidence of benefit receipt.

Furthermore, it is imperative to contextualize the results presented in this chapter in light of one notable qualification. Due to data limitations, this chapter cannot take into account individuals' eligibility for benefit programs. Our assumption now is that people who do not receive benefits do not have a need for it because they have a paid job or other resources to get by. However, some individuals meeting the criteria for either social assistance or unemployment insurance might not have received a benefit for various reasons (i.e., not applying, not obtaining and not qualifying) (Janssens & Van Mechelen, 2022). Conversely, individuals who are not eligible may still receive the benefits associated with these programs. Based on our results, it cannot be determined what part of an intersectional difference in benefit receipt is due to some social groups being more often eligible for benefit receipt, having a higher application rate for benefit programs, or having a higher success rate when applying for benefits. A noteworthy recent advance in studies of benefit receipt involves the use of machine learning models to predict eligibility (Areias & Wai-Poi, 2022). However, this avenue of research requires further refinement and validation before it can be effectively employed in empirical studies focusing on benefit receipt.

The present chapter is the first study that comprehensively explored intersectional inequalities in benefit receipt quantitatively. Substantial intersectional effects were found in benefit incidence. This means that some groups are disproportionately vulnerable to benefit receipt while others are relatively advantaged and that prior research on inequalities in benefit receipt has under- and overestimated the incidences for these intersectional groups. Our results have a direct implication for social policy: to understand inequality in benefit receipt, it is important to consider the interrelatedness of various social characteristics individuals might have.

Chapter 3

The mediating role of resources in shaping intersectional inequalities in benefit receipt

A different version of this chapter has been submitted to an international journal.

Jos Slabbekoorn: Conceptualization, Methodology, Formal analysis, Writing –- Original Draft, Visualization. **Ineke Maas:** Conceptualization, Writing –- Review & Editing. **J. Cok Vrooman:** Conceptualization, Writing – Review & Editing, Funding acquisition.

ABSTRACT

While research shows that gender, age, and migration background intersect to influence benefit receipt, the mechanisms driving these inequalities remain unclear. This chapter studies how economic, social, cultural, and person capital explain differences in benefit receipt across 40 intersectional strata. Using Bayesian multilevel structural equation models with Dutch register and longitudinal survey data, we find that inequalities in benefit receipt are linked to variations in capitals. Financial resources emerge as the most influential factor, while cultural capital and mental well-being provide smaller yet notable influences. Additionally, non-additive effects show that some intersectional groups—such as second-generation non-western women in their forties—experience disproportionate resource disadvantages, contributing to elevated benefit receipt rates. This chapter makes a twofold contribution by empirically testing capital-based mediation mechanisms and offering a more detailed understanding of intersectional inequalities in benefit receipt. Our results underscore the importance of comprehensive, targeted policies that address the capital disparities underlying social vulnerabilities and promote equitable labor market outcomes.

This work benefited from discussions at the Migration and Social Stratification Seminar (2022), the ICS Forum Day (2022), and the ISA World Congress in Melbourne (2023). I sincerely thank all participants for their thoughtful and constructive input.

3.1 Introduction

There are considerable social inequalities in benefit receipt: women, migrants, young and old people are found to have an increased vulnerability for benefit receipt (Cappellari & Jenkins, 2014; Connor & Koenig, 2015; J. Hansen & Lofstrom, 2009; Ilmakunnas, 2023; Königs, 2014b, 2018; Riphahn & Wunder, 2013). Recent intersectional studies on social assistance and unemployment insurance receipt find that gender, age and migration background are mutually influential co-determinants of benefit receipt (Hussénius, 2021; Slabbekoorn et al., 2024). These findings emphasize that inequalities underlying benefit receipt are complex and that it is crucial to consider multiple group membership because the effect of being part of one social group (e.g., being a migrant) can be affected by memberships of other social groups (being a man and older). This means that benefit receipt incidence for some intersectional groups has been either over or underestimated in most prior research. Especially the finding that some intersectional groups experience an increased vulnerability to benefit receipt is relevant because they may be more likely to fall into poverty, depression and isolation (Saatcioglu & Corus, 2014).

While these results underscore the complexity of social inequalities in benefit receipt, the question remains why some social groups are disproportionately vulnerable to incur periods of benefit receipt. The heightened vulnerability for benefit receipt at some intersections, might be resulting from deficiencies in economic, social, cultural and person capital (Bourdieu, 1986; Vrooman et al., 2023). These capitals are valuable assets in the labor market and can benefit individuals who seek employment. They are also instrumental to securing a stable position in the labor market and prevent losing one's job (de Keere, 2022; Hyggen, 2006; Kristiansen, 2021; Riphahn & Wunder, 2013) and consequently being less likely to receive a benefit. Gender, age and migration background inequalities in capitals are observed in the literature. For instance, women often have smaller networks with fewer employment-related resources than men (Lin, 2000), yet this gender gap has been found to be converging in recent studies (Addis & Joxhe, 2017).

In this chapter, we fill two gaps in the literature on social inequalities in benefit receipt. In particular, this chapter will concentrate on social assistance and unemployment insurance programs, which enable individuals who experience unemployment to partially maintain their quality of life. First, studies that examine the influence of capitals (i.e., the effect of capital disparities) on benefit receipt typically focus on a limited set of capitals (i.e., education and social capital: Connor & Koenig, 2015; Riphahn & Wunder, 2013), others merely controlled for differences in capitals (Cappellari & Jenkins, 2014; J. Hansen & Lofstrom, 2009; Königs, 2014b, 2018). We investigate a broader range of capitals. This has the potential to guide the development of social policies. For example, while extensive research has demonstrated the crucial role of cultural capital in achieving higher-status positions (Georg, 2004), it remains uncertain to what extent it can assist individuals in avoiding economically precarious employment. Therefore, the first question this chapter addresses is: *To what extent do economic, social, cultural and person capital reduce benefit receipt incidence?* Second, the emerging literature on intersectional inequalities in benefit receipt (Hussénius, 2021;

Slabbekoorn et al., 2024) calls for empirical tests of mechanisms that induce the disproportionate vulnerability for benefit receipt at some intersections. Whether certain intersectional groups are especially disadvantaged with regard to capitals and the consequences of these disadvantages for benefit receipt, is still unknown. By combining an intersectional framework with a capital-based approach, this chapter is a first attempt at studying explanatory factors of intersectional inequalities in benefit receipt. Therefore, the second question this chapter addresses is: *To what extent can intersectional inequalities in social benefit receipt be explained in terms of economic, social, cultural and person capital?*

We use a unique combination of datasets: longitudinal survey data from the Longitudinal Internet Studies for the Social Sciences [LISS] by CentERdata (Tilburg University, The Netherlands), linked with Dutch register data from the System of Social Statistical Datasets (SSD) by Statistics Netherlands [CBS] (Bakker et al., 2014).These data provide accurate and reliable information on benefit receipt (Bruckmeier et al., 2018) and a wide range of information on capitals for a representative sample of the Dutch population. For our analysis, we expanded Multilevel Analysis of Individual Heterogeneity and Discriminatory Accuracy (MAIHDA) models to a Structural Equation Modeling (SEM) framework, which allows us to test intersectional capital-based mediation mechanisms that may underlie benefit receipt incidence.

3.2 Theory

In this section, we aim to explore how deficits in different types of capital contribute to the incidence of benefit receipt and how these processes may vary across different social groups. First, we take an additive approach by examining the distinct contributions of gender, age, and migration background to capital-related disparities in benefit receipt. This allows us to assess how each characteristic independently relates to benefit receipt, and provide an overview of the status-quo of this literature. Second, we adopt an intersectional perspective, recognizing that the combined influence of these social characteristics can create unique patterns of (dis)advantage. Some groups may experience compounded capital deficits due to the intersection of multiple marginalized characteristics, leading to disproportionately higher levels of benefit receipt. By integrating both perspectives, we provide a comprehensive framework for understanding how social inequalities in capitals shape benefit receipt.

3.2.1 Capitals and benefit receipt

Economic capital is made up of the individual resources that can be directly monetized, as well as the resources that have monetary value (Fan, 2014; Vrooman, 2014), including property rights, stocks, and savings as they represent the financial resources owned by an individual. It also includes forms of human capital because education, knowledge, and skills are monetizable assets on the labor market. Employers select job candidates based on the provided information about economic capital on their resumes, since this information may indicate an individual's productivity and suitability, resulting in a better competitive position of higher educated people on the labor market (G. S. Becker, [1963] 1993) and a reduction of their risk for benefit receipt. Additionally, wealth affects the eligibility for benefit recipiency, particularly for social assistance. Wealthy households may not be eligible for social assistance, but can qualify for unemployment insurance. Contingent on the fact that people with a migration background often have a lower educational attainment (Gries et al., 2022; Nauck, 2019; van de Werfhorst & Heath, 2019; van Ours & Veenman, 2001), their risk for benefit receipt may be increased. Younger people benefited from educational expansion and generally hold a higher educational attainment than older age groups (Kraaykamp et al., 2013). This education-related advantage may lower the likelihood of benefit receipt among young people. Lastly, the gender gap in educational attainment has closed recently, and women are outperforming men in educational performance and attainment (Traag, 2020; van den Brakel et al., 2020). Thereby, the education related disadvantage that women previously might have had in terms of benefit receipt has vanished. That is why we expect that especially migrants and older people have a higher incidence of benefit receipt because they have a lower educational attainment. For an overview of additive mechanisms, see Table 3.1.

Furthermore, wealth may make individuals ineligible for some benefit schemes, such as social assistance (which are means tested per household) and unemployment insurance (when individuals are not employed), which is especially true for individuals who generate income as a business owner, shareholder, or landlord. Because older people have the highest earnings and accumulated wealth compared to other age groups in the Netherlands (CBS, 2021a, 2021b), a larger fraction of this group may be non-eligible. Migrants may face more difficulty acquiring wealth. For instance, on the housing market, people with a migration background may face ethnic discrimination and language barriers when attempting to buy real estate. This reduces the opportunities for migrants to acquire wealth through housing. Additionally, (first-generation) migrants are less likely to inherit from their parents, since they migrated from countries where on average people (including their relatives) are less wealthy. For second generation migrants, the ethnic penalty in acquiring wealth may be smaller, since they experience less of a language barrier on the housing market and some of their parents may have accumulated wealth. Gender differences in wealth are less pronounced, but the gendering of work and family roles results in women generating less wealth than men (Denton & Boos, 2007; Mustosmäki et al., 2017). Therefore, we expect that migrants, younger people and women have a higher incidence of benefit receipt because they have fewer financial resources.

Cultural capital encompasses individuals' mastery of legitimate cultural codes, the symbolic value ascribed to their aesthetic preferences, and their ability to engage in distinctive highbrow practices (Bourdieu, 1986; Georg, 2004; Lamont, 1992; Lamont & Lareau, 1988; Yodanis, 2006). A key dimension of cultural capital is its embodied form, which refers to deeply ingrained cultural competencies, such as language proficiency and familiarity with social norms. Many employers interpret higher levels of embodied cultural capital—often reflected in the way job candidates articulate themselves in cover letters and express ideas during interviews—as a sign of greater

Table 3.1: Additive resource-based mechanisms

	Capital					
	Economic		Cultural	Social	Person	
	EDU	FR			GH	MW
Gender (ref. Men)						
Female		–		–		
Migration Background (ref. Dutch)						
1st gen. migrant	– –	– –	– –	–	– –	– –
2nd gen. migrant	–	–	–	–	–	–
Age (ref. Middle)						
Young	+	–		–	+	-
Old	–	+				

The + and –- signs represent additive effects. The + sign indicates that on average, this social group has a higher amount of the respective resource compared to the other group(s) and consequently a lower incidence of benefit receipt. The –- sign indicates that on average, this social group has a lower amount of the respective resource compared to the other group(s) and a higher incidence of benefit receipt. EDU = Educational Attainment, FR = Financial Resources, GH = General Health, MW = Mental Well-Being

competence and professional suitability (de Keere, 2022; Rivera & Tilcsik, 2016; Thomas, 2018). This gives individuals with more cultural capital a competitive edge in the job market, reducing their likelihood of benefit receipt. Highbrow cultural capital, including participation in cultural activities, can also enhance labor market outcomes by signaling social skills, adaptability, and shared cultural knowledge—assets particularly valued in high-skilled or culturally specific job sectors. In the Dutch context, embodied cultural capital such as language proficiency and knowledge of local customs is especially relevant for employment. Individuals with a migration background may have accumulated less cultural capital applicable in this context due to being socialized in different cultural environments. For example, they are often less proficient in Dutch and less familiar with Dutch cultural customs. While research finds inconclusive evidence for gender and age differences in cultural capital, some studies show that women tend to participate more in cultural activities (e.g., attending theater performances, museums, and concerts). Nevertheless, embodied cultural capital, such as language mastery, does not appear to differ significantly between men and women (Dumais, 2002). Therefore, we expect migrants to experience a higher incidence of benefit receipt due to lower levels of highbrow cultural capital and poorer language proficiency.

Social capital pertains to resources that individuals can access via their social and instrumental support networks (Flap & Völker, 2008; Lin, 1999). Social capital can improve individuals' employment prospects as contacts can (1) provide relevant information on job opportunities, (2) help during the job application process (e.g., to prepare for a job interview), (3) vouch for the individual at their current employer and influence the hiring process, and (4) serve as social credentials of the individual (Kristiansen, 2021; Lin & Ao, 2008; Wilson, 2012). Accordingly, the number of employed people (Cappellari & Jenkins, 2014) as well as the occupational status of people within an individual's social network (Flap & Völker, 2008; Sprengers et al., 1988) are found to improve the chance of (re-)employment. Migrants often have access to fewer social resources (Cederberg, 2012; Lin, 2000) because their networks are ethnically segregated, and their contacts often have less resources. Younger people have fewer social resources because they are still developing their social networks. Therefore, their networks are smaller, and their contacts may on average have fewer resources (McDonald & Mair, 2010). On average, women have less resourceful contacts, which can be largely attributed to the child-rearing effect. After childbirth, women develop more kin and neighborhood ties, which have less employment-related information (O'Neill & Gidengil, 2013). Therefore, we expect that migrants, younger people, and women have a higher incidence of benefit receipt because they have less social capital.

Person capital encompasses advantages associated with an individual's physical and mental condition (O'Rand, 2006; Vrooman et al., 2023), drawing inspiration from Pareto's overlooked proposition that an individual's life opportunities depend on social competition driven by their unique characteristics. Pareto (1935) recognized the inherent heterogeneity among individuals in terms of their physical, moral, and intellectual traits within a society, which have a fundamental role in determining one's social position. One form of person capital is individuals' general health, which affects the productivity of employees directly by increasing job performance or indirectly through reducing absenteeism (Paul & Moser, 2009; Stauder, 2019; Wanberg, 2010). Additionally, health deficiencies may negatively influence employability (Mastekaasa, 1996), and further elevate the incidence of benefit receipt. Naturally, older people are more likely to experience a deteriorating health and incur health adversities (Levinsky & Schiff, 2021). Migrants often have a poorer general health than their Dutch counterparts, which can be largely attributed to their lower socio-economic status (SES, Blom et al., 2016). This leads to our expectation that migrants and older people have a higher incidence of benefit receipt because they on average have a poorer general health.

Similarly, mental health problems can make individuals more likely to become dependent upon a social benefit. For one, people that experience a burn-out, may become reliant on benefit programs. Secondly, people with mental health problems with a fixed-term contract might be less likely to have their contract extended or offered a permanent contract. Therefore, they are more likely to become unemployed and become reliant on a social benefit. Younger people and migrants have a higher prevalence of mental health problems (Chittleborough et al., 2011; Maksimović et al., 2014). It is argued that young adults are more likely to experience a poorer mental well-being, since they are faced with changing life circumstances (e.g., moving out of their parental households, starting a new study or job). First generation migrants might be more likely to experience psychological distress due to migration related traumas and stress. The poorer mental well-being of second generation migrants is often explained in terms of their lower SES, but also by experience of ethnic discrimination (Maksimović et al., 2014). There are no pronounced gender differences in the prevalence of mental health problems, yet men and women have different forms of psychopathology and express psychological distress differently (Rosenfield & Mouzon, 2013). Women tend to internalize mental health issues (e.g., become depressed and have panic-attacks), whereas men externalize (e.g., become dependent on substances). Both internalized and externalized forms of mental health problems can make people more likely to become reliant on social benefit. Therefore, it remains uncertain how mental well-being differences might explain gender inequalities in benefit receipt. In sum, we expect that migrants and younger people have a higher incidence of benefit receipt because they on average have a poorer mental well-being.

3.2.2 Intersectional differences in capitals and benefit receipt

In the previous section we considered factors such as gender, age, and migration background separately. However, intersectionality posits that multiple social characteristics interact to create interlocking systems of inequality (Cole, 2009; Else-Quest & Hyde, 2016). As a result, it is necessary to study these social characteristics in relation to each other rather than simply adding up their effects. Complex and overlapping (dis)advantages can contribute to resource shortages for certain social groups, exacerbating the challenges they face in the labor market. When considering the intersectionality of multiple social characteristics, it is important to acknowledge that it can also result in a decreased disadvantage, and consequently a lower likelihood of benefit receipt (e.g., Slabbekoorn et al., 2024).

Intersectional disadvantage arises when the combination of multiple disadvantaged characteristics results in greater disadvantage than the simple sum of individual factors. Intersectionality theory (Crenshaw, 1989; King, 1988) argues that multiple forms of disadvantage can amplify and reinforce each other, leading to a disproportionate accumulation of disadvantage, see Section 2.1 or Slabbekoorn et al. (2024). Certain individuals are disadvantaged not only by individual factors, but by the compounded effects of multiple factors (Vauclair & Rudnev, 2023). For example, a woman who is also a member of an ethnic minority group may face additional gender-related challenges compared to native women. This could be due to limited access to educational and financial resources, and cultural barriers that hinder their social mobility. First-generation non-western migrant women in the Netherlands typically have lower proficiency in Dutch compared to their male counterparts (Bernhard & Bernhard, 2022); in part this can be attributed to the influence of traditional gender roles. First-generation (non-western migrant) women are on average lower educated than their husbands, are more likely to be stay-at-home mothers, and interact primarily with co-ethnics, reducing their need to learn Dutch. Additionally, migrant women generally reduce working hours more after childbirth than native women, which can lead to a loss of work-related connections (Begall & Grunow, 2015). Another example concerns young people with a migration background, who may face more challenges in acquiring social capital than their Dutch counterparts (Cederberg, 2012). Young migrants may have fewer opportunities to build professional networks through their parents, while Dutch young people may gain social resources through their parents' connections, which can further aid their careers.

Intersectionality of multiple social characteristics can also result in a decreased disadvantage, which we refer to as a *relative advantage*. There are three ways in which this can occur: through attenuated disadvantage, through compensation, and through accumulated advantage. First, attenuated disadvantage refers to the idea that having multiple sources of disadvantage might not always lead to an amplification of disadvantage but can sometimes lead to a reduction in the level of disadvantage. For instance, the social capital of young women. Considering their gender and youth, one might initially expect that young women possess limited social capital. However, the gender-related impact on social capital appears to be relatively less pronounced among younger individuals because young men and women actively participate in the workforce (CBS, 2023; Erlandsson, 2023). It is typically in later stages of life that certain women may temporarily withdraw from the labor market due to caregiving responsibilities (Begall & Grunow, 2015). As a result, young women likely possess a higher degree of social capital than what might be initially predicted, solely based on the additive combination of their youthful age and gender.

Second, compensation refers to the idea that disadvantage can be counteracted by an advantaged social characteristic, more than one would expect on the basis of the additive effects. As an example, women have recently surpassed men in terms of educational performance and attainment (Traag, 2020; van den Brakel et al., 2020). This is particularly true for younger second-generation migrant women, who perform better in education than their male counterparts, to a greater extent than Dutch girls outperform boys (Dronkers & Kornder, 2014). People with a Dutch background may experience a lower age-related disadvantage than those with a migration background due to several reasons. For example, general health may decline less quickly for Dutch natives in later life than for those with a migration background (Levinsky & Schiff, 2021). People with a non-western migration background are often engaged in physically demanding occupations, which increases their risk of work-related injuries. This may be particularly true for older men with a non-western first-generation migration background, while their wives typically take care of household tasks.

Third, advantages can accumulate and lead to a relative advantage for individuals. For instance, a person with advantageous social characteristics, such as being native and male, may have access to better job opportunities, promotions, and higher salaries, leading to further advantages (Erlandsson, 2023). This, in turn, can lead to the accumulation of more wealth, which can be invested in further education, housing, and other assets, further enhancing their advantage. As a result, they may experience fewer obstacles and challenges in achieving their goals and may be more likely to succeed in various domains. Advantages can accumulate and compound over the life course, leading to a relative advantage for individuals who possess them. This advantage can result in various opportunities that may not be available to those without these advantages, further enhancing their relative advantage.

In summary, while intersecting forms of disadvantage can lead to a relative disadvantage, intersecting forms of advantage or combinations of advantage and disadvantage can also lead to a relative advantage. Through attenuated disadvantage, compensation and accumulated advantage, individuals can leverage their multiple social characteristics to counteract the disadvantages they may experience due to their intersecting characteristics. The compound of (dis-)advantages is not merely the simple sum of parts, but also includes all non-additive combinations of gender,

Table 3.2: Intersectional resource-based mechanisms leading to (+) relatively higher and (−) lower amounts of capitals

	Capital					
	Economic		Cultural	Social	Person	
	EDU	FR			GH	MW
Bi-dimensional						
1st gen. migrant women	–		–	–		
Younger women	+			+		
Younger migrants				–		
Tri-dimensional						
Older native men	+	+		+		
Older 1st gen. migrant men					–	
Younger 2nd gen. migrant women	+					

The + and –- signs represent non-additive effects. The + sign indicates a relative advantage, meaning that the combined effect of two or more social characteristics leads to more resources than the sum of their individual effects. The – sign indicates a relative disadvantage, where the combined effect of two or more social characteristics leads to less resources than the sum of their individual effects. EDU = Educational Attainment, FR = Financial Resources, GH = General Health, MW = Mental Well-Being

age, and migration background associated (dis-)advantages. Consequently, the multiplicity of (dis-)advantages can lead to disproportionate deficits in capitals and, as a result, a disproportionately higher incidence of benefit receipt. The intersectional mechanisms that are described in the text are summarized in Table 3.2. Our theoretical argument draws on the existing, though sparse, literature on intersectional disparities in benefit receipt and capital. As a result, we take an exploratory approach to uncover non-additive intersectional mediation mechanisms, acknowledging the limited empirical evidence and the need for new insights to guide future research in this underexplored area.

3.3 Data and methods

3.3.1 Data

This chapter utilized panel data from the Longitudinal Internet Studies for the Social Sciences (LISS), supplemented with administrative data. LISS is an ongoing survey that began in October 2007 and included a random sample of Dutch households (Scherpenzeel & Das, 2010). The initial sample involved 4,500 households and 7,000 individuals, but single households, those with first-generation immigrants and households with an older average age were underrepresented. To account for this and sample attrition, four refreshment samples were drawn in 2009, 2011, 2013 and 2016. The survey involves monthly web-questionnaires, which include eight core modules that are repeated annually. For this chapter, the focus was on two of these core modules, which cover the respondents' social contacts and networks and health, collected from 2008 until 2020. Information from 2020 and after was not used to exclude any COVID-related influences. The response rate for each module varied between 58% and 79% over the years. Research suggested that individuals tend to underreport periods of benefit receipt in surveys; therefore, utilizing administrative data provides more accurate information (Bruckmeier et al., 2018). For the most accurate information on benefit receipt, the panel data were enriched with administrative data obtained from Statistics Netherlands. This dataset includes monthly information about people's major sources of income, as well as individual and household demographic information. Although some respondents did not consent to link their survey responses with register data, research from Germany suggested that bias resulting from non-consent (a) is relatively small and (b) does not affect substantive variables, such as employment, income and benefit receipt (Sakshaug & Kreuter, 2012).

The analytical sample is obtained as follows. First, out of the 12,002 participants of the LISS panel, a connection with register data could be established for 11,655 individuals. Of the unlinked cases 10% did not consent to this connection to be made, while the remaining cases did not yield a reliable match (Das & Couper, 2014). Next, we excluded individuals who had participated in the survey for only one year, leaving us with a sample of 9,726 individuals. We also excluded individuals younger than 20 or older than 60 to focus on the working-age population, which led to the exclusion of an additional 5,475 participants (Bäckman & Bergmark, 2011). To limit potential bias from multiple individuals in the same household, we randomly selected one individual per household, resulting in the exclusion of another 1,720 participants. Our final sample size was 3,755 individuals, comprising 24,572 yearly observations.

3.3.2 Operationalization

3.3.2.1 Endogenous variable

The dependent variable, *benefit receipt*, was constructed to indicate whether someone has received either social assistance benefit or unemployment insurance benefit as their major source of income for at least one month per year. The information on major income sources originated from the national income register. This register contains information about individuals' major source of income per month, which were aggregated per calendar year. Unlike in Chapter 2, where social assistance and unemployment benefits were operationalized separately, these benefits are grouped together in the present operationalization to ensure sufficient statistical power.

3.3.2.2 Exogenous variables

Gender was operationalized as a binary variable, using the registered gender in the person register in 2019. Information from the 2019 register was used to include all potential changes in registered gender.

Migration background was operationalized as a categorical variable according to the CBS (Statistics Netherlands) classification of migration background, which distinguishes between western and non-western origin and first and second generation migrants (Alders, 2002). The migration background information was taken from the person register of 2019. Individuals were categorized as having a migration background if they, or at least one of their parents, was born outside the Netherlands. Individuals who met this criterion were further categorized according to their country of origin, using the CBS classification of western and non-western origin. Then, individuals with a migration background were differentiated according to their generation status. First-generation migrants are those who were born outside the Netherlands, while second-generation migrants are those who were born in the Netherlands but have at least one parent who was born elsewhere.

Age was operationalized as a categorical variable, with individuals being categorized into one of four age groups: (20-30), (30-40), (40-50), or (50-60). We used the age on January 1st in 2014, such that time-invariant age groups could be constructed, which is required by our analytical models. The age was calculated using the date of birth registered in the person register in 2019.

Intersectional *strata* were operationalized as a combination of three categorical variables: gender, migration background and age group. This operationalization allows for the identification of unique intersectional groups based on the combination of these three variables (using an approach similar to Evans, 2019a). The combination of these three variables allows for the identification of 40 unique intersectional strata, including male/female, within each of the five migration background groups and the four age groups ($2 \times 5 \times 4$).

3.3.2.3 Mediation variables

The mediation variables were constructed as manifest variables, based on confirmatory factor analyses (CFA) which assessed the underlying structure of the indicators. All models yielded good to excellent model fit, indicating satisfactory internal validity of constructed manifest variables. For a summary of the CFA model specification and results and a more detailed description of the variables underlying the manifest constructs, see Table B.1 and Table B.2 in Appendix B. The manifest variables were derived from measurements taken in the previous year to ensure that individuals had access to these resources before receiving benefits. Lastly, the resulting factor scores were saved, to reduce the number of variables in our analytical models to ensure computational efficiency.

For economic capital we constructed two variables. The first variable, *financial resources*, was computed as a formative manifest construct using financial assets and income from the tax register and self-reported dwelling ownership. The value of the financial assets and income were recoded into percentiles to reflect the wealth distribution. The second variable, *education*, was not constructed using CFA, but was operationalized as the highest level of educational attainment, which was self-reported as primary school, vmbo, havo/vwo, mbo, hbo, or wo. These categories were recoded to reflect the number of years spent in education to reach the respective educational attainment, with values of 8, 12, 13, 15, 16 and 18 years.

Social capital was operationalized as a formative manifest variable based on three indicators: the number of employed and higher education contacts in the core network and the network density.

Participants were asked to list up to five of their closest contacts and provide their employment and education information. They were also asked to indicate which contacts knew each other, which was used to calculate the network density.

To operationalize cultural capital, two variables were constructed. The first variable, *cultural capital*, was computed as a formative manifest construct based on the number of times an individual had visited cultural institutions such as museums, theater plays, dance and ballet performances, classical music concerts, opera, art galleries, or art-house movie theaters in the past 12 months (van Hek & Kraaykamp, 2013). Individuals could indicate the frequency of their visits on a scale of 1 (0 times) to 5 (12 times or more). *Dutch language proficiency*, was not constructed using CFA. Instead, it was operationalized as an indicator of whether an individual had trouble speaking or reading Dutch. This was measured by two questions asking individual whether they had problems with reading and writing or speaking in Dutch.

Two manifest variables were constructed to operationalize person capital. The first variable, *general health*, was computed as a formative manifest construct using self-reported general health and BMI. Self-reported general health was assessed using a single question about participants' overall health (Bowling, 2005), as well as a retrospective question, where respondents indicated in which year they were unable to work due to health reasons.BMI was calculated using self-reported height and weight, with univariate outliers in the overall and intrapersonal distributions removed. Observations were censored when they lied outside 99.5% of the overall height and weight distributions and 99% of the intrapersonal distributions. Then, censored observations were replaced with the previous year's information when available (Muthalagu et al., 2014). To model the non-linear effect of BMI, in addition to the linear effect of BMI two dichotomous variables were included for people with normal weight and overweight. The second indicator, *mental well-being*, was computed as a reflective manifest variable based on five questions about anxiety, depression, gloominess, calmness and happiness experienced in the past month.

For a summary of the variables used in our analyses, see Table 3.3

3.3.3 Analytical strategy

To analyze the data, we used Bayesian multilevel structural equation modeling (BM-SEM). BM-SEM is a powerful method for examining complex relationships among multiple manifest constructs while accounting for both within- and between-person variation (Asparouhov & Muthén, 2021). Our models were estimated in `Mplus` (version 8.1, Muthén & Muthen, 2017), using the `MplusAutomation` package (Hallquist & Wiley, 2018) in `R` (version 4.1.3, R Core Team, 2017). We estimated our models using default prior settings, a burn-in phase of 10000 iterations and an equally sized posterior distribution.

Our analytical strategy builds on the works that have employed MAIHDA (Evans, 2019a) to study intersectional inequalities. Similar to MAIHDA models, our analytical approach compares

Table 3.3: Descriptive statistics

	N	M	S.D.	1%	99%
		Observations (N=24,572)			
Benefit Receipt	24572	0.072		0.000	1.000
Resources					
Financial Resources	17874	0.000	1.000	-2.306	1.726
Education	22021	0.000	1.000	-3.142	1.574
Highbrow Cultural Capital	22031	0.000	1.000	-0.719	3.649
Language Proficiency	23659	0.000	1.000	-3.262	0.363
Social Capital	19001	0.000	1.000	-2.315	2.542
General Health	19095	0.000	1.000	-2.803	2.654
Mental Well-Being	22923	0.000	1.000	-3.205	1.249
		Individuals (N=3755)			
Gender					
Female	3755	0.574		0.000	1.000
Migration Background					
Dutch Native	3755	0.800		0.000	1.000
1st gen. Non-Western	3755	0.038		0.000	1.000
2nd gen. Non-Western	3755	0.056		0.000	1.000
1st gen. Western	3755	0.067		0.000	1.000
2nd gen. Western	3755	0.039		0.000	1.000
Age					
20-30	3755	0.214		0.000	1.000
30-40	3755	0.249		0.000	1.000
40-50	3755	0.275		0.000	1.000
50-60	3755	0.262		0.000	1.000

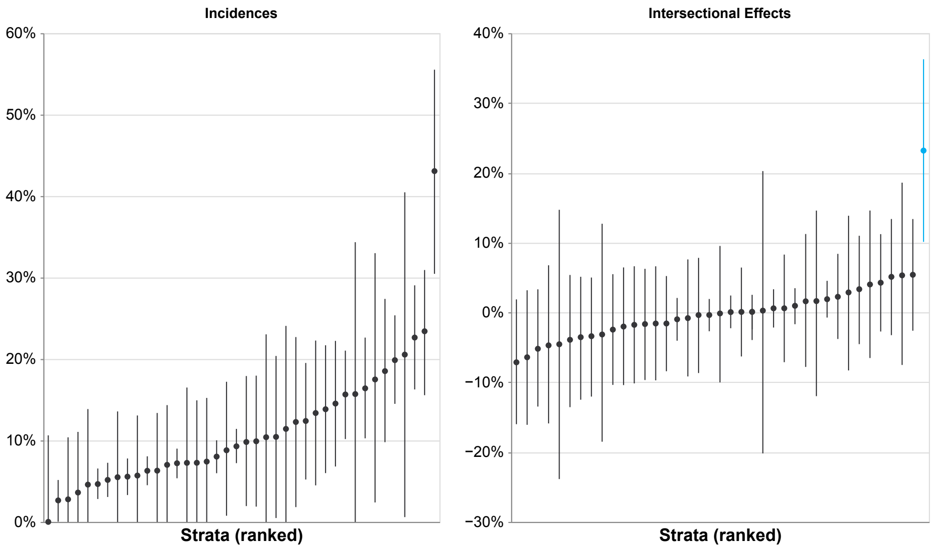
Note: For categorical or binary variables, the mean reflects the proportion. **Source**: Authors' own calculation based on non-public individual level register data from the Social Statistical Database (SSD) provided by Statistics Netherlands (CBS) and the Longitudinal Internet studies for the Social Sciences (LISS) from CenterData.

intersectional estimates with additive estimates. This yields the advantage that groups are not compared with a (fixed) reference category, but rather the additive and multiplicative estimates per stratum are compared. Furthermore, in similarity to MAIHDA models, Bayesian estimation is used. This is advantageous for multiple reasons: (1) it is more robust for smaller group sizes, which is crucial to include smaller intersections, (2) it uses all available data and can be run on incomplete data and (3) it is more robust for non-normally distributed data. We apply this MAIHDA-like approach to a SEM framework to study underlying mediation mechanisms and to identify whether these mediating effects have a non-additive component.

Our analytical approach was structured as follows. Model 0 served as our baseline model and included only a random intercept at the individual level to account for clustering of yearly observations within individuals. This model allowed us to estimate the incidence of benefit receipt and the intra class correlation at the individual level. The subsequent models were estimated using both an additive (indexed a) and intersectional (indexed i) version. In Model 1a, we included gender, migration background and age simultaneously as additive effects to assess the unique contribution of each predictor while controlling for the others. In Model 1i, we introduced the intersectional strata variable to capture the joint effects of gender, migration background and age. This model predicts benefit receipt incidences for all strata. To examine the mediating effects, we first estimated separate models (Models 2a and 2i) that included each of the mediating variables (wealth, education, social capital, highbrow cultural consumption, language proficiency, general health and mental well-being) separately. Finally, we estimated models (Model 3a and 3i) that included all seven mediating variables simultaneously to examine their joint mediating effects on benefit receipt.

We used the posterior distributions of the additive models (a) and intersectional models (i) to calculate the non-additive effects. The non-additive effects were calculated as the difference between the predicted effects of the additive and intersectional models per intersectional stratum, as (i) – (a). The calculated non-additive effects allowed us to investigate to what extent there were disproportionately high or low incidences of benefit receipt (for the direct effects, in Model 1 specifically) and to what extent these disproportionate incidence rates in benefit receipt could be attributed to disproportionate differences in the mediation variables (for the indirect effects, in Model 3 specifically).

The indirect effects were calculated using the posterior distributions, as a 2−1−1 between level mediation (Preacher et al., 2010). In this 2−1−1 between level mediation, the predictor variable (X) was measured at the between level (level 2, or the individual) and the mediator variable (M) and outcome variable (Y) at the within level (level 1, or the yearly observation). To calculate between level mediation, we multiplied the direct effect of X on M (a-path) and the direct effect of M on Y (b-path) at the between level. This allows determining whether diversity in resources can help to explain intersectional differences in benefit receipt.



Note: Medians of posterior distributions, calculated using Model 0 (Incidence) and Model 1 (Intersectional Effects), 95% credible intervals between as error bars. Strata are ranked based on the mean of the posterior distribution of the corresponding y-axis. N(strata) = 40, N(individuals) = 3,755; N(observations) = 24,572. **Source:** Authors' own calculation based on non-public individual level register data from the Social Statistical Database (SSD) provided by Statistics Netherlands (CBS) and the Longitudinal Internet studies for the Social Sciences (LISS) from CenterData.

Figure 3.1: Estimated incidence per stratum of benefit receipt and intersectional effects

3.4 Results

3.4.1 Incidences of benefit receipt

In Model 0 a random intercept model is estimated for benefit receipt. We find that 48.9% of the variance in benefit receipt can be attributed to between level differences. This means that about half of the variance in benefit receipt can be attributed to individual differences, the remaining variance is caused by differences within individuals over time.

In the left panel of Figure 3.1 the predicted incidences per stratum are presented, see Table B.3 in Appendix B for a complete overview. The highest predicted benefit receipt incidence of 43.1% is for second generation non-western women in their forties. First generation women in their twenties with a western migration background have the lowest predicted incidence of benefit receipt of 0.1%. This is a large difference, considering the overall incidence among all the individuals in our sample is 7.2%

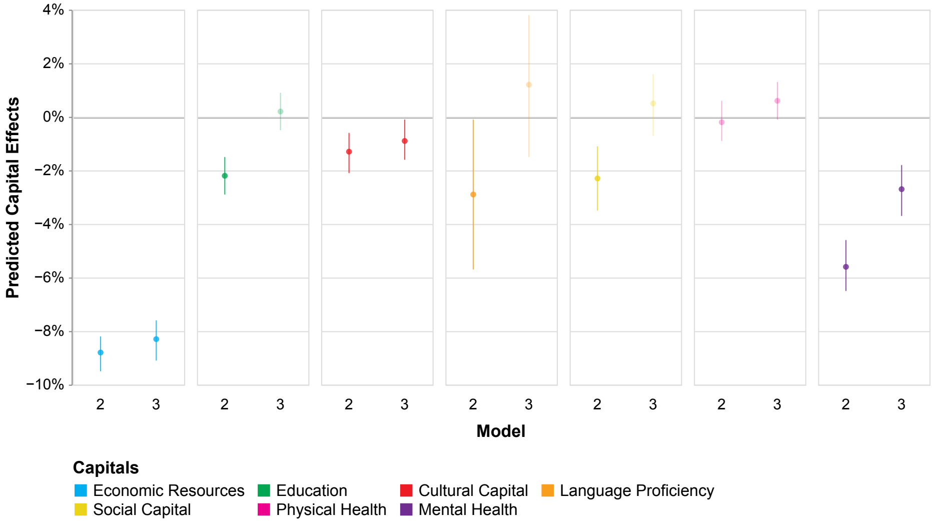
In Models 1 social demographic variables are included. In the right panel of Figure 3.1 the non-additive incidences are presented, see Table B.3 in Appendix B for a complete overview. These incidences denote the differences between the predicted incidence of the intersectional and the additive models 1. These non-additive effects capture to what extent the incidence of benefit is disproportionate (i.e., higher or lower than what is expected on additive rounds). We find one of the 40 intersectional strata to have a disproportionately high incidence. The benefit receipt incidence for women with a second generation non-western migration background in their forties is disproportionately high, their incidence is 23.2%pt higher than we would expect using an additive model. For all other effects zero lies within the 95% credible interval, although the size of some of these effects is quite substantial. In previous studies on benefit receipt prevalence using a much larger sample, more non-additive differences between intersectional strata in benefit receipt were found (Slabbekoorn et al., 2024). Therefore, we deem it worthwhile to take a closer look at the role of resources underlying benefit receipt.

3.4.2 Resource effects on benefit receipt

Figure 3.2 presents the effect of resources of Models 2 (squares) and 3 (circles). We find *financial resources*, *cultural capital* and *mental well-being* to reduce benefit receipt incidence even when controlling for the impact of other resources. The more wealth and income, high-brow cultural capital and the better ones mental well-being, the lower is the likelihood for benefit receipt. All other resources were not found to affect benefit receipt, when controlled for the effect of other resources. *Education*, *language proficiency* and *social capital* were found to affect benefit receipt uncontrolled for the effects of other resources. These results highlight the multiple correspondence of resources (Vrooman et al., 2023). For instance, individuals with higher educational attainment tend to possess more financial resources, which ultimately reduces their susceptibility to benefit receipt. *General health* was not found to affect benefit receipt in neither Model 2 nor in Model3. Therefore, in the following section only the mediation effects for financial resources, cultural capital and mental well-being will be discussed.

3.4.3 Additive mediation effects

Figure 3.3 presents the additive mediation effects for financial resources, cultural capital and mental well-being per social characteristic on benefit receipt (for a complete overview see Table B.4 and Table B.5 in Appendix B). These are thus the effects ignoring the possibility that at certain intersections of these social characteristics the mediation effect may be especially strong or weak. We find that differences in *financial resources* mediate migration background and age disparities in benefit receipt incidence. First generation and second generation migrants of western origin and first generation non-western migrants have fewer financial resources compared to Dutch natives, leading to a higher incidence of benefit receipt by 5.0%pt, 5.1%pt and 1.9%pt respectively. These are substantial effects, considering that the overall incidence of benefit receipt in our sample is 7.2%. Second generation migrants of non-western origin have similar amounts of financial resources compared to Dutch natives, resulting in the absence of a mediation effect. Moreover, individuals in their thirties, forties and fifties have more financial resources compared to those in their twenties, resulting in a lower incidence of benefit receipt by 2.7%pt, 3.3%pt and 2.6%pt on

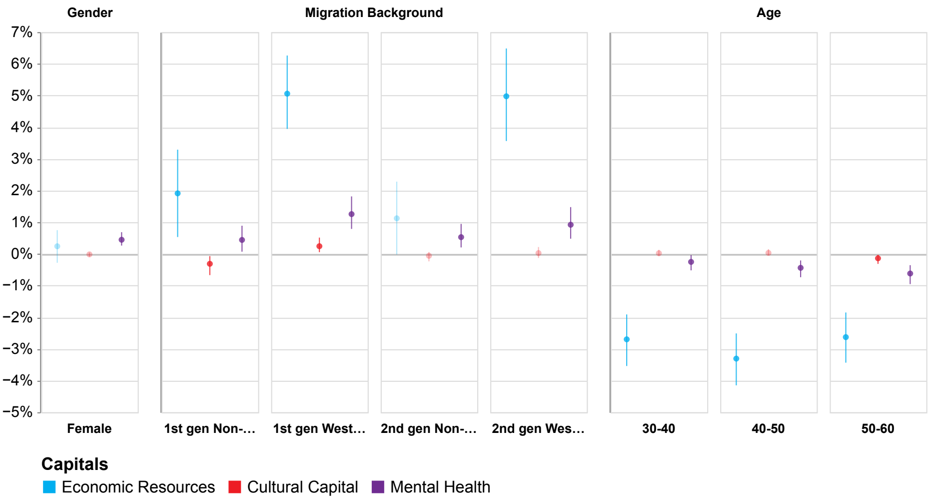


Note: Medians of capital effects' posterior distributions, calculated using Model 2 (uncontrolled for other capitals), Model 3 (controlled for other capitals). 95% credible interval are presented as errorbars. Predictions statistically not distinct from zero are shaded lighter. N(strata) = 40, N(individuals) = 3,755; N(observations) = 24,572. **Source:** Authors' own calculation based on non-public individual level register data from the Social Statistical Database (SSD) provided by Statistics Netherlands (CBS) and the Longitudinal Internet studies for the Social Sciences (LISS) from CenterData.

Figure 3.2: Estimated main effects for resources on benefit receipt

average. Lastly, we do not find gender differences in financial resources and thus no mediation effect. Overall, these findings suggest that migration background and age differences in benefit receipt incidence can be partially explained by inequalities in financial resources, but not for women and people with a second generation non-western migration background.

Differences in *cultural capital* are found to mediate migration background and age differences in benefit receipt incidence, yet the influence of cultural capital on benefit receipt incidence is small. First generation western migrants have less cultural resources, leading to 0.2%pt higher benefit receipt incidence. Conversely, first generation non–western migrants have more cultural resources than Dutch natives, resulting in a 0.3%pt lower benefit receipt incidence. No substantial differences were found between Dutch natives and people with a second generation (non-) western migration background. People in their fifties were found to have more cultural resources than people in their twenties, leading to a 0.1%pt lower incidence in benefit receipt. However, no differences are found between individuals in their twenties, thirties and forties. Furthermore, we find no significant differences in cultural capital between women and men, resulting in a mediating effect of cultural capital that is not substantially distinct from zero. Thus, we find little support for our expectation that migrants have fewer cultural resources, leading to higher incidences of benefit receipt. Moreover, the impact of cultural resources appears to be minimal, indicating that cultural capital has a marginal influence on shielding individuals from benefit receipt.



Note: Medians of posterior distributions, 95% credible interval is presented as error bars. Reference categories are (Gender: Men), (Migration background: Dutch Natives) and (Age: 20-30). Predictions statistically not distinct from zero are shaded lighter. N(strata) = 40, N(individuals) = 3,755; N(observations) = 24,572. **Source**: Authors' own calculation based on non-public individual level register data from the Social Statistical Database (SSD) provided by Statistics Netherlands (CBS) and the Longitudinal Internet studies for the Social Sciences (LISS) from CenterData.

Figure 3.3: Additive indirect effects per resource and social characteristic

Mental well-being disparities were found to mediate gender, migration background and age differences in benefit receipt incidence. All migrant groups indicate to have a poorer mental well-being than natives, leading to a higher incidence of benefit receipt. Individuals in their thirties, forties and fifties had a better mental well-being compared to those in their twenties, resulting in a lower incidence of benefit receipt by 0.3%pt, 0.4%pt and 0.6%pt on average, respectively. Furthermore, women indicate to have a poorer mental well-being, which in turn corresponded with an 0.4%pt higher incidence of benefit receipt. These findings are generally in line with our expectations.

3.4.4 Non-additive mediation effects

In the upcoming section, we will present the non-additive mediation effects. These effects denote to what extend intersectional disparties in capitals (i.e. having more or fewer resources than based on additive expectations) result in variations in benefit receipt. In essence, we explore whether certain groups exhibit relatively low or high levels of a particular resource, which, in turn, may influence their incidence of benefit receipt. Table 3.4 presents a summary of the intersectional effects that are different from zero, for a complete overview see Table B.6 in Appendix B.

For *financial resources*, we find two cases where disproportionate differences in resources may explain the relatively high incidence of benefit receipt. Women with a second generation non-western migration background in their forties and men with a first generation western migration

Table 3.4: Intersectional indirect effects for benefit receipt

Migration Background	Age	Gender	B	95%CI
Financial Resources				
Western 1st Gen.	20<30	Male	0.055	(0.010; 0.101)
Non-Western 2nd Gen.	40<50	Female	0.059	(0.015; 0.104)
Cultural Capital				
Non-Western 2nd Gen.	50<60	Male	-0.010	(-0.021; -0.002)
Non-Western 2nd Gen.	20<30	Male	0.004	(0.000; 0.009)
Western 1st Gen.	50<60	Male	0.005	(0.000; 0.011)
Mental Well-Being				
Non-Western 2nd Gen.	40<50	Male	-0.023	(-0.042; -0.006)

Note: Medians of the intersectional effects posterior distributions, 95% credible intervals between parentheses. In this table, only the intersectional effects are presented that were credibly distinct from zero. N(strata) = 40; N(individuals) = 3,755; N(observation) = 24,572. **Source**: Authors' own calculation based on non-public individual level register data from the Social Statistical Database (SSD) provided by Statistics Netherlands (CBS) and the Longitudinal Internet studies for the Social Sciences (LISS) from CenterData.

background in their twenties have fewer financial resources than we expected on additive grounds. Thus, these two strata have disproportionately fewer financial resources than would be expected based on additive effects, which in turn increases their benefit receipt incidence by 5.9%pt and 5.5%pt respectively. The stratum with the largest disproportionate difference in economic capital (second generation non-western women in their forties) is also the one with the highest incidence of benefit receipt.

We find three cases with a non-additive indirect effect via *cultural capital*. In addition to the additive effects, men with a second generation non-western migration background in their fifties possessed relatively more cultural resources, resulting in a relatively 1%pt lower incidence of benefit receipt. Conversely, women in their forties with a similar migration background and men in their fifties with a first generation western migration background have relatively less cultural capital, resulting in a higher incidence of benefit receipt of 0.4%pt and 0.5%pt respectively.

Men with a second generation non-western migration background in their forties, were found to report better *mental well-being* than would be expected on additive grounds. Consequently, this improved mental well-being is associated with a 2.3% lower benefit receipt incidence. We conclude that we do find intersectional advantages and disadvantages in resources affecting benefit receipt, but that they do not coincide with the examples we described in Table 3.2.

3.5 Conclusion

This chapter focused on the complex interplay between gender, age, migration background and benefit receipt incidence, focusing on the mediating effects of various resources. By employing Bayesian multilevel structural equation models and combining register data with longitudinal survey data, we aimed to study the role of resources in explaining disparities in benefit receipt across forty intersectional strata. The findings of this research shed light on the factors contributing to inequalities in benefit receipt, using a comprehensive number of resources (Bourdieu, 1986; Vrooman et al., 2023). Our analysis showed that age and migration background inequalities in benefit receipt can be attributed to variations in financial resources, mental well-being and to a lesser extent cultural capital. With respect to gender-based inequalities in benefit receipt, we only find these to be mediated by mental well-being disparities. Benefit receipt of some ethnic minorities and age groups and women is associated with disparities in these resources and this may be part of the reason why these groups are more vulnerable on the labor market. General health and social resources do not seem to play an independent role in explaining differences in benefit receipt, nor did educational attainment. This underscores the intricate interplay of various resources as these resources often go together and interact with each other. For example, individuals who are in good health, possess higher levels of education and have access to a strong social network, are more likely to secure stable employment, because they accumulate more financial resources and can also benefit from their cultural capital. Our results show the importance of studying a broad selection of capitals and not merely focus on education and social resources. Additionally, previously, cultural capital has been mainly theorized as to how it might aid the attainment of high-status secure employment. Our research shows that cultural capital offers limited protection against the need for social benefits, reinforcing the idea that it primarily benefits individuals with higher social standing and good language proficiency.

The focus of this chapter is an intersectional view on inequalities in benefit receipt and to assess whether some groups are disproportionately (dis-)advantaged in terms of benefit receipt and resources as argued in previous research (Cole, 2009; Crenshaw, 1989; Else-Quest & Hyde, 2016; King, 1988; Settles & Buchanan, 2014). We uncovered some non-additive indirect effects, solely among migrant groups. This indicates that specific intersectional groups experience disproportionate disparities in these resources, thus influencing their likelihood of receiving benefits. Especially the indirect effects through financial resources are substantially large. This indicates that, in part, these intersectional groups are more likely to receive a benefit because of a shortage of these financial resources. In the theory section we described a number of possible intersectional advantages and disadvantages that we expected to appear, but we did not find support for any of these. However the cases for which we did find that they possessed disproportionately little or much of the resources are not too unsurprising. For instance, the group of young men with a first generation western migration background may largely consist of people that moved to the Netherlands from Eastern Europe for work and mainly have short-term contracts, low paying jobs, little wealth and generally economically vulnerable positions on the labor market. We also find an exceptionally high incidence of benefit receipt for older women with a second generation migration background. Although we had argued that women with a first generation migration background would have especially few financial resources, this might still apply to second generation migrant women as traditional gender roles may be passed down to second generation migrants by their parents.

This chapter has certain limitations that should be acknowledged. Firstly, it assumes that the effect of resources is the same for all groups, without considering the potential impact of discrimination, which may result in diminished returns of resources for certain groups. To address this, future research should explore whether resources have differential outcomes among various groups, to gain a more profound understanding of the complex role that resources may have. Secondly, despite this chapter was performed on a dataset comprising a large number of people, there was an insufficient number of cases to be able to distinguish intersectional strata based on specific countries of origin (Jacobs et al., 2009) without these groups becoming too small. This limitation highlights the need for longitudinal data with larger sample sizes to capture the complexity of migration backgrounds and their associated experiences. Lastly, while this chapter demonstrates the linkage between resources and benefit receipt, future research should investigate how resources are utilized by jobseekers in avoiding the need for social benefits. Incorporating qualitative research methods could offer valuable insights into the ways individuals employ resources in these contexts. Overall, recognizing and addressing these limitations would further enhance the understanding of resource dynamics and their impact on different social groups.

In sum, this chapter provides empirical evidence on the mediating role of resources and the complex interplay of gender, age and migration background in benefit receipt disparities. Individuals with a second generation non-western migration background and first generation western migration background exhibit substantially (disproportionately) higher incidence rates of benefit receipt. financial resources emerge as the primary drivers of these variations, with mental well-being and cultural capital exerting secondary influences, while other resources have more indirect effects. By empirically examining the mediating role of resources in the context of benefit receipt, we provide a valuable insight into the underlying mechanisms driving inequalities in benefit receipt. Additionally, by analyzing the mediating role of resources intersectionally, this chapter enhances our understanding of complexities that shape benefit receipt patterns. Recognizing the distinct challenges faced by individuals at the intersections of gender, age and migration background is crucial for designing inclusive and equitable social policies.

Chapter 4

Heterogeneous returns of capital in terms of benefit receipt: An empirical study of intersectional inequalities

A different version of this chapter has been submitted to an international journal.

Jos Slabbekoorn is the sole author of this chapter

ABSTRACT

This chapter studies the heterogeneous effects of economic, social, cultural and person capital on benefit receipt in the Netherlands, focusing on intersectional inequalities across gender, migration background and age. Drawing from a combination of Dutch register and longitudinal survey data, I employ Multilevel Analysis of Individual Heterogeneity and Discriminatory Accuracy (MAIHDA) to analyze the differential returns on capital across 40 intersectional strata. The findings show that while economic and person capital generally reduce the likelihood of benefit receipt, credible disparities emerge at the intersection of multiple social characteristics. Specifically, economic capital exerts a buffering effect for disadvantaged groups, providing higher returns for individuals at more marginalized intersections. This chapter contributes to the literature by employing a quantitative intersectional approach to investigate a potential mechanism underlying intersectional inequalities. These findings have implications for social policy, particularly regarding the potential of targeted interventions to enhance economic capital among disadvantaged groups and thereby reduce benefit dependency.

Earlier drafts of this work were presented at the Migration and Social Stratification Seminar (2024), de Dag van de Sociologie [NSV] (2024), and the ISA RC28 Summer Meeting (2024). I am deeply grateful to the participants for their feedback. Special thanks to Ineke Maas, Cok Vrooman, and Joey Tang for their extensive and insightful comments on earlier versions of this work.

4.1 Introduction

This chapter studies how different forms of capital (Bourdieu, 1986; Vrooman et al., 2024) – economic, cultural, social and person capital[1] – influence the likelihood of receiving benefits among various disadvantaged groups. Traditionally, studies that have focused on the influence of capitals, have held the idea that the precariousness for benefit receipt arises from having fewer resources (e.g., Heggebø et al., 2020; Hyggen, 2006; Kristiansen, 2021; McArdle et al., 2007; Slabbekoorn et al., 2024). For instance, individuals with fewer social resources may not find stable employment as easily and are consequently more likely to become a recipient of social benefits (Heggebø et al., 2020; Hyggen, 2006; Kristiansen, 2021). Others have found economic resources, cultural capital and mental health (as part of person capital) to be influential in lowering the likelihood of benefit receipt (Heggebø et al., 2020; Slabbekoorn et al., 2024). The implicit assumption commonly used in these studies is that all individuals can utilize capitals in similar ways and the returns on capitals are homogenous.

The assumption that various forms of capital yield homogenous returns across individuals is increasingly contested by a growing body of literature. This research emphasizes the heterogeneous effects of capital returns, arguing that disadvantaged individuals often receive fewer returns on their capitals. These returns can vary significantly based on characteristics such as gender, migration background, and age. Discrimination and stigmatization can hinder some individuals from fully utilizing their capitals (Baalbergen & Jaspers, 2023; Castilla, 2008; Consiglio & Sologon, 2022; Heath et al., 2008; Lietzmann & Hohmeyer, 2022; Lin, 2000; van Tubergen & Volker, 2015), thereby increasing their likelihood of needing social benefits. Lin (2000) introduced the concept of return deficits in social capital, demonstrating that disadvantaged groups—such as migrants—may not leverage their social capital as effectively as their advantaged counterparts. Similarly, studies on economic capital have identified performance-reward biases, where disadvantaged groups, particularly migrants, are less likely to be promoted or granted job security based on their productivity and work-related skills compared to advantaged groups (Castilla, 2008; Lietzmann & Hohmeyer, 2022). These lower returns on capital for disadvantaged groups exacerbate inequalities, including those related to benefit receipt.

While much of the literature has focused on the diminished returns experienced by disadvantaged groups, some evidence suggests that, in certain contexts, these groups may actually experience greater returns from their resources, partially buffering the disadvantages they face. For example, migrant groups have been observed to derive higher returns from their social capital when seeking secure employment (Andersson & Weber, 2024; Bernardi, 2012). This could be due to strategic use of their resources—such as emphasizing language proficiency to counteract ethnic

[1] In this chapter I use the capital framework as developed by the Netherlands Institute for Social Research [SCP] (Vrooman et al., 2024). This framework is a slight adaptation of Bourdieu's capital framework and includes person capital which comprises an individual's bodily and mental state. This concept, building on Bourdieu's 'embodied' capital and Pareto's idea of individual heterogeneity, is divided into physical, mental and aesthetic subtypes and highlights the significance of health, attractiveness and psychological traits in determining life chances.

discrimination in the labor market. Despite these insights, limited research has examined the heterogeneous effects of economic, cultural, and person capital in relation to benefit receipt. Most studies have focused instead on employment-related outcomes, such as job promotions, tenure, and unemployment (e.g., Baalbergen & Jaspers, 2023). However, since unemployment often precedes benefit receipt, similar heterogeneous effects of capitals are likely to apply. By exploring how disadvantaged individuals may experience reduced returns on their capitals, this chapter sheds light on the structural barriers they encounter and their potential impact on social benefit reliance.

This chapter will study the disparities in the returns on four forms of capital at the intersection of gender, migration background and age. In this way, this chapter aims to contribute to the literature in two ways. Firstly, by applying an intersectional approach to the analysis of heterogeneous effects, it seeks to study the subtle ways in which different forms of capital may affect benefit receipt across 40 intersectional strata, thereby potentially highlighting the complex interplay between social characteristics and capital returns on benefit receipt. Although the intersectional framework has long been popular in qualitative social science research, it has recently gained traction among some quantitative scholars (Gross & Goldan, 2023). These quantitative studies model multiplicative complexities of inequalities, thereby bridging the literatures of gender studies, social welfare and social inequality studies. For instance, recent studies have shown, that some intersectional groups are more reliant upon social welfare programs, which highlights the economic vulnerability of these groups, such as males with a first and second generation migration background (Hussénius, 2021; Slabbekoorn et al., 2024). Using an intersectional framework allows for a more granular study of social inequalities in society. This is an advancement over the status quo of research on the heterogeneous returns of capitals, which may have over- or underestimated the effects of capitals for some intersectional groups. Thus, we gain a better understanding on who is the most vulnerable for benefit receipt and how disadvantages stemming from multiple social characteristics accumulate. This chapter considers the intersection of gender, migration background and age, since inequalities along these lines have been most prevalent in social welfare research (e.g., Königs, 2018). Additionally, studying heterogeneous capital effects as a potential explanation for intersectional disparities in benefit receipt allows for testing why these inequalities exist. This approach provides an opportunity to investigate the mechanisms underlying benefit receipt, complementing the lived experiences reported in qualitative studies.

Secondly, it is the first study to simultaneously examine the differential effects of four forms of capital on benefit receipt. Analyzing the effects of these capitals concurrently is crucial due to their mutual correspondence (Veenstra, 2009). Individuals who possess one form of capital typically have access to other forms as well. Focusing on a single form of capital in isolation risks attributing effects to that form, when in reality, they may be influenced by other interconnected forms of capital. Therefore, the research question of this chapter reads: *To what extent do the effects of economic, social, cultural and person capital on benefit receipt vary at the intersection of gender, migration background and age?*

In this chapter, I analyze the differences in capital return on benefit receipt by focusing on two main types of programs: unemployment insurance (werkloosheidsuitkering) and social assistance (bijstand). In the Netherlands, unemployment insurance provides benefits for a limited duration, ranging from 3 months to 3 years depending on work history, to those who have involuntarily lost their jobs and are actively seeking new employment. Social assistance offers income support to households without other income sources or whose total income falls below the social minimum, with aid provided to all adults in multi-person households, and is means-tested based on the income and assets of all household members[2]. Unemployment insurance and social assistance in the Netherlands form an interconnected system that addresses the risk of income loss due to joblessness. Individuals who exhaust their unemployment insurance benefits without finding employment typically transition to social assistance, which acts as a subsequent support mechanism. Given the intertwined nature of these programs, my analyses will focus on the total receipt of benefits. Studying benefit receipt offers a more comprehensive understanding of social and economic disparities than solely focusing on unemployment. While unemployment studies primarily address joblessness and its immediate effects, examining benefit receipt includes a broader range of social and structural inequalities.

4.2 Theory

In this section, I begin by defining each type of capital –economic, cultural, social and person – and discussing how they influence the likelihood of receiving benefits. Next, I discuss heterogeneous capital returns, emphasizing that not everyone can leverage their capitals equally due to systemic inequalities. This section discusses two potential mechanisms, (1) disadvantaged groups often experience reduced returns on their capitals, leading to higher incidences of benefit receipt and (2) capitals may shield disadvantage groups, leading to lower incidence of benefit receipt.

4.2.1 Capitals and benefit receipt

Economic capital consists of individual resources that can be directly monetized, such as property rights, stocks, savings, along with economic capital like educational attainment, knowledge and skills (Fan, 2014; Vrooman, 2014). These resources enhance an individual's competitive position in the labor market. Higher levels of economic capital typically translate into better job prospects and lower risks of unemployment, which in turn reduce the likelihood of benefit receipt. For instance, educational qualifications and job-related skills are critical in securing employment and job stability, making individuals with substantial economic capital less dependent on social benefits (G. S. Becker, [1963] 1993). Furthermore, accumulated wealth can affect eligibility for benefit schemes such as social assistance, which are means-tested in the Netherlands. Specifically,

[2]An exception to this rule is that the income of co-residing adult children (whether from work, disability, or unemployment insurance) is not considered in the means test for determining parental social assistance eligibility. Therefore, parents can receive social assistance benefits in most cases regardless of their co-residing children's income from employment or welfare benefits. However, in recent years the income of children older than 21 can be taken into account.

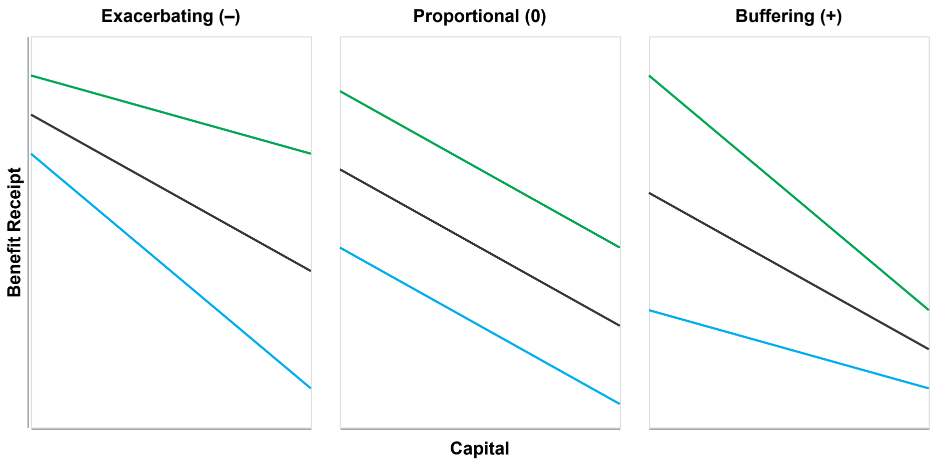
individuals with significant wealth might be ineligible for certain benefits, as their financial resources exceed the thresholds set by social policies. In summary, economic capital influences both the risk of benefit receipt and eligibility (Castronova et al., 2001; Heggebø et al., 2020; Lietzmann & Hohmeyer, 2022; Strockmeijer et al., 2020).

Cultural capital pertains to individuals' command of legitimate cultural codes, the symbolic value of their aesthetic preferences and their participation in highbrow activities (Bourdieu, 1986; Georg, 2004). This form of capital influences employability as it affects perceptions of competence during job applications and interviews (Rivera & Tilcsik, 2016; Thomas, 2018). Individuals with higher levels of cultural capital are often seen as more suitable candidates, which enhances their employment prospects and reduces their risk of benefit dependency. Cultural capital is also demonstrated through language proficiency, which serves as a signaling mechanism of embodied cultural capital, enhancing individuals' perceived competence and improving their employment prospects, thereby reducing the need for social assistance. The ability to engage in culturally valued practices and being proficient in the native language can thus significantly mitigate the risk of benefit receipt.

Social capital involves the resources accessible through an individual's social networks (Flap & Völker, 2008; Lin, 2000). These social resources can provide support in job searches and career advancement. Examples of these social resources include contacts that can help with job referrals, assistance with applications, endorsements and information about job opportunities (Kristiansen, 2021). A well-connected individual can leverage their social networks to secure employment more effectively, thereby reducing their likelihood of needing social benefits. The strength and resourcefulness of social networks play a role in employment prospects. Individuals with extensive and resourceful social networks are better positioned to find and retain employment, which diminishes their reliance on social benefits.

Person capital encompasses the physical and mental conditions that affect an individual's capacity to work (O'Rand, 2006; Vrooman et al., 2023). Good physical health and mental well-being are crucial for maintaining productivity and job performance (Paul & Moser, 2009; Stauder, 2019; Wanberg, 2010). Individuals with better health are more likely to sustain employment and are therefore less likely to need social benefits. Mental health issues, such as burnout or psychological distress, can adversely impact employability and stability in the workforce. Those with good mental health can maintain consistent employment and reduce their reliance on social benefits. Conversely, health deficiencies elevate the risk of benefit receipt.

The argument above outlines how different forms of capital influence benefit recipiency. Capitals provide resources that individuals can leverage to secure stable employment and enhance their employability. Prior studies have predominantly focused on the isolated effect of these forms of capital, while not considering the mutual correspondence with other forms of capital. I propose this following hypothesis: *while keeping the effect of other forms of capital constant, economic, social, cultural and person capital each are negatively associated with benefit receipt* **(Hypothesis 1)**



Note: The disadvantaged case is colored blue, the advantaged case is colored green and the reference case is colored black.

Figure 4.1: Hypothesized associations between benefit receipt and capitals

4.2.2 Heterogeneous returns of capital in terms of benefit receipt

While capitals play a pivotal role in determining the likelihood of benefit recipiency, not everyone may reap the same (i.e. proportional) advantages from these resources. In the literature two types of differences in returns of capitals can be distinguished. Most literature on the heterogeneous returns on capitals has focused on return deficits of disadvantaged groups, exacerbating inequalities (see the left panel of Figure 4.1). Systemic inequalities may hinder the returns that individuals with certain social characteristics can obtain from the resources they possess. This means that disadvantaged individuals have on average higher incidences of benefit receipt compared to advantaged others with similar amounts of capitals. The lower returns on capitals are often attributed to discrimination and stigmatization on the labor market, which means that employers often do not respond as positively to job applications from disadvantaged groups (Bygren et al., 2017; Correll et al., 2007; Di Stasio & Larsen, 2020; Quillian & Lee, 2023).

4.2.2.1 Exacerbating returns of capitals

Discrimination and stigmatisation may play a central role in the *exacerbating* returns on various forms of capital along the lines of gender, migration background and age. For women, pervasive gender biases and stereotypes in the workplace result in unequal opportunities and pay disparities (e.g., Correll et al., 2007). Despite having similar or even higher qualifications and experience compared to their male counterparts, women often face glass ceilings that limit their career advancement and job security (Boudarbat et al., 2010; Castilla, 2008; Rivera & Tilcsik, 2016). Migrants encounter ethnic discrimination in the labor market (Correll et al., 2007; Quillian &

Lee, 2023). In the classic work of Blau & Duncan (1967), it was already found that black men did not reap the same advantages from higher educational attainment than white men in the 1960s; black men with a higher education were paid less and received fewer job promotions. Castilla (2008) highlights that ethnic minorities, as well as women, receive lower compensation and fewer promotions than their white male counterparts, even when performance evaluations are equivalent. These findings illustrate that ethnic minorities' qualifications and performance are judged differently by employers, affecting employment outcomes and potentially increasing the likelihood of benefit receipt. The elderly face age-related discrimination that devalues their accumulated experience and skills. Stereotypes about declining productivity and adaptability hinder their employment opportunities, leading to lower economic returns on their lifelong investments in economic capital (Ayalon & Tesch-Römer, 2018). The few studies that examine the combined effects of ethnicity and gender are Parks-Yancy (2006) and S. Yang et al. (2021), which investigated the heterogeneous returns of social capital for white men and women, as well as black men and women. This study found that white men experienced the highest returns on social capital, while black women experienced the lowest. In essence, discrimination and stigmatization devalue the capitals of women, migrants, and the elderly by limiting their recognition and rewards in the labor market. For instance, for women, this devaluation may occur through gender biases that undermine the perceived value of their educational credentials or professional skills. Similarly, cultural capital – such as communication styles – or person capital – aesthetic preferences – may be overlooked or penalized when it does not align with dominant norms, further constraining the valuation of these capitals.

This notion of devalued capitals ties in well with the multiple jeopardy hypothesis, which has been developed in the intersectional literature. The multiple jeopardy hypothesis posits that individuals who belong to multiple marginalized groups face compounded disadvantages that amplify, rather than simply add to, their marginalization (King, 1988; Settles & Buchanan, 2014; Vauclair & Rudnev, 2023). For example, a Black woman does not merely experience the sum of ethnic and gender discrimination but faces unique, intensified barriers that emerge from the intersection of both forms of discrimination. These compounded barriers can result in significantly lower returns on her social capital, limiting her access to resources and opportunities more severely than individuals facing a single axis of marginalization. As a result, individuals at highly disadvantaged intersections face disproportionately lower returns on their capitals, further limiting their access to stable employment and increasing their reliance on social assistance and unemployment insurance. Thus, the more marginalized an individual's intersectional position, the greater the devaluation of their capitals and the fewer economic returns they can achieve. This leads to the following hypothesis: *The more disadvantaged an intersection is the lower the returns of economic, cultural, social and person capital are in terms of benefit receipt* **(Hypothesis 2a)**

4.2.2.2 Buffering returns of capitals

Some studies have identified returns on capitals that may be partially *buffering* disadvantage (see the right panel of Figure 4.1). In these cases, disadvantaged individuals reap higher capital returns. In this way, individuals within disadvantaged groups can buffer some of the experienced disadvantage the more capital they have. These buffering returns can occur in two ways. First, disadvantaged individuals may more strategically use their capitals to attain secure employment, reducing the likelihood of benefit receipt. For instance, job applicants with a migration background can alleviate some of the ethnic discrimination by demonstrating proficiency in the native language (Edo et al., 2019). Research on gender differences in the returns on social capital shows contrasting findings. It has been suggested that women benefit more from their social capital due to their ability to maintain stronger relational ties and leverage support effectively, particularly in collaborative and community-oriented settings (Collischon & Eberl, 2021). Conversely, others find no significant gender differences in the advantages gained from social capital, particularly in professional environments, suggesting that men and women may derive similar benefits from their networks (Parks-Yancy, 2006; S. Yang et al., 2021). When examining person capital, particularly in relation to employment and health, Ng & Feldman (2013) found in their meta-analysis that older individuals experience a reduced negative impact of poor (mental) health on employment outcomes. Older individuals actively engage in strategies that help them cope with the health challenges associated with aging, thereby reducing the negative impacts on their overall well-being and functionality (Ng & Feldman, 2013). Additionally, it is argued that as individuals age, they perceive their remaining time as limited, which leads them to prioritize emotionally meaningful experiences and relationships (Ng & Feldman, 2013). This focus on positive emotional regulation helps older adults to maintain better mental health despite the decline in physical health, effectively mitigating some of the negative consequences associated with poorer health.

Second, capital-based advantages may constitute less of an added advantage for privileged individuals than for (multiply) disadvantaged individuals. For instance, white men may already be privileged to such an extent on the labor market that they can prevent unemployment and lower their likelihood of benefit receipt. They, for example, might not need to rely on their social resources to find re-employment. Conversely, migrant women, who are multiply disadvantaged, might need to rely upon social support and job-referrals to find secure employment. Empirical studies have shown that social resources, contacts and networks are particularly beneficial for migrant women, helping them to mitigate some of the adverse effects of multiple marginalizations (O'Neill & Gidengil, 2013). This suggests that when individuals at highly disadvantaged intersections possess more social, economic, cultural or person capital, they can leverage these resources more effectively to navigate and overcome structural barriers (Andersson & Weber, 2024; Bernardi, 2012). Consequently, the more disadvantaged an intersection is, the more critical these forms of capital become in reducing reliance on social assistance and unemployment insurance. This leads to the following opposing hypothesis: *The more disadvantaged an intersection is, the higher the returns of economic, cultural, social and person capital are in terms of benefit receipt* **(Hypothesis 2b)**.

4.3 Data and methods

4.3.1 Data

This research used panel data from the Longitudinal Internet Studies for the Social Sciences (LISS), supplemented by administrative data. The LISS survey started in October 2007, involving a random sample of Dutch households (Scherpenzeel & Das, 2010). Initially, 4,500 households and 7,000 individuals participated. In this initial sample single households, first-generation immigrant households and those of older age were underrepresented. To address this and sample attrition, refreshment samples were added in 2009, 2011, 2013 and 2016. The survey comprises monthly web-questionnaires, including eight core modules repeated annually. This chapter focused on two core modules related to social contacts and networks and health, from 2008 up until 2019. Data from 2020 onwards were excluded to avoid COVID-related impacts. Response rates for these modules ranged between 58% and 79% over the years. The panel data were enhanced with administrative data from Statistics Netherlands, which includes monthly information on major income sources and demographic information. Survey-based reports often understate periods of benefit receipt, hence, administrative data provide more precise information (Bruckmeier et al., 2018). Some participants did not consent to link their survey responses with register data, but research based on German survey data indicated that bias resulting from denial of register-linkage is small and does not significantly affect key variables such as employment, income and benefit receipt (Sakshaug & Kreuter, 2012).

The analytical sample was derived as follows. First, from the 12,002 LISS-panel participants, 11,655 individuals were successfully linked to register data. Of the unlinked cases, 10% did not consent to data linkage and the rest did not yield a reliable match (Das & Couper, 2014). Individuals who participated for only one year were excluded, resulting in 9,726 individuals. Then, individuals were constricted to be of working-age (20-60 years), leading to the exclusion of 5,475 individuals. To minimize bias from multiple respondents in the same household, one individual per household was randomly selected, which resulted in the exclusion of 1,720 participants. The final sample included 3,756 individuals, with 24,325 yearly observations. These numbers slightly differ from Chapter 3, due to the random selection procedure I used to create this sample.

4.3.2 Operationalization

4.3.2.1 Dependent variable

The dependent variable, *benefit receipt*, indicates whether an individual received social assistance or unemployment insurance benefits as their primary income source for at least one month per year. This information was sourced from the national income register, which was aggregated to major income sources per calendar year.

4.3.2.2 Independent variables

Four capital variables were constructed and validated through confirmatory factor analyses (CFA), demonstrating satisfactory internal validity. Detailed CFA model specifications and results can be found in Table C.1 and Table C.2 in Appendix C. The resulting variables were saved and used in my analyses with a time lag of one year to ascertain that individuals possessed these forms of capital before the measurement of benefit receipt.

Economic Capital was operationalized as a formative manifest variable based on financial assets and income from the tax register, self-reported dwelling ownership and the education in education years. Financial assets were recoded into percentiles to reflect the wealth distribution and educational attainment was converted to years of education.

Social Capital was defined as a formative manifest variable derived from three indicators: the number of employed and higher education contacts in the core network and network density. Participants listed up to five close contacts, provided their employment and education details and indicated interconnections among these contacts to calculate network density.

Cultural Capital was measured as a formative manifest construct based on the frequency of visits to cultural institutions in the past 12 months (van Hek & Kraaykamp, 2013), rated on a scale from 1 (0 times) to 5 (12 times or more) and Dutch language proficiency, which indicated whether individuals had difficulty speaking or reading Dutch. This was measured by two questions on reading and writing or speaking in Dutch.

Person Capital was operationalized as a formative manifest construct combining indicators of both general and mental health. These indicators included self-assessed general health, a retrospective question indicating whether someone was unfit to work in a given year, BMI and five items measuring mental health. General health was assessed via a single question (Bowling, 2005). BMI was calculated from self-reported height and weight, with outliers removed and censored observations replaced with previous year's data when available (Muthalagu et al., 2014). To model BMI's non-linear effect, both linear and dichotomous variables for normal weight and overweight were included. Mental health was assessed through five questions about anxiety, depression, gloominess, calmness and happiness experienced in the past month, rated on a six-point scale from 1 (never) to 6 (continuously).

4.3.2.3 Sociodemographic variables

Gender was operationalized as a binary variable based on the registered gender in the 2019 person register.

Migration background was categorized according to the CBS classification, distinguishing between western and non-western origin and first and second-generation migrants (Alders, 2002). Individuals were classified as having a migration background if they or one of their parents were born outside the Netherlands. These individuals were further classified by country of origin and generation status, using 2019 register data.

Age was categorized into four groups: 20-30, 30-40, 40-50 and 50-60, based on age as of January 1, 2014. This categorization creates time-invariant age groups required by my analytical models.

Intersectional *strata* were defined by combining gender, migration background and age group, resulting in 40 unique intersectional groups (2 genders × 5 migration backgrounds × 4 age groups) (using a similar approach as: Evans, 2019a).

4.3.2.4 Control variables

In the analyses, I included number of children and relationship status as time varying control variables to account for potential confounding effects. The number of children, was categorized to 0, 1, 2, 3 and 4 or more children to reduce the influence of outliers. Similarly, relationship status was controlled, which was categorized into four groups: single, married, divorced and widowed. For a complete overview of the variables used in my analyses see Table 4.1.

4.3.3 Analytical strategy

To analyze the data, I used MAIHDA (Evans, 2019a) to study intersectional inequalities in the effect of capitals on benefit receipt. In MAIHDA models, individuals are also grouped within intersectional strata primarily for computational reasons. This approach allows for the calculation of intersectional differences in random intercepts and slopes without modeling interactions between social characteristics, resulting in a more parsimonious model. From a substantive perspective, social characteristics such as gender, migration background and age are treated as group-level characteristics. This clustering method accounts for the shared experiences of individuals within these groups. In my models, individuals are grouped within intersectional strata and observations are grouped within individuals. By using multiple observations per individuals, I use all available information. My models were estimated using the PyMC package (Abril-Pla et al., 2023) in `Python` (version 3.10.3, van Rossum & Drake, 2009). These models use narrow prior settings, a burn-in phase of 10000 iterations and an equally sized posterior distribution. This modelling approach is advantageous for multiple reasons: (1) it is more robust for smaller group sizes compared to non-bayesian models, which is crucial to include smaller intersections, (2) it uses all available data and can be run on incomplete data and (3) it is more robust for non-normally distributed data. I estimate linear probability models (LPM)[3] in which missing data was handeld using bayesian imputation.

The analytical approach was structured as follows. The baseline model, Model 1, includes random intercepts at the individual and stratum levels. This model is used to calculate the intra-class

[3]Linear probability models yield the risk of predicting unrealistic probabilities outside the [0, 1] interval. To ascertain realistically predicted probabilities at the stratum level, I performed prior and posterior predictive checks, which yielded satisfactory results.

Table 4.1: Descriptive statistics

	N	M	S.D.	1%	99%
		Observations			
Benefit Receipt	24325	0.072		0.000	1.000
Resources					
Economic Capital	21781	0.002	0.999	-2.510	1.339
Cultural Capital	21277	0.003	0.998	-2.692	1.990
Social Capital	18855	0.001	1.000	-2.315	2.542
Person Capital	19040	0.001	1.000	-2.291	2.386
Number of Children					
0	24325	0.476		0.000	1.000
1	24325	0.162		0.000	1.000
2	24325	0.252		0.000	1.000
3	24325	0.088		0.000	1.000
4 or more	24325	0.022		0.000	1.000
Relationship Status					
Divorced	24325	0.100		0.000	1.000
Married	24325	0.470		0.000	1.000
Single	24325	0.417		0.000	1.000
Widow	24325	0.014		0.000	1.000
		Individuals			
Gender					
Female	3756	0.574		0.000	1.000
Migration Background					
Dutch	3756	0.800		0.000	1.000
1st gen Non-Western	3756	0.038		0.000	1.000
2nd gen Non-Western	3756	0.056		0.000	1.000
1st gen Western	3756	0.067		0.000	1.000
2nd gen Western	3756	0.039		0.000	1.000
Age					
20-30	3756	0.214		0.000	1.000
30-40	3756	0.249		0.000	1.000
40-50	3756	0.275		0.000	1.000
50-60	3756	0.262		0.000	1.000

Note: For categorical or binary variables, the mean reflects the proportion. Due to rounding, the proportions of some categorical variables may not add up to exactly 100%. **Source**: Authors' own calculation based on non-public individual level register data from the Social Statistical Database (SSD) provided by Statistics Netherlands (CBS) and the Longitudinal Internet studies for the Social Sciences (LISS) from CenterData.

correlation (ICC), which was calculated as the stratum level variance divided by the total variance. In Model 2, gender, migration background and age were included simultaneously as additive effects. Models 1 and 2 together, serve the mere purpose of decompositioning the variance in benefit receipt and to control for gender, migration background and age differences in benefit receipt incidence and therefore will be discussed briefly. To examine the effects of capitals, all the capitals were included simultaneously in Model 3 to examine their effects on benefit receipt while controlling for the effect of other forms of capital. Model 3 will be used to test Hypothesis 1. In Model 4, the capital effects were allowed to vary per intersectional stratum. These random effects show how much each stratum's capital effects on benefit receipt differed. Model 4 will be used to test Hypotheses 2.

In post-estimation, I analyze the posterior distributions of the random slopes of capitals on benefit receipt by the level of disadvantage per intersectional stratum. The level of disadvantage for each stratum is determined as follows: For each social dimension (i.e., gender, migration background, generation and age), values are assigned based on theoretical considerations (Castronova et al., 2001; Heggebø et al., 2020; Lietzmann & Hohmeyer, 2022; Strockmeijer et al., 2020): gender (0: men, 1: women), ethnic origin (0: native, 1: western, 2: non-western), generation (0: no migration background, 1: second generation, 2: first generation) and age (0: 30-40, 1: 20-30 and 40-50, 2: 50-60). For each intersectional stratum, the total disadvantage score is calculated by summing these assigned values. These scores are then correlated with the random slope values. If I find a negative association between disadvantage and the random effects of capital, it will serve as confirmatory evidence for Hypothesis 2a. Conversely, if I observe a positive association between disadvantage and the random effects of capital, it will be considered confirmatory evidence for Hypothesis 2b.

4.4 Results

4.4.1 Capital effects on benefit receipt

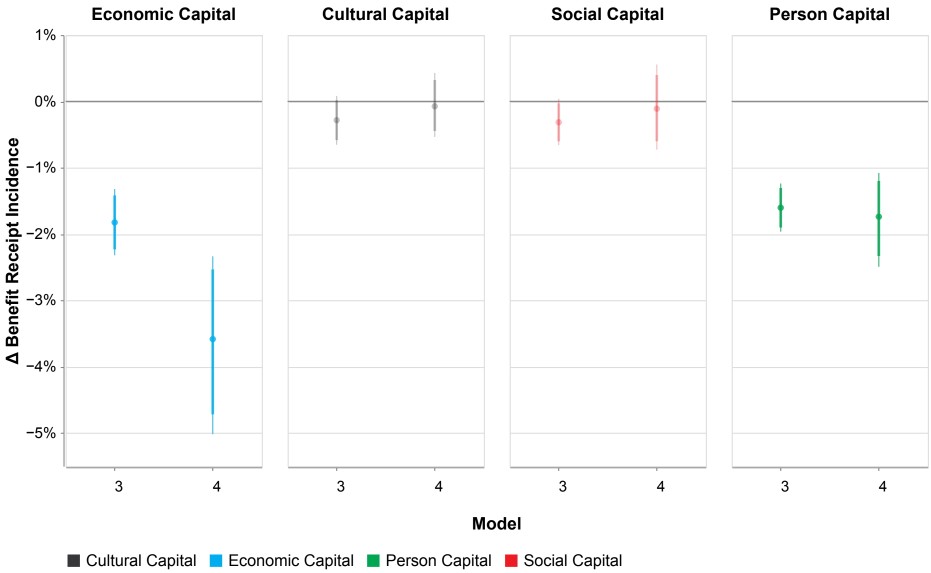
Model 1 served as the baseline, including random intercepts for individuals and intersectional strata. See Table 4.2 for a summary of the results. The intercept estimate was 0.102 (95% CI: 0.081, 0.124), indicating that, on average, individuals had a 10.2% probability of receiving benefits. The random intercept variance for benefit receipt at the individual level was 0.190 (95% CI: 0.189, 0.192), indicating substantial variability among individuals in their likelihood of benefit receipt. The variance attributable to the strata level was 0.057 (95% CI: 0.037, 0.076), suggesting that differences across strata contribute to the total variation in benefit receipt, albeit to a lesser extent compared to individual differences.

In Model 2, gender, migration background and age were introduced as additive fixed effects to examine their associations with benefit receipt while controlling for other variables. Women had a slightly higher probability of benefit receipt compared to men, but the effect was negligible as

Table 4.2: Summary of additive effects on benefit receipt

	Model 1	Model 2	Model 3	Model 4
Intercept	0.102	0.079	0.070	0.060
	(0.081; 0.124)	(0.047; 0.111)	(0.034; 0.101)	(0.035; 0.085)
Gender (ref. Male)				
Female		0.004	0.001	-0.002
		(-0.016; 0.025)	(-0.021; 0.022)	(-0.017; 0.013)
Migration Background (ref. Native)				
Non-Western 1st gen.		0.105	0.088	0.048
		(0.075; 0.135)	(0.058; 0.121)	(0.023; 0.073)
Non-Western 2nd gen.		0.110	0.100	0.037
		(0.071; 0.151)	(0.062; 0.141)	(0.007; 0.069)
Western 1st gen.		0.008	0.001	0.000
		(-0.029; 0.046)	(-0.036; 0.039)	(-0.029; 0.027)
Western 2nd gen.		0.009	0.005	0.007
		(-0.022; 0.041)	(-0.028; 0.038)	(-0.016; 0.031)
Age (ref. 20-30)				
30-40		0.028	0.033	0.020
		(0.002; 0.058)	(0.001; 0.063)	(0.000; 0.043)
40-50		0.066	0.070	0.043
		(0.037; 0.096)	(0.040; 0.103)	(0.020; 0.065)
50-60		0.072	0.079	0.056
		(0.040; 0.105)	(0.044; 0.113)	(0.032; 0.080)
Economic Capital			-0.018	-0.036
			(-0.023; -0.013)	(-0.049; -0.022)
Cultural Capital			-0.003	-0.001
			(-0.007; 0.001)	(-0.005; 0.004)
Social Capital			-0.003	-0.001
			(-0.007; 0.000)	(-0.008; 0.005)
Person Capital			-0.016	-0.017
			(-0.020; -0.012)	(-0.025; -0.010)
Number of Kids (ref. 0)				
1		-0.019	-0.015	-0.010
		(-0.031; -0.008)	(-0.027; -0.004)	(-0.020; 0.000)
2		-0.023	-0.018	-0.012
		(-0.034; -0.011)	(-0.029; -0.006)	(-0.022; -0.001)
3		-0.010	-0.005	-0.003
		(-0.027; 0.007)	(-0.022; 0.012)	(-0.017; 0.011)
4 or more		-0.015	-0.011	-0.010
		(-0.047; 0.016)	(-0.041; 0.021)	(-0.037; 0.015)
Relationship Status (ref. Divorced)				
Married		-0.080	-0.071	-0.048
		(-0.097; -0.063)	(-0.088; -0.054)	(-0.062; -0.033)
Single		-0.039	-0.037	-0.027
		(-0.059; -0.021)	(-0.055; -0.017)	(-0.043; -0.011)
Widow		-0.042	-0.041	-0.056
		(-0.089; 0.003)	(-0.087; 0.006)	(-0.094; -0.019)
Random Effects				
var(be)	0.190	0.191	0.191	0.153
	(0.189; 0.192)	(0.189; 0.193)	(0.189; 0.193)	(0.151; 0.155)
var(strata)	0.057	0.014	0.017	0.010
	(0.037; 0.076)	(0.000; 0.027)	(0.004; 0.031)	(0.001; 0.020)
var(rinpersoon)	0.176	0.173	0.168	0.080
	(0.171; 0.181)	(0.168; 0.178)	(0.163; 0.173)	(0.073; 0.087)

Note: Averages of the fixed effect posterior distributions, 95% credible intervals between brackets. N(individuals) = 3755, N(strata)= 40. **Source**: Authors' own calculation based on non-public individual level register data from the Social Statistical Database (SSD) provided by Statistics Netherlands (CBS) and the Longitudinal Internet studies for the Social Sciences (LISS) from CenterData.



Note: Averages of the fixed effect posterior distributions from Models 3 and 4, 95% and 89% credible intervals as error bars.Predictions statistically not distinct from zero are shaded lighter. N(individuals) = 3755, N(strata)= 40. **Source:** Authors' own calculation based on non-public individual level register data from the Social Statistical Database (SSD) provided by Statistics Netherlands (CBS) and the Longitudinal Internet studies for the Social Sciences (LISS) from CenterData.

Figure 4.2: Estimated effects of capitals on benefit receipt

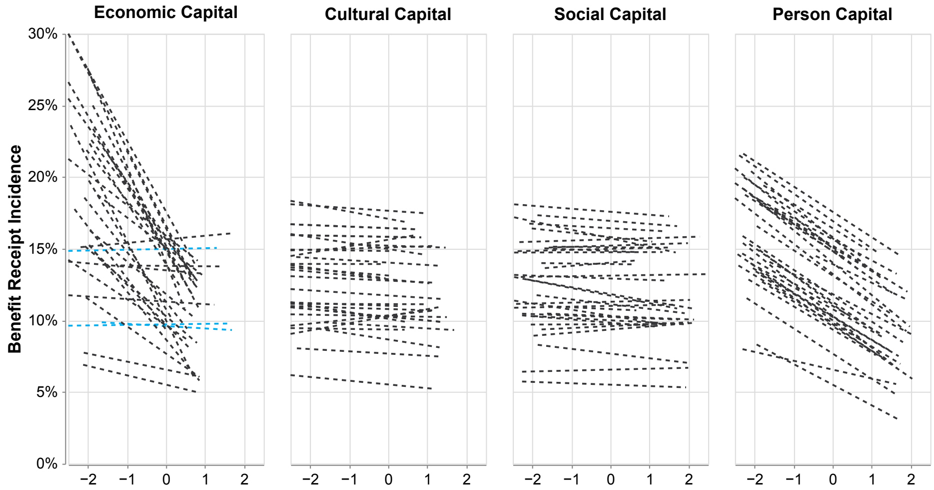
the 95% CI includes 0, indicating no meaningful difference (B = 0.004, 95% CI: –0.016, 0.025). Migration background had notable effects: individuals from a non-western, first-generation background had a credibly higher probability of benefit receipt compared to natives, with an effect of 0.105 (95% CI: 0.075, 0.135), meaning that being from a non-western, first-generation background increased the likelihood of receiving benefits by 10.5%pt. Similarly, second generation migrants had a credibly higher probability of benefit receipt (B = 0.110, 95% CI: 0.071, 0151). For other migration backgrounds, the 95% CI includes 0, indicating no meaningful difference. Age also influenced benefit receipt, compared to people in their 20s, all other age groups had a higher incidence. The random effect variance for the individual level remained relatively unchanged at 0.191 (95% CI: 0.189, 0.193), while the variance for strata decreased to 0.014 (95% CI: 0.000, 0.027), indicating that much of the between-strata variability could be explained by these demographic factors.

Model 3 included the effects of different forms of capital—economic, cultural, social and person—to examine their impact on benefit receipt while controlling for gender, migration background and age. See Figure 4.2 for a visual representation of the effects of different forms of capital on benefit receipt. Economic capital had a credible negative association with benefit receipt (–0.018, 95% CI: –0.023, –0.013), indicating that individuals with 1 standard deviation more economic capital had a lower probability of receiving benefits by 1.8%pt. Social and cultural capitals were not found to affect benefit receipt. Person capital had a small negative impact (–0.016, 95% CI: –0.020, –0.012), suggesting that individuals with 1 standard deviation more person capital were 1.6%pt less likely to receive benefits. This partially confirms Hypothesis 1. This model's variance estimates for individual-level random effects remained consistent at 0.191 (95% CI: 0.189, 0.193) and variance for strata slightly increased to 0.017 (95% CI: 0.004, 0.031).

4.4.2 Random effects of capitals on benefit receipt

In Model 4, the effect of capitals on benefit receipt varies across each intersectional stratum, allowing to study the intersectional heterogeneity in capital effects. The predicted effects of the different forms of capital on benefit receipt are presented in Figure 4.3. For a complete overview of the predicted and random effects see Table C.3, in Appendix C. Cultural, social and person capital are proportionally associated with benefit receipt, meaning their effects are generally homogenous across different intersectional strata. However, the effect of economic capital shows considerable variation among intersectional groups, exhibiting a buffering association.

For most intersectional strata, the predicted random effects (represented by the dashed lines) do not substantially differ from the overall average effect. In three intersectional groups, however, the effect of economic capital is credibly distinct from the overall effect, as detailed in Table 4.3.



Note: Averages of the random effect posterior distributions from Model 4. Black dashed lines represent strata where the association is not credibly different from the average effect at a 95% level. Blue dashed lines indicate a credibly distinct association from the average at a 95% level. N(individuals) = 3755, N(strata)= 40. **Source:** Authors' own calculation based on non-public individual level register data from the Social Statistical Database (SSD) provided by Statistics Netherlands (CBS) and the Longitudinal Internet studies for the Social Sciences (LISS) from CenterData.

Figure 4.3: Estimated random effects of capitals on benefit receipt per stratum

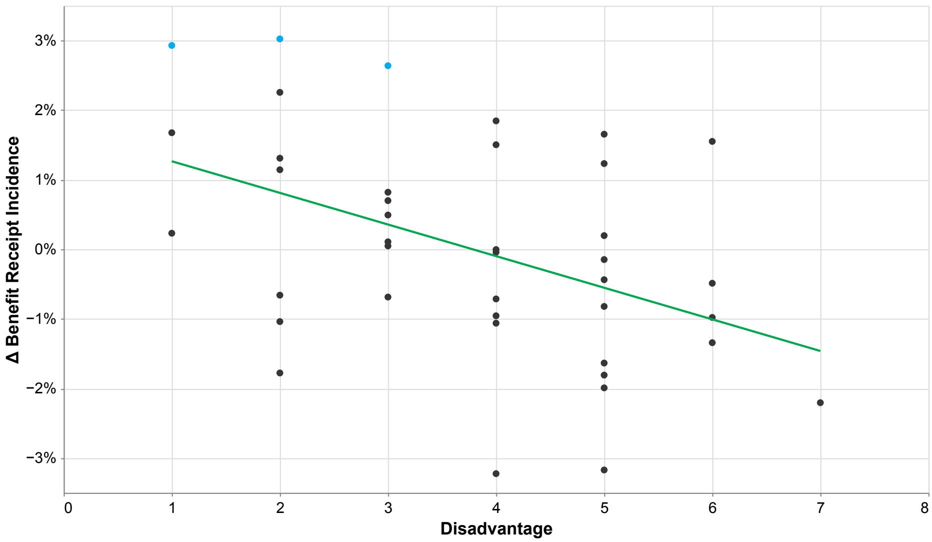
Table 4.3: Random effects of economic capital on benefit receipt

	Predicted Effect		Random Effect	
Strata	**B**	**95%CI**	**B**	**95%CI**
Native 20<30 Female	-0.006	(-0.024; 0.013)	0.030	(0.009; 0.052)
Native 20<30 Male	-0.007	(-0.027; 0.015)	0.029	(0.006; 0.054)
Native 50<60 Female	-0.009	(-0.026; 0.007)	0.026	(0.005; 0.048)

Note: Averages of the random effect posterior distributions from Model 4, 95% credible intervals between brackets. N(individuals) = 3755, N(strata)= 40. **Source**: Authors' own calculation based on non-public individual level register data from the Social Statistical Database (SSD) provided by Statistics Netherlands (CBS) and the Longitudinal Internet studies for the Social Sciences (LISS) from CenterData.

Specifically, in three groups—native men and women in their 20s and native women in their 30s and 50s—the effect of economic capital is lower than the overall average, suggesting that economic capital does not credibly affect benefit receipt in these groups.

Finally, I set out to test hypotheses 2a and 2b by analysing the association between the disadvantageous and the random effect of economic capital. The results, summarized in Figure 4.4, indicate that economic capital is negatively associated with benefit receipt as the level of disadvantage



Note: Averages of the random effect posterior distributions from Model 4 (Economic Capital), Points are blue if credibly distinct at a 95% level from the average effect of economic capital on benefit receipt and black if not. N(individuals) = 3755, N(strata)= 40. **Source:** Authors' own calculation based on non-public individual level register data fromSimilarly, it has the Social Statistical Database (SSD) provided by Statistics Netherlands (CBS) and the Longitudinal Internet studies for the Social Sciences (LISS) from CenterData.

Figure 4.4: Estimated random effects of economic capital and benefit receipt incidence by disadvantage per intersectional stratum

increases for an intersectional group. This association is credibly distinct from zero (r = 0.171, 95% CI = [0.005; 0.378]). These findings imply that economic capital is particularly effective in buffering against benefit receipt in more disadvantaged intersectional groups. The results provide supporting evidence for Hypothesis 2b, specifically regarding the unique role of economic capital.

4.5 Conclusion

This chapter analyzed how economic, cultural, social, and person capital shape the likelihood of benefit receipt, with a focus on the heterogeneity of capital returns across intersectional groups defined by gender, migration background, and age. By employing the MAIHDA approach, I assessed whether the returns to different forms of capital varied across intersectional strata.

First, the analysis aimed to corroborate that capitals help to mitigate benefit receipt. The findings show that economic and person capital generally reduce the likelihood of receiving benefits, supporting the notion that access to these forms of capital plays a protective role. These results suggest that economic and person capital act as stabilizing resources that reduce individuals' reliance on social benefits. However, I did not find social and cultural capital to be associated with benefit receipt, indicating that these forms of capital may play a less direct or limited role in mitigating benefit reliance.

Second, the analysis tested whether the effects of capital differed across intersectional groups. The returns to cultural, social, and person capital were generally homogenous across groups, but the returns to economic capital varied notably. I tested two theoretical expectations regarding these variations: exacerbating effects, where the returns to capital are lower the more disadvantaged a group is, and buffering effects, where the returns to capital are higher the more disadvantaged a group is. The findings provided evidence of a buffering role for economic capital, with a negative association between economic capital returns and disadvantage. Further, the results showed that while economic capital provided notable protection against benefit receipt in most intersectional strata, its effects were diminished and absent for others, particularly for native men and women in their twenties and native women in their thirties and fifties. Notably, I did not find that multiply disadvantaged groups experienced higher-than-average returns to economic capital. Contrary to some findings in the literature (Anderson et al., 2010; Bernardi, 2012), which suggest that economic capital can serve as a buffering resource for disadvantaged groups, my results indicate that privileged groups do not need to rely on economic capital to reduce their likelihood of benefit receipt.

These findings have significant implications for our understanding of privilege and the utilization of capital in terms of benefit receipt. Generally, individuals with more economic capital can mitigate the risk of receiving benefits. This means that individuals with fewer economic resources are more likely to rely on social benefits, such as social assistance and unemployment insurance, which serve as crucial safety nets protecting against poverty. The buffering case posits that disadvantaged or multiply disadvantaged groups may use economic capital more strategically to overcome systemic labor market barriers, such as discrimination and limited access to stable employment (Andersson & Weber, 2024; Bernardi, 2012). However, my results paint a different picture. Rather than finding that disadvantaged groups yield higher returns on economic capital, the findings show that privileged groups experience lower returns on economic capital. This suggests that privileged individuals do not need to rely as heavily on their economic resources to mitigate their likelihood of receiving benefits, highlighting the differential reliance on capital based on one's social position.

While the findings of this chapter provide important insights into the role of different forms of capital in shaping benefit receipt, there are several limitations that must be acknowledged. Under the constraints of the available data in the LISS panel, the operationalization of different forms of capital in this chapter still captures key aspects of these resources, but there are certain limitations to note. Economic capital, while including financial assets, dwelling ownership and educational attainment, does not account for work experience, job skills, or employment stability, which could influence its full impact (Heggebø et al., 2020; Lietzmann & Hohmeyer, 2022). Social capital was operationalized using network size and density, capturing part of its importance, though for instance relationship quality and practical support were not directly measured (Shirado et al., 2013). Cultural capital (Bourdieu, 1986) included highbrow participation and language proficiency but did not include soft aspects, like lowbrow cultural participation (Thomas, 2018). While lowbrow cultural activities may operate through different mechanisms, I encourage future research to focus on the returns of lowbrow forms of cultural capital. Lastly, person capital was based on health indicators from self-reports, effectively capturing health status but not traits like appearance and attractiveness. Despite these constraints, the current conceptualization of capital already encompasses a broad and meaningful set of resources.

Although the use of time-lagged data strengthens the estimation of capital effects on benefit receipt in this chapter, it comes with limitations concerning the modeling of causality. Ideally, I would have employed (quasi-)fixed effects models to directly assess whether changes in individuals' capitals over time lead to corresponding changes in their likelihood of receiving benefits (Gunasekara et al., 2014). However, the LISS dataset's sample size was too small to model intersectional heterogeneous capital effects with sufficient statistical power. Additionally, while the time-lagged approach reduces reverse causality concerns, it does not fully isolate causal effects. More robust approaches for making stronger causal claims would be fixed effects regression, as these would control for unobserved individual characteristics that remain constant over time (Angrist & Pischke, 2008) and focus on the effects of changes in capital on benefit receipt. In this regard, future studies with larger samples would be better equipped to explore these causal relationships and offer more robust causal conclusions (Falkenström, 2024).

Despite these limitations, the results provide a useful starting point for understanding the role of different forms of capital across intersectional groups in terms of benefit receipt. The findings indicate that privileged groups require less reliance on economic capital to avoid benefit receipt, while disadvantaged groups do not show disproportionately higher returns from economic capital. This suggests that economic capital functions differently depending on an individual's social position. Importantly, this chapter underscores the potential of targeted interventions to enhance the economic capital of disadvantaged groups, thereby reducing their reliance on social benefits. As one of the first quantitative intersectional studies to examine a potential mechanism underlying intersectional inequalities, this chapter contributes to our understanding of how different forms of capital interact with structural inequalities. By incorporating an intersectional lens and quantifying heterogeneous returns to capital, this study enhances our understanding of the mechanisms behind social stratification in benefit receipt.

Chapter 5

Social assistance persistence at the intersection of gender and migration background

A different version of this chapter has been submitted to an international journal.

Jos Slabbekoorn: Conceptualization, Methodology, Formal analysis, Writing – Original Draft, Visualization. **Edvard Larsen:** Conceptualization, Writing – Original Draft, Writing – Review & Editing. **Gunn Birkelund:** Conceptualization, Writing – Review & Editing.

ABSTRACT

This chapter focuses on the complex inequalities in the receipt and persistence of social assistance by examining the interplay of two social characteristics: gender and migration background (including generation). Persistent receipt of social assistance, defined as prolonged or recurrent reliance on benefits, is a phenomenon with far-reaching consequences. Previous research has primarily studied gender and migrant background inequalities in persistent social assistance receipt in isolation from one another. This chapter takes a novel approach by investigating the multiplicative effects of these social characteristics, while also considering the potential mutual influences that arise from multiple group membership. It employs longitudinal Multilevel Analyses of Individual Heterogeneity and Discriminatory Accuracy (MAIHDA) to study the accumulating likelihood of social assistance receipt, using Norwegian register data. We find substantial (disproportionate) intersectional differences in social assistance receipt and persistence. Our findings demonstrate the intersectional complexity underlying the persistence of social assistance receipt and how the intersection of multiple group memberships can create unique challenges and opportunities for people.

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5.1 Introduction

Individuals who have received social assistance in one period are consistently shown to be more likely to experience further receipt in subsequent periods, giving rise to a pattern of persistent reliance on social support (Cappellari & Jenkins, 2014; H.-T. Hansen, 2009; J. Hansen et al., 2014; Jenkins & García-Serrano, 2004; Königs, 2014b; Kyyrä & Pesola, 2020; Schels, 2018). This phenomenon of the persistent use of social assistance can be thought of as a Matthew effect (DiPrete & Eirich, 2006; Merton, 1968, 1988), resulting in an exacerbated risk for individuals who have previously used social assistance. The persistence can be attributed to two primary factors. First, prior social assistance receipt may directly influence an individual's future opportunities in the labor market through various mechanisms, such as human capital deterioration or potential negative signals to future employers. Second, individuals who initially receive social assistance might be selected on unobserved characteristics that also predict future social assistance receipt (Aradhya et al., 2023; Arulampalam et al., 2000; Biewen & Steffes, 2010).

Differences in persistent use of social assistance can further exacerbate social inequality between different groups more generally. Thus far, the phenomenon has predominantly been studied along the lines of gender, migration background and generation separately. These studies find that benefit receipt persistence is more prevalent among women (Jenkins & Rigg, 2004; Königs, 2014b) and immigrants (J. Hansen & Lofstrom, 2009; Königs, 2014b). However, less attention has been paid to the complexity of individuals holding multiple group identities and experiencing recurrent episodes of social assistance receipt. We aim to make a dual contribution to this literature. First, we introduce an intersectional perspective into the analysis of disparities in social assistance receipt persistence. Intersectionality theory posits that the (dis)advantages associated with membership in various groups may interact and amplify or attenuate disadvantage (Settles & Buchanan, 2014). A range of studies have demonstrated that disadvantaged groups are more likely to experience social assistance receipt (e.g. Cappellari & Jenkins, 2014; J. Hansen et al., 2014; J. Hansen & Lofstrom, 2009; Jenkins & Rigg, 2004; Königs, 2014b), and individuals belonging to multiple disadvantaged groups may face an amplified likelihood of social assistance receipt (Hussénius, 2021; Slabbekoorn et al., 2024). These intersectional studies show that the interplay of disadvantageous social characteristics is complex and that previous research (which conventionally implies an additive accumulation of disadvantageous social characteristics) may have over- and/or underestimated the social assistance receipt persistence for certain groups. Such quantitative intersectional analysis has not yet been performed in Norway, and this chapter will fill this gap. Second, we employ a modeling approach that extends Multilevel Analysis of Individual Heterogeneity and Discriminatory Accuracy (MAIHDA, Evans et al., 2018), by introducing a lagged effect of (prior) social assistance receipt. Thereby, this chapter aims to uncover a potential factor that may be a root cause for intersectional inequalities in social assistance receipt. This modelling approach simultaneously considers the long and/or recurrent spells of social assistance receipt. Research on unemployment persistence has shown that it is essential to account for recurrent episodes of unemployment as an integral component of overall persistence, as individuals who have previously experienced unemployment are more likely to face unemployment again in the future (Aradhya et al., 2023; Arulampalam et al., 2000; Biewen & Steffes, 2010).

Thus, we set out to answer the following research questions: *Does prior social assistance receipt increase the likelihood of subsequent social assistance receipt (i.e. the persistence effect)?*; and *To what extent are there intersectional heterogeneities (i.e. the non-additive effects of gender, migration background and generation) in (the persistence of) social assistance receipt?*

Our empirical case is Norway, a context characterized by a strong welfare state and relatively high levels of labor market participation (Nilsen, 2020). In this chapter we focus on social assistance (tiltakspenger). Social assistance is available to all registered inhabitants of Norway that cannot cover basic subsistence costs through paid work, savings, other cash benefits and other financial entitlements. Social assistance in Norway provides temporary financial support to individuals and families unable to meet basic needs, with eligibility determined by a comprehensive assessment of income and assets. Applicants must demonstrate that they have exhausted all other means of support and, if capable, are required to actively seek employment (NAV, 2024). The incidence of social assistance receipt increased by 66.7% from – 1.2% to 2.0% – between 2007 and 2018, which is considerably higher than other OECD countries who saw 9% increase (OECD, 2019b).

We use register data provided by Statistics Norway (SSB), which comprises a broad set of inter-linked administrative records. Using administrative data has two main advantages. It contains information on all residents of Norway including populations that are harder to reach for survey-based research and record-based social welfare information is considerably more reliable and detailed compared to self-reported information in survey-based research (Tourangeau et al., 2014). We build upon Multilevel Analysis of Individual Heterogeneity and Discriminatory Accuracy (MAIHDA, Evans et al., 2018) and make one extension to model Matthew effects by introducing a variable measuring a (lagged) effect of prior social assistance receipt, which allows us to estimate intersectional variations in the persistence effect of social assistance.

We recognize the risk of reinforcing stereotypes and stigmas against (multiply) disadvantaged groups by reporting detailed findings on social assistance incidence and persistence. In extreme cases, such reporting could unintentionally reinforce or even exacerbate the disadvantaged position of certain groups. However, providing detailed insights into inequality-generating processes—particularly those informed by an intersectional perspective—is essential to addressing and reducing these inequalities. This tension is an inherent challenge when studying and reporting on disadvantaged groups. While not unique to our research, our detailed analysis may make this concern more pronounced. Lastly, we wish to emphasize that we view social assistance receipt primarily as a reflection of external structural factors, such as systemic inequality and discrimination. It serves as an indicator of economic precarity, representing a social safety net designed to support individuals during periods of unemployment and poverty.

5.2 Theory

5.2.1 Differences in the incidence of social assistance receipt

In the literature on social assistance receipt, theoretical arguments revolve around two synchronous mechanisms, namely labor market dynamics and processes of benefit take-up. The former explains why certain groups are more prone to experience (partial) unemployment. The latter explains why certain groups exhibit unequal access to social assistance despite facing (partial) unemployment (Bennett, 2024; Janssens & Van Mechelen, 2022). Variations in take-up may be due to factors such as individuals not applying for eligible social assistance, challenges in obtaining benefits after applying, or ineligibility despite being unemployed (Bennett, 2024). Most theoretical discussions focus on labor market dynamics and unemployment, as these are prerequisites for eligibility for social assistance. Nevertheless, the process of obtaining social assistance can vary between unemployed people and is a crucial step in receiving social assistance. Therefore, we will discuss labor market position and social assistance take-up in conjunction in our theoretical argumentation.

A substantial literature demonstrates gender and migration background differences in social assistance receipt (Cappellari and Jenkins 2014; Hansen 2008; Hoff et al. 2019; Königs 2014a). The findings for gender differences in social assistance receipt are inconsistent; some find men have a higher incidence of benefit receipt (Hansen 2008), others find no gender differences (Cappellari & Jenkins, 2014; J. Hansen & Lofstrom, 2009; Hoff et al., 2019; Königs, 2014a). These inconclusive findings possibly reflect diverse factors driving gender differences in labor market positions. First, because women often assume primary caregiving roles, they tend to face less job security and lower wages, due to their higher propensity to work part-time. Career choices, such as seeking employment in sectors deemed "motherhood friendly" and accepting less secure jobs, also contribute to this disparity (Cappellari & Jenkins, 2014; Hoff et al., 2019; Königs, 2014a). Additionally, employers may deem women more suitable for jobs in female-dominated sectors, increasing their chances to be hired in these sectors (Birkelund et al., 2022). Second, women may face fertility discrimination,which further hampers their employment prospects by limiting their opportunities for being hired, promotion, or retention due to concerns about potential absences related to pregnancy and parental leave (S. O. Becker et al., 2019; Correll et al., 2007). However, Bygren et al. (2017) found that employers in Sweden did not discriminate based on gender and parental status, indicating that fertility discrimination may play a minor role in Nordic labor markets.

Differences in social assistance receipt are more consistently found in relation to migration. Immigrants, especially with a non-western background, are found to receive social assistance more often than natives (Königs, 2014a). This is mainly attributed to the poorer labor market positions of immigrants, partly driven by ethnic discrimination (Birkelund et al., 2014; Birkelund et al., 2019; Blommaert et al., 2012; Connor & Koenig, 2015; Thijssen et al., 2021), language barriers (Sevinç, 2016), non-recognition of credentials (Lancee & Bol, 2017), social network homophily and resource and health disparities (Behtoui, 2007; Bolíbar, 2020; Connor & Koenig, 2015; Greve, 2016; Jongen et al., 2020). On the flipside, the aforementioned factors also potentially hamper take-up of social assistance: Immigrants that have a poorer language proficiency may experience more difficulty applying for social assistance and some immigrants that recently arrived may not be eligible for social assistance (Strockmeijer et al., 2020). However, findings show that non-take-up only marginally lowers social assistance receipt rates among immigrants (Castronova et al., 2001).

Despite being born, raised and educated in the host country, the children of immigrants still face persistent disadvantages compared to the children of native parents. Their weaker labor market outcomes can be partly attributed to lower levels of human, social and cultural capital (Crul & Vermeulen, 2003; Drouhot & Nee, 2019; Hermansen, 2016). For example, the descendants of immigrants tend to have lower educational attainment than people with native-born parents, mostly due to the lower socio-economic status of their parents (Hermansen, 2016; van de Werfhorst & Heath, 2019). Studies suggest that parents with a migration background find it harder to help their children navigate the education system in the host country (Heath et al., 2008). However, these resource disparities mainly affect the labor market entry of second-generation immigrants, and do not seem to compound into larger ethnic differences in the labor market over time (Hermansen, 2016). Additionally, second-generation immigrants experience ethnic discrimination in similar ways as their parents, as demonstrated by field experiments both internationally (e.g., Quillian & Lee, 2023) and in Norway (Di Stasio & Larsen, 2020; Midtbøen, 2016). Having a minority-sounding name reduces call-back rates after applying for a job, which limits people's employment chances (Zschirnt & Ruedin, 2016). In summary, although children of immigrants fare better on the labor market than their parents, they still face additional challenges that lead to poorer labor market outcomes compared to natives (Aradhya et al., 2023; Hermansen, 2016). This, in turn, could lead to a higher incidence of social assistance receipt.

5.2.2 Persistence in social assistance receipt

It is well-established in the empirical literature on social assistance receipt that past social assistance receipt is predictive of subsequent incidence of social assistance receipt. There are multiple theoretical arguments explaining this finding.

The first set of arguments explain the persistence of social assistance receipt in terms of initial differences and selection over time, as opposed to a causal effect of past social assistance recipiency. In addition to the mechanisms explaining group differences in the incidence of social assistance receipt discussed earlier, individuals who become unemployed potentially differ from those who do not on certain unobserved variables that, in turn, influence their probability of subsequent unemployment or social assistance receipt. Even in the absence of a direct effect of unemployment or social assistance recipiency on subsequent outcomes, a selection effect on unobserved characteristics causing both initial and subsequent unemployment might create a correlation in itself (Heckman & Borjas, 1980). Machin & Manning (1999) referred to this mechanism as "unobserved heterogeneity", defined in opposition to "true duration dependence". Additionally, one could assume that such a selection effect becomes clearer over time, in that those who remain long-term unemployed are even more selected on unobserved characteristics.

The other set of arguments thus revolves around "true duration dependence" and focuses on the actual effects of unemployment or social assistance receipt on re-employment. These arguments can roughly be divided into two mechanisms. The first mechanism focuses on how unemployment affects an individual's resources, social networks, health and motivations for re-entry into employment. Remaining outside the labor market can lead to skills and knowledge becoming outdated (Machin & Manning, 1999) and ties to former colleagues may weaken over time (Kristiansen, 2021). Moreover, financial strain and uncertain employment prospects can negatively impact mental well-being (Cooper et al., 2015; Goldsmith et al., 1997). This decay of resources could hinder re-employment prospects, given their significant influence on employers' hiring decisions. Another aspect to consider is the financial adjustment that occurs during unemployment. Individuals often become accustomed to their altered financial circumstances, which can include a higher "cost" associated with seeking employment (such as transportation and childcare expenses). Previous studies have highlighted the potential for reduced motivation to return to work, particularly among those facing prolonged periods of unemployment (Andersen, 2020; Bennmarker et al., 2007; Jenkins & García-Serrano, 2004; Jenkins & Rigg, 2004).

The second mechanism revolves around stigmatization and how prospective employers perceive unemployed individuals. Long and repeated spells of social assistance receipt and unemployment can signal low productivity and poor employability to employers who use the limited information available to make inferences about job applicants (Birkelund et al., 2017; Eriksson & Rooth, 2014; Weisshaar, 2018). In the short term, this may affect the chances of finding re-employment (Arulampalam et al., 2000), but may also have long term consequences (Eliason & Storrie, 2006). The persistence of unemployment stems from a genuine reliance on state assistance, wherein current reliance on social support programs predicts subsequent dependence on such aid. This dependency contributes to a continuous buildup of unemployment over individuals' lifetimes, particularly affecting those who are already unemployed. Moreover, if this dependency is more pronounced among individuals and groups with a higher risk of unemployment, it exacerbates the cycle. Long-term recipients of social assistance may opt for employment in sectors characterized by unstable job opportunities and lower wages. Consequently, this choice may heighten the likelihood of subsequent spells of unemployment and reliance on social assistance (Aradhya et al., 2023; McQuaid & Lindsay, 2002).

5.2.3 Heterogeneity in the persistence of social assistance receipt

So far, we have discussed two well-established findings in the literature on social assistance receipt: that there are differences along the dimensions of gender and migration background in the incidence of social assistance receipt and that social assistance receipt is "sticky" (i.e. prior social assistance receipt predicts subsequent social assistance receipt). However, there is also reason to assume that heterogeneity in social assistance persistence is due to state dependency, which affects different population groups to varying degrees. Some of this heterogeneity has been studied empirically: previous studies have documented differences in persistence effects between genders (Altuzarra, 2015; Baussola & Bartoloni, 2016; Cuesta & Budría, 2017), and ethnic or immigrant groups (Aradhya et al., 2023; Constant et al., 2011).

Several studies have shown gender differences in the persistence effects of unemployment and social assistance receipt, but the conclusions are mixed: some find women have smaller persistence effects (Altuzarra, 2015; Baussola & Bartoloni, 2016), others find no gender differences (Cuesta & Budría, 2017; García, 2017). Nevertheless, in recent times, particularly in egalitarian contexts, this gender disparity in persistence effects may have diminished. Women may (have) experienced lower persistence effects, while they generally tend to work in sectors less susceptible to economic fluctuations, such as education and health, while men are more commonly found in highly cyclical industries like construction and manufacturing (Baussola & Mussida, 2017; Sahin et al., 2010). Moreover, the growing number of policy measures supporting job security and family leave may have further mitigated gender disparities in persistence effects, particularly in traditionally stable sectors. Additionally, temporarily exiting the labor market without using benefits may be more socially acceptable for women, as they often (temporarily) exit the labor market during motherhood (Weisshaar 2018).

As in studies on the incidence of social assistance receipt, more consistent are the findings of migration background differences in persistence effects, as immigrants and decedents of immigrants are found to have higher persistence effects compared to the majority (Aradhya et al., 2023; Constant et al., 2011). The combination of ethnic stereotypes and (prior) unemployment may reinforce the assumptions employers hold regarding the productivity and suitability of job applicants with a migration background and a history of unemployment. Therefore, these disadvantages may amplify each other, worsening their chance of finding (re-)employment and increasing the risk of subsequent social assistance receipt. However, in a recent Norwegian field experiment no evidence was found for such scarring effects of unemployment being more severe for ethnic minorities (Birkelund et al., 2017). Immigrants may adjust to their financial circumstances while receiving social assistance, as their costs associated with finding re-employment might be higher compared to natives, one can think about this as a habituation effect (Aradhya et al., 2023). This could potentially offset the economic advantages linked with obtaining re-employment, leading to prolonged periods of social assistance receipt.

Second-generation immigrants typically exhibit improved integration into the labor market compared to their parents, resulting in reduced reliance on social assistance. They experience shorter and less frequent periods of unemployment (Constant et al., 2011) and consequently utilize social assistance less persistently. Nonetheless, in contrast to native populations, they still rely more often on social assistance (Hansen 2009). While second-generation immigrants encounter ethnic discrimination, it is generally less severe than that faced by first-generation immigrants (Fangen & Lynnebakke, 2014), although it still impedes their access to stable employment, thereby increasing the likelihood of dependence on social assistance (Smedsvik et al., 2022). Conversely, the enhanced integration of second-generation immigrants helps alleviate some of the barriers faced by first-generation immigrants in accessing social assistance, yet still potentially leading to slightly higher receipt rates in these groups compared to natives.

Overall, the reviewed literature underscores that disparities in benefit receipt are influenced by factors such as gender, migration background, and generation, with numerous studies documenting differences in both the incidence and persistence of social assistance. However, comparatively less attention has been given to the intersection of gender, migration background and generation and how this affects social assistance persistence.

5.2.4 Intersectionality in social assistance incidence and persistence

We thus have reasons to expect group differences in the incidence of social assistance receipt and in any potential persistence effects. However, less is known about how these group characteristics might be interconnected multiplicatively leading to disproportionate differences in outcomes. Intersectional approaches to studying inequality have grown increasingly more common over the past decade, among both quantitatively and qualitatively oriented social scientists (Bauer et al., 2021; Brown et al., 2016; Settles & Buchanan, 2014). These perspectives build on the common assumption that multiple social characteristics are mutually influential in potentially complex ways. The original formulation of the concept of intersectionality can be traced back to black feminist US scholarship, but has been impactful in European contexts investigating a range of domains and inequality outcomes (for a meta analysis see: Bauer et al., 2021). In these studies, the main focus has been to describe the multiple jeopardy of groups with multiple disadvantageous social characteristics, such as black women in the United States (King, 1988). Recent quantitative intersectional studies have documented attenuating and compensating combinations of (dis-)advantageous social characteristics, of which the reverse gender gap is the most concrete example. In European contexts, immigrant women are found to have a relative advantage compared to immigrant men (Arai et al., 2016; Di Stasio & Larsen, 2020).

An intersectional approach has both theoretical and analytical implications (Cole, 2008; Else-Quest & Hyde, 2016; Hancock, 2007). Firstly, intersectionality recognizes that individuals embody multiple social characteristics, such as gender, race, ethnicity, generation, class and sexual orientation, simultaneously; and that these characteristics are interconnected, shaping and influencing one another. This means that the experience of each social category cannot be understood in isolation but must be analyzed in the context of its interaction with other categories. Secondly, inherent within each socially constructed category is an aspect of assumed inequality or power, status and wealth. This means that social categories are not neutral classifications but are hierarchically organized, with certain categories being valued more highly than others. Consequently, individuals experience varying degrees of advantage or disadvantage depending on their specific combinations of these categories. For instance, a person belonging to a privileged ethnic group will generally enjoy more power and opportunities than someone from a marginalized one. Thus, these social categories systematically influence the distribution of resources, opportunities and privileges, perpetuating social hierarchies and disparities. Thirdly, intersectionality attends to social categories as properties of both the individual and the social context. These categories and their significance are regarded as contextually influenced and as such based on societal structures, institutions and interpersonal relationships.

Although intersectional approaches to the study of social assistance persistence are uncommon, there are many relevant empirical examples of other inequality outcomes in a labor market context. One such example is labor market discrimination: In the experimental literature on hiring discrimination, the analytical scope has shifted from investigating gender discrimination and ethnic discrimination separately, to studying how they are interconnected in different contexts. In a Swedish study, Bursell (2014) finds that ethnic discrimination particularly targets immigrant men. Di Stasio & Larsen (2020), explicitly applying an intersectional framework, find that ethnic discrimination depends not only on gender, but also on the occupational context. If barriers to entry into the labor market, such as discrimination based on ethnicity and gender, contribute to social assistance receipt and unemployment, then it is likely that the patterns of social assistance receipt will also vary depending on the intersections of these factors. This implies that individuals will experience different levels of social assistance receipt based on the combined effects of their ethnicity, gender and the specific occupational contexts they face.

In summary, we aim to explore intersectional heterogeneity in the incidence and persistence of social assistance receipt. Given the scarcity of previous research we have no specific hypotheses regarding the outcomes of particular social groups. Instead, we aim to answer the more general question of whether there is intersectional heterogeneity in social assistance receipt and persistence, i.e. if social characteristics are interconnected in more complex ways than simply the sum of their parts, leading to disproportionate inequalities in social assistance receipt. In other words, our approach seeks to uncover intersectional inequalities in social assistance receipt and its persistance, recognizing that the interplay of social characteristics may yield complexities beyond mere additive assumptions. By adopting an agnostic stance and exploring the broader question of intersectional heterogeneity, we aim to gain a comprehensive understanding of how gender, migration background and migration generation interact and shape the dynamics underlying social assistance receipt (persistence).

5.3 Data and methods

5.3.1 Data

For this chapter, we make use of administrative data from the Norwegian Register, provided by Statistics Norway (SSB).[1] This database comprises a collection of inter-linkable administrative registers, which consist of individual level data for the full Norwegian population. These registers provide an excellent basis for an intersectional study on the inequalities in the persistence of social assistance receipt. First, they provide longitudinal and nationally representative data, allowing to observe individual changes in social assistance receipt over time. Second, since the data comes from administrative registers, it provides reliable information on social assistance receipt and sample attrition is avoided. In Norway, social assistance usually considers household finances, making household-level data ideal. However, like most studies, our data focuses on individuals (e.g., J. Hansen & Lofstrom, 2009).

The observation period was limited from 01-01-2004 until 31-12-2019 because the data from the employment register start in 2004 and we want to exclude potential COVID19-related biases. From the total population we selected individuals who are part of the core-workforce (ranging between 25 and 60 years of age), eliminating the influence of young people living with their parents, students and pensioners. We further exclude individuals who were fishers and former military personnel, as they can apply for dedicated provisions and are therefore not eligible for social assistance. Lastly, for individuals who emigrated, subsequent observations were excluded. We excluded individuals who only had one yearly observation, to allow for time-lagged persistence effects. For our analyses, we take a stratified sample, where we randomly select 300 individuals from each intersectional stratum (i.e. the unique combinations of gender, migration background and generation). This results in a sample of 12,600 individuals with 107,433 yearly observations. For our robustness analyses, we first select individuals who have received social assistance during our observation period. We take a stratified sample using the same approach as for our analytical sample.

5.3.2 Operationalization

5.3.2.1 Dependent variable

The dependent variable for our analysis is *social assistance receipt*. Using information from the social assistance register, we constructed a variable that indicates whether an individual has received social assistance in any given year during our observation period. Note that this operationalization differs from the preceding chapters, where benefit receipt as a major source of income was used, due to data availability constraints.

[1] Under certain conditions, these register data are accessible for statistical and scientific research. For further information: mikrodata@ssb.no.

5.3.2.2 Socio-demographic variables

Gender was operationalized as the gender according to the person register of 2019, where individuals could be registered as either (0) male or (1) female.

Migration background was operationalized using registered country of origin in the person register of 2019. We distinguish between seven different regions of origin (Nordic Countries, Western Europe, Eastern Europe (excluding Poland), North America and Oceania, South and Latin America, Africa (excluding MENA) and Asia (excluding MENA and PIB)); this is similar to J. Hansen & Lofstrom (2009). We also distinguish people from 3 major migration origins, being: Poland, MENA (i.e. Middle Eastern and Northern African countries, UNICEF, 2019) and Pakistani, Indian and Bangladeshi (PIB). For individuals that migrated to Norway their country of birth was used, for descendants of immigrants the country of birth of their mother was used. If the mother was born in Norway, but the father was not, the country of birth of the father was used to determine the migration background of the individual. Individuals whose parents were also born in Norway were distinguished to be native. This results in eight different origin regions.

Generation is a variable indicating whether individuals are natives (0), people who migrated to Norway themselves (first generation, 1), or who are direct descendants of immigrants (second generation, 2).

Intersectional strata were operationalized as all possible combinations of gender, migration background and generation (following the approach of Evans et al., 2018). We thus identify 42 distinct intersectional groups, ranging from native-born women to second- generation men from Asia.

5.3.2.3 Independent variables

Social assistance receipt in the prior year is a similar operationalization of the persistence effect as in Aradhya et al. (2023) and Wooldridge (2005). This means that for 2005 the variable indicates whether an individual has received social assistance in 2004.

5.3.2.4 Control variables

To control for miscellaneous effects in social assistance receipt, we control for education (included as a categorical variable for all ISCED 2011 levels, ref. ISCED 01), socio-economic status (ISEI, Ganzeboom, 2010), reason for migration (ref. born in Norway), the number of children younger than 18 (included as a linear term) and relationship status (included as a categorical variable, distinguishing between: Partnered (ref.), Separated, Widowed, or Single). Missing observations in socio-economic status are mean imputed and an additional variable was included to indicate whether an observation was missing[2]. In the case of missing values for education, an additional

[2] Note that the handling of missing data differs from the preceding chapters, where bayesian imputation was used which the statistical software used in this chapter does not do by default.

category has been included to indicate this. For descriptive statistics of the control variables per intersectional stratum see see Table D.1 in Appendix D

5.3.3 Methodological approach

Modelling intersectional heterogeneity empirically presents some key challenges. First, modelling complex interaction terms in a classical frequentist regression framework leads to issues of multiple hypothesis testing and interpretation[3]. Second, from a theoretical point of view, we would like to avoid (1) using native men as a reference group to make intersectional comparisons and (2) to test accumulated (dis-) advantage using interactions. In line with the core idea of the intersectionality framework that the combination of social characteristics is more than the simple sum of parts, it would be more appropriate to isolate this non-additive component to test the relative disadvantage of intersectional groups. In order to address these challenges, we analyzed our data using longitudinal Multilevel Analyses for Individual Heterogeneity and Discriminatory Accuracy (MAIHDA). Originally developed in the context of medical sciences (Evans et al., 2018), the core idea of the MAIHDA approach is to model interactions of social characteristics directly through intersectional strata. These are theoretically informed subgroups made by combining demographic variables of interest, such as gender and migration background. These strata are then used in a hierarchical multilevel framework, thus conceptualizing social characteristics as group-level properties with individuals nested within these groups. MAIHDA has become the state-of-the-art method for studying intersectional inequalities and addresses some of the key challenges of intersectional modelling. First, it addresses the problem of multiple testing by shrinking the estimates of intersectional effects towards the mean, reducing the likelihood of chance significance for small-sample intersections. This differs from ordinary regression models, where including separate parameters for each intersection amplifies the risk of chance significance for about 5% of the intersections at the 95% level Evans (2019b). Second, it is a parsimonious approach to study multidimensional intersectional inequalities, as it models multiplicative effects as random intercept variations. Third, it closely follows theoretical reasoning of the predominantly qualitative intersectional literature, by distinguishing additive and non-additive effects. Fourth, it is a flexible framework, which was initially developed for cross-sectional studies (Evans et al., 2018), but now has been expended to longitudinal studies (Alonso-Perez et al., 2023; Evans et al., 2023). The MAIHDA approach has been used to study educational (Keller et al., 2023), well-being (Kern et al., 2020) and health inequalities (Evans, 2019b).

Our models were estimated in `R 4.2.2` using the `brms` package (Bürkner et al., 2023). The

[3]While hierarchical modeling typically nests observations within individuals and individuals within strata, a cross-classification of strata and years is appropriate in our case because the primary focus is on estimating strata-level effects rather than individual-level trajectories. This approach allows for the simultaneous estimation of year-specific trends and strata-level differences without assuming strict nesting or requiring longitudinal dependence to be explicitly modeled. By doing so, we ensure that the strata-level effects remain the central focus while accounting for temporal variability across years (Raudenbush & Bryk, 2002).

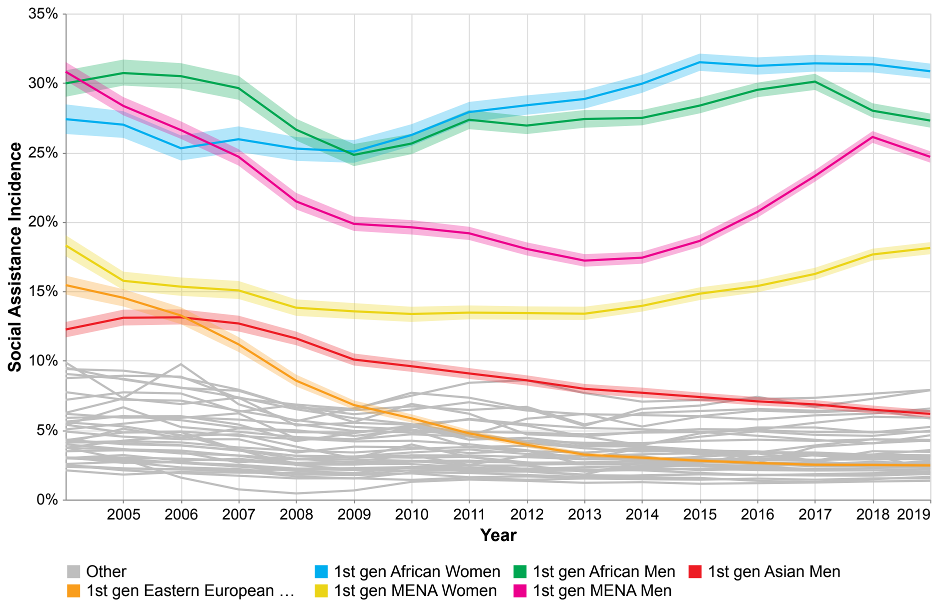
posterior distributions were summarized using the `tidybayes` package (Kay, 2023). We estimated our models as Bayesian multilevel linear probability models, using 2 chains, narrow prior distributions (Reasch, 2014), a burn-in phase of 2500 iterations and equally sized posterior distributions. The posterior distributions of both chains were combined, resulting in posterior distributions of 5000 iterations. We compute both 95% and 89% credible intervals. The 89% credible intervals reminds us about the arbitrary nature of the 95% limit for significance testing (McElreath, 2020).

Our analytical strategy was structured as follows: Model 1 introduces a cross-classified multilevel structure, nesting observations within time (as calendar years) and strata. This model estimates the social assistance incidence rate per specific intersectional stratum. It further allows us to calculate the intra-class correlations at both the stratum and year levels, to infer the proportion of variance that is attributable across these distinct hierarchical levels. Model 2 incorporates the additive effects of gender, migration background and generation. This extension allows for a more detailed examination of disparities in social assistance receipt across these socio-demographic characteristics. Moreover, this model dissects the non-additive effects as manifest in random intercept variations. We use this information to calculate the proportional change of variance (PCV) at the stratum level, which shows to what extent the additive effects of gender, migration background and generation contribute to the variation between strata in social assistance incidence. Model 3 introduces the random effect of social assistance receipt in the prior year. This allows us to estimate the persistence effect in social assistance receipt in the overall sample and the variation in persistence effects per stratum. Model 4 introduces interaction effects between prior social assistance receipt and demographic variables. These interactions enable the assessment of (non-)additive effects per stratum, providing a more intricate understanding of the dynamics between prior receipt and demographic characteristics. Model 5 represents an extension of Model 4 by encompassing control variables. This variation serves the purpose of testing the robustness of our findings against potential spurious effects, thereby enhancing the reliability and validity of our analytical outcomes.

5.4 Results

5.4.1 Descriptive statistics

Our exploration of social assistance receipt and persistence in Norway begins by illustrating the landscape through descriptive statistics, followed by an analysis of empirical results to offer a more comprehensive understanding. The incidence rates of social assistance in each stratum per year is presented in Figure 5.1. Most of the strata maintained a comparatively stable incidence rate, ranging between 0.3% and 9.8% throughout the observed period. Six cases show notable deviations in incidence patterns. Among these, individuals – both men and women – with a first-generation African migration background exhibit a notably high incidence of social assistance receipt, ranging from 24.8% to 31.5% throughout our observation period. Moreover, while most



Note: Calculated as a bootstrapped mean for each stratum and year. Bootstrapped 95% Confidence Intervals shown as area, using 1000 bootstraps for each stratum and year. **Source:** Authors' own calculation based on non-public individual level register data from the FD-trygd database provided by Statistics Norway (SSB).

Figure 5.1: Social assistance incidence by year and stratum in the full core-workforce population

strata maintain relatively stable incidence patterns over time, the group originating from Africa experienced a significant increase in social assistance incidence by 6 percent points following the 2008 financial crisis. For both men and women who migrated from MENA countries, we observe elevated social assistance incidence levels. However, men consistently show substantially higher incidence rates, ranging from 17.2% to 30.8%. Notably, first-generation MENA men experienced a steady decline in incidence between 2004 and 2013. In contrast, women's incidence rates remained relatively stable, ranging between 12.8% and 18.3% throughout the observation period. In a similar fashion to immigrants from Africa, people that migrated from MENA countries show an increasing trend in the incidence of social assistance after 2014, although the increase among the latter group is more gradual. Similarly, first-generation Asian men have relatively heightened levels of social assistance incidence, fluctuating between 6.1% and 13.1%. In contrast, first-generation men from Eastern Europe initially exhibited a relatively high incidence of 15.4%, which steadily decreased to 2.5% by 2019. This trend change can be mainly attributed to the expansion of the European Union, which enabled a large inflow of guest workers from new member states.

5.4.2 Empirical results

5.4.2.1 Social assistance incidence

In the first stage of analysis, we focus on mapping out intersectional variation in the incidence of social assistance receipt. In Model 1 the observations are cross-classified in strata and time, to calculate the predicted incidences per stratum and calculate ICCs. Table 5.1 summarizes these results. We find that the overall predicted incidence rate in our sample is 5.9% (B = 0.059, 95%CI = [0.040;0.079]). It should be noted that this rate is slightly higher than in the general Norwegian population as we took a stratified sample and have oversampled sub-populations which on average have a higher incidence rate of social assistance receipt. We find that of the overall variance in social assistance receipt 22.5% (ICC=0.225, 95%CI = [0.192;0.265]) is attributable to heterogeneity at the group level, while 1.8% (ICC=0.018, 95%CI = [0.010;0.029]) can be attributed to changes over time at the stratum level. This underscores the substantive influence of social factors on the incidence patterns of social assistance receipt, a finding reinforced by the estimated incidence rates per stratum. The remaining 75.7% (ICC=0.757, 95%CI = [0.718;0.790]) of the variance is due to individual heterogeneity. The predicted incidence rates per stratum are shown in the left panel of Figure 5.2. We find the highest social assistance incidence rate of 28.9% among first generation African Men, and the lowest incidence rate of 1% is found among first generation Western European Men. Table D.3 in the Appendix D provides a detailed overview of the predicted incidences per stratum.

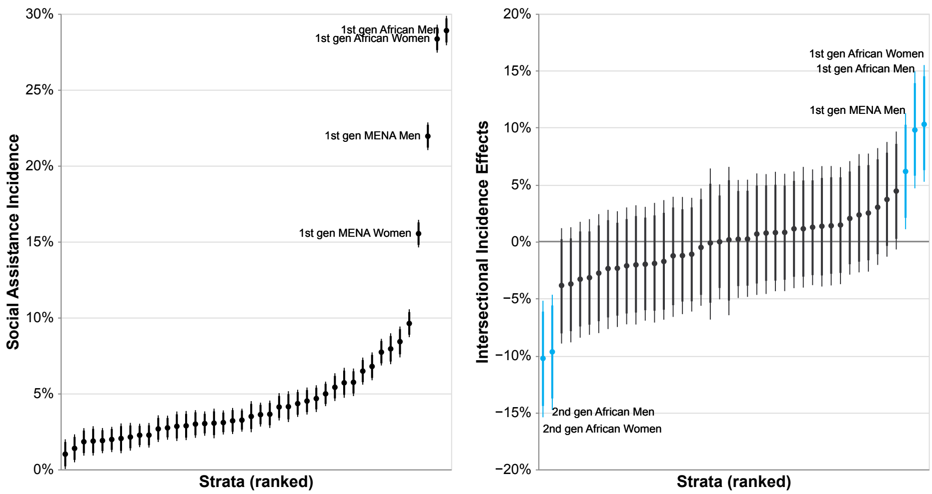
In Model 2 we include the additive effects of gender, migration background and generation. The inclusion of the additive terms explains 27.4% of the strata level variance. This means that about 27% of the difference in social assistance incidence between groups can be explained along additive lines. We find that people of African descent have a 16.0%pt higher incidence of social assistance receipt than natives (B = 0.160, 95%CI = [0.081;0.239]). Similarly, people with a MENA background were found to have an elevated incidence of social assistance receipt of 12.7%pt (B = 0.127, 95%CI = [0.046;0.205]). For all other immigrant groups, we cannot say with 95 percent certainty that their incidence rate is higher than natives. Descendants of immigrants generally have a lower incidence than immigrants; their incidence is 3.6%pt lower (B = –0.036, 95%CI = [–0.066;–0.006]). Lastly, we do not find overall gender differences in social assistance receipt (B = –0.010, 95%CI = [–0.039;0.019]).

In addition to calculating the additive effects, this model is used to calculate the non-additive intersectional effects. The non-additive intersectional effects are shown in the right panel of Figure 5.2, for a complete summary of the intersectional effects see Table D.3 in Appendix D. In most strata, the intersectional effect hovers around 0. This suggests that the incidence of social assistance receipt within these groups is well explained by additive effects. In five cases we do find intersectional effects. Within these strata, the incidence of social assistance receipt diverges from predictions based on additive assumptions, suggesting that social dimensions at these intersections could mutually influence and act as co-determinants, resulting in either a

Table 5.1: Summary of additive effects and random effects for social assistance receipt

	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	0.059 (0.040; 0.079)	0.031 (-0.034; 0.098)	0.015 (-0.014; 0.045)	0.015 (-0.014; 0.043)	0.044 (0.026; 0.063)
Migration Background (ref. Native)					
Scandinavia		0.021 (-0.058; 0.099)	0.008 (-0.026; 0.043)	0.007 (-0.027; 0.042)	0.001 (-0.018; 0.020)
Western Europe		0.017 (-0.065; 0.099)	0.004 (-0.031; 0.039)	0.004 (-0.029; 0.039)	-0.001 (-0.020; 0.018)
Eastern Europe		0.034 (-0.045; 0.114)	0.008 (-0.028; 0.045)	0.007 (-0.027; 0.043)	-0.007 (-0.026; 0.012)
Polish		0.017 (-0.065; 0.097)	0.006 (-0.029; 0.041)	0.005 (-0.028; 0.040)	-0.002 (-0.021; 0.017)
North America & Oceania		0.010 (-0.071; 0.092)	0.002 (-0.034; 0.037)	0.001 (-0.032; 0.035)	-0.004 (-0.023; 0.014)
South America		0.056 (-0.024; 0.132)	0.022 (-0.014; 0.057)	0.021 (-0.013; 0.057)	0.010 (-0.009; 0.029)
MENA		0.127 (0.046; 0.205)	0.053 (0.017; 0.087)	0.052 (0.018; 0.086)	0.021 (0.002; 0.041)
PIB		0.037 (-0.044; 0.114)	0.011 (-0.024; 0.046)	0.010 (-0.025; 0.046)	-0.003 (-0.022; 0.016)
Asia		0.038 (-0.042; 0.123)	0.013 (-0.023; 0.049)	0.012 (-0.023; 0.045)	-0.004 (-0.022; 0.015)
Africa		0.160 (0.081; 0.239)	0.068 (0.033; 0.104)	0.067 (0.033; 0.102)	0.034 (0.015; 0.053)
Gender (ref. Male)					
Female		-0.010 (-0.039; 0.019)	-0.004 (-0.016; 0.009)	-0.004 (-0.016; 0.009)	-0.003 (-0.010; 0.003)
Generation (ref. Native and First Generation)					
Second Generation		-0.036 (-0.066; -0.006)	-0.014 (-0.027; -0.002)	-0.014 (-0.028; -0.001)	-0.003 (-0.010; 0.005)
SA (t-1)			0.627 (0.598; 0.656)	0.550 (0.429; 0.668)	0.516 (0.396; 0.633)
Included Variables					
Interaction Effects				YES	YES
Control Variables					YES
Random Effects					
sigma	0.220 (0.219; 0.221)	0.220 (0.219; 0.221)	0.174 (0.173; 0.174)	0.174 (0.173; 0.174)	0.172 (0.171; 0.172)
var(sigma) strata	0.065 (0.053; 0.081)	0.047 (0.036; 0.061)	0.020 (0.015; 0.026)	0.020 (0.015; 0.026)	0.010 (0.008; 0.014)
var(sigma) year	0.005 (0.003; 0.009)	0.005 (0.003; 0.009)	0.004 (0.002; 0.006)	0.004 (0.002; 0.006)	0.004 (0.002; 0.006)
var(SA (t-1)) strata			0.079 (0.062; 0.102)	0.081 (0.061; 0.108)	0.080 (0.060; 0.107)
var(SA (t-1)) year			0.022 (0.013; 0.033)	0.022 (0.013; 0.033)	0.022 (0.014; 0.033)

Note: Averages of the fixed effect posterior distributions, 95% credible intervals between parentheses. SA (t-1): Social Assistance Receipt in the prior year. N(strata) = 42, N(individuals) = 12600. **Source**: Authors' own calculation based on non-public individual level register data from the FD-trygd database provided by Statistics Norway (SSB).



Note: Incidences calculated using Model 1. Intersectional effects calculated using Model 2. 95% and 89% credible intervals as errorbars, based on a posterior distribution of 5000 iterations. Intersectional incidence effects statistically distinct from zero are colored blue. N(individuals) = 12600. **Source:** Authors' own calculation based on non-public individual level register data from the FD-trygd database provided by Statistics Norway (SSB).

Figure 5.2: Estimated incidence per stratum of social assistance receipt (left) and estimated intersectional effects (right)

higher or lower incidence of social assistance receipt. Second generation African men and women have a 6.4%pt and 10.4%pt lower incidence than would be expected on additive grounds (B = −0.064, 95%CI = [−0.121;-0.008]; B = −0.104, 95%CI = [−0.158;-0.048]). Conversely, disproportionately higher incidences are found among first generation African men and women, they have a 9.2%pt and 7.6%pt higher incidence (B = 0.092, 95%CI = [0.036;0.148]; B = 0.076, 95%CI = [0.022;0.128]). Lastly, first generation men originating from MENA countries had a 6.2%pt higher incidence of social assistance receipt (B = 0.062, 95%CI = [0.011;0.113]).

In summary, we find the highest incidence of social assistance receipt among groups who also face the highest levels of labor market discrimination (E. N. Larsen & Midtbøen, 2024). We find that to a substantial extent, these patterns are explained by additive components related to country of origin, migrant generation and gender, with some exceptions: Second-generation African men and women, first-generation African men and women and first-generation MENA women.

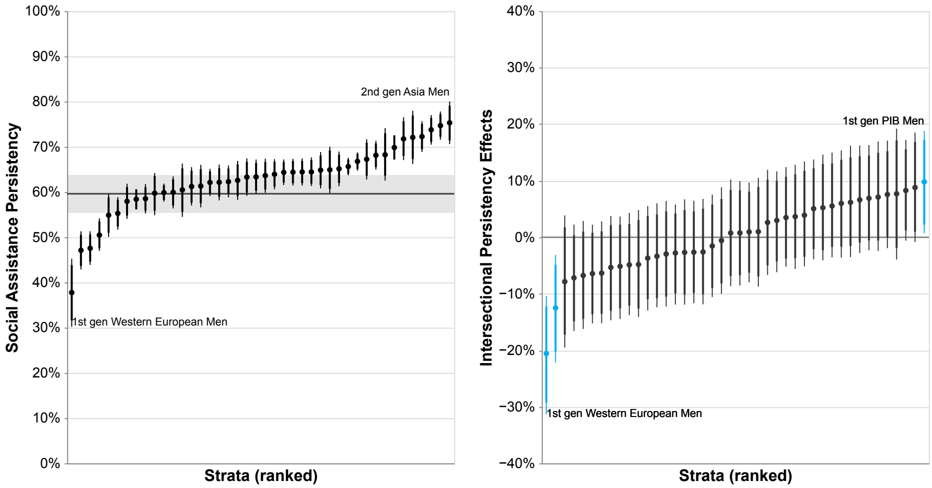
5.4.2.2 Social assistance persistency

We now turn to estimating potential social assistance persistence effects and the variation of these effects between intersectional strata. In Model 3 we include the (random) effect of prior social assistance receipt. We find that the inclusion of the heterogeneous persistence effects explain about 41.8% of the differences in social assistance incidence between strata. Combined with the gender, migration background and generation terms, Model 3 explains 69.3% of the strata level variance. We find that on average 62.7% of people who received social assistance in the prior year, also received social assistance in the present year (B = 0.627, 95%CI = [0.598; 0.656]). This overall persistence effect is visualized as the horizontal line in the left panel of Figure 5.3. Figure 5.3 also shows that the predicted persistence effect varies considerably per intersectional stratum. The lowest persistence effect is found among first generation men from Western Europe, in this stratum prior social assistance receipt increases the chances of social assistance receipt in the present year with 37.8% (B = 0.378, 95%CI = [0.302; 0.452]). The highest persistence effect is found among second generation men from Asia; in this stratum prior social assistance receipt increases the chances of social assistance receipt in the present year with 75.3% (B = 0.753, 95%CI = [0.706; 0.800]). For a complete summary of the persistence effects see Table D.4 in Appendix D.

Just as the inclusion of the heterogeneous persistence effect explains a considerable fraction of the variance at the stratum level, so too does the inclusion of this effect influence some of the additive gender, migration background and generational differences. While the additive patterns similar to Model 2 persist, incorporating the persistence effect leads to a reduced predicted incidence of 6.8%pt for individuals of African descent (B = 0.068, 95%CI = [0.031; 0.104]) and 5.3%pt for individuals with a migration background from MENA countries (B = 0.053, 95%CI = [0.017; 0.087]), which remains notably higher than that of native individuals. Essentially, the persistence of social assistance receipt notably contributes to the heightened incidence rate observed among individuals with these migration backgrounds.

Within Model 4, we introduce interaction effects between the additive social characteristics and the persistence effect. The inclusion of the additive persistence effects as interactions does not increase the explained variance in the strata level variance, which remains at 69.3%. We do not find additive gender, migration background and generation differences in the persistence effect. The non-additive intersectional persistence effects are depicted in the right panel of Figure 5.3. For most strata, the non-additive persistence effect remains close to 0, indicating that within these groups, the persistence effect aligns well with additive expectations. However, three cases exhibit intersectional persistence effects, showing groups with notably higher or lower persistence effects than anticipated based on additive assumptions. Specifically, first generation men from Western Europe and second generation Polish men display disproportionately reduced persistence effects (B = −0.206, 95%CI = [−0.313; −0.104]; B = −0.125, 95%CI = [−0.222; −0.031]). In these instances, prior social assistance receipts demonstrate a notably lesser persistence. Conversely, first generation men from Pakistan, India and Bangladesh exhibit disproportionately increased persistence effects (B = 0.098, 95%CI = [0.007; 0.188]). In this case, prior social assistance receipt disproportionately increases the likelihood of social assistance receipt. For a complete summary of the intersectional persistence effects see Table D.4 in Appendix D.

In Model 5 we include the control variables. The control variables explain an additional 14.8%



Note: Persistency effects calculated using Model 3. Intersectional persistency effects calculated using Model 4. 95% and 89% credible Intervals as errorbars, based on a posterior distribution of 5000 iterations. Intersectional persistency effects statistically distinct from zero are colored blue. N(individuals) = 12600. **Source:** Authors' own calculation based on non-public individual level register data from the FD-trygd database provided by Statistics Norway (SSB).

Figure 5.3: Estimated persistency effects per stratum of social assistance receipt (left) and estimated intersectional persistency effects (right)

of the stratum level variance; in total the additive terms explain 84.2% of the variance in social assistance incidence between strata. The additive patterns similar to Model 4 persist after the inclusion of our control variables. Our control variables loaded in the expected directions. The inclusion of the control variables marginally reduced the non-additive persistence effects for first generation Western European, Polish and Pakistani, Indian and Bangladeshi men, yet these effect remain substantally distinct from zero. This implies that differences in education, status, relationship status and migration motive only marginally affect the persistence of social assistance receipt.

5.5 Conclusion

Our focus in this chapter has been on intersectional heterogeneity in both the incidence and possible persistence effects of social assistance receipt. Using the MAIHDA approach, we have explored variation by intersectional strata and shown how different dimensions of inequality – gender, migration background and generation – interact to produce different patterns of social assistance receipt incidence and persistence.

Our first main finding is that we find substantial variation in the incidence of social assistance receipt and that this variation is mainly driven by a few particularly vulnerable groups. These findings are in line with studies of labor market inequality in general and of ethnic hiring discrimination in particular; people with a migration background from African or MENA countries and in particular men, are most likely to receive social assistance overall. These groups are also the most severely penalized ones in research on hiring discrimination (Bursell, 2014; E. N. Larsen & Midtbøen, 2024). Additionally, we find that while the incidence of social assistance receipt generally aligns with the expected levels based on the additive contributions of the underlying dimensions of inequality, a few observations exhibit non-additive effects, indicating multiplicative effects between these dimensions. However, we find significant deviations among a few groups, where the dimensions interact to multiplicate the risk of social assistance incidence, such as for first- and second-generation men and women with a migration background. People with a second-generation African migration background have a considerably lower incidence than people with a first-generation African migration background.

Second, turning to persistence effects, i.e. that social assistance receipt produces subsequent receipt through i.e. state dependency, we find more heterogeneity. This also possibly explains our first two findings, in that the higher incidence in some groups may in part be explained by their persistent use of social assistance and their inability to find re-employment. Once again, we find that the variation between groups in persistence effects is in large part explained by the additive components constituting the intersectional strata. In three instances our findings indicate that the persistence of social assistance receipt deviates significantly from expected levels. First-generation men from Western Europe and second-generation Polish men exhibit a lower persistence of social assistance receipt than would be expected on the basis of additive factors. For individuals at these intersections, social assistance receipt may not convey as negative a signal, thereby minimally affecting their employment prospects and consequently reducing the probability of subsequent social assistance receipt. Alternatively, as these groups have generally migrated to Norway for employment purposes, they may have a different work ethic and different cultural or personal attitudes towards work and social assistance than other groups. A strong work ethic or a cultural stigma against receiving benefits could lead people to seek employment more intensively, implying that they leave social assistance sooner. On the other hand, first-generation Pakistani, Bangladeshi and Indian men showed a disproportionately higher persistence, indicating that previous social assistance receipt may adversely affects their likelihood re-employment and consequently subsequent social assistance receipt.

Third, we find that, among the intersectional strata studied in this chapter, the most influential axis of inequality in both the incidence and the persistence of social assistance receipt is a person's migration background and country of origin. Some migrant groups need to rely upon social assistance more often and do so more persistently. Gender does not appear to be very influential. In a few notable cases, we find evidence that disadvantages from gender, migration background and generationality compound multiplicatively. Groups at these intersections – first generation African men and women and first generation MENA men – have a disproportionately high incidence of social assistance receipt and/or make more persistent use of social assistance.

The findings presented in this chapter should be interpreted in light of several limitations. While this study has identified intersections where individuals are particularly vulnerable to relying on social assistance, only a limited number of intersections exhibit more persistent social assistance use. This persistence suggests that individuals at these intersections may encounter greater barriers to re-employment and face more difficulty exiting social assistance programs. To better understand the specific challenges experienced by benefit recipients at these intersections, future qualitative and quantitative studies should further investigate their lived experiences and structural constraints, thereby providing more detailed insights to inform social policy.

Additionally, this chapter represents the first analysis of heterogeneities in the persistence of social assistance receipt from an intersectional perspective and is among the few studies that examine heterogeneity in state dependence more broadly (e.g., Arulampalam et al. (2000); Plum & Ayllón (2015); Aradhya et al. (2023)). While our results indicate significant heterogeneity in the persistence of social assistance receipt, both additively and multiplicatively, we cannot determine whether these patterns arise from true state dependence or from selection processes, such as Matthew effects. Future research should aim to disentangle these mechanisms to better understand the pronounced differences in social assistance persistence. Clarifying these processes is essential for comprehending the complexities surrounding long-term social assistance receipt.

Despite its limitations, this chapter offers a novel understanding of how multiple, intersecting inequalities collectively function to create disparities in the incidence of social assistance receipt and its persistent use. Social policy should address the barriers to (re-) employment that people with a migration background face. Policies should focus on equipping immigrants with the knowledge and skills necessary for effective participation in the Norwegian labor market. In particular first-generation African and MENA immigrants may need additional help finding suitable employment.

This chapter bridges the literatures on intersectionality, social welfare and social stratification by examining intersectional inequalities in the incidence and persistence of social assistance receipt at the intersection of gender, migration background and generation. Our novel theoretical and methodological approach enabled the quantification of inequalities between intersections in the welfare context. Importantly, it shows that these inequalities do not necessarily stem from non-additive intersectional effects – a key assumption in much of the qualitative intersectionality literature. The findings underscore the complexity of social assistance inequalities for a limited number of intersectional groups, demonstrating how disadvantages tied to gender, migration background and generation intersect can compound, creating hierarchies of disadvantage in reliance on social assistance, particularly in its persistent form.

Appendix A

Supplements to Cchapter 2

A.1 Technical description of the analytical strategy

In this appendix, we provide more detailed and technical information on the Multilevel Analyses of Individual Heterogeneity and Discriminatory Accuracy (MAIHDA: see Axelsson Fisk et al., 2018) that were performed in this study. This appendix aims to provide additional information to facilitate the replication of similar models by explicating model configurations, prior distributions and formulas used of key statistics used in the paper.

We estimated Bayesian Multilevel Logistic Regression Models in `Stata 16.1`, using a Metropolis-Hastings algorithm for the Markov Chain Monte Carlo (MCMC) resampler. All models were estimated using 4 chains with a burn-in length of 10,000 iterations, after which we ran 10,000 iterations to estimate the posterior distributions. We used the posterior distribution of the first chain to calculate the average and 95% credible interval for all model statistics. Information of the other chains were used for model diagnostics.

In the remainder of this appendix we explicate the prior distributions used formulas used for all model statistics such as (Log Likelihoods, ICCs, PCVs and predicted incidences). In our models, we use narrow prior distributions, since these operate more reliably with logistic models and because they scale better to the odds ratio level. We informed our prior distributions using the data from our train-split.

A.1.1 Baseline model

For our baseline model, we estimated a random intercept model, where individuals (i) are nested in intersectional strata (j). In the realm of MAIHDA, these models are generally referred to as unadjusted models. In the realm of multilevel regression, these models are named variance components models. We configured our baseline model as:

$$
\begin{aligned}
\text{model:} \qquad & Y_{_{0ij}} \sim \text{Bernouli}(\pi_{_{0ij}}) \\
& \log\left(\frac{\pi_{0ij}}{1-\pi_{0ij}}\right) = \beta_{0_{0ij}} + u_{0_{0j}} \\
\text{prior:} \qquad & \beta_{0_{0ij}} \sim \text{cauchy}(-1, 4) \\
& u_{0_{0j}} \sim N(0, \sigma^2_{0j}) \\
& \sigma^2_{0j} \sim \text{igamma}(0.01, 0.01)
\end{aligned}
$$

Here Y_{ij} is the discrete outcome variable for SA or UI benefit receipt, which can only take values 0 or 1. We estimate the probability $\pi_{_{0ij}}$, which denotes the predicted probability of benefit receipt as a function of the overall intercept $\beta_{0_{0ij}}$ and the random intercepts per stratum $u_{0_{0j}}$. We calculate the predicted unadjusted incidences as:

$$\pi_{_{0ij}} = \frac{e^{(\beta_{0_{0ij}} + u0_{0j})}}{1 + e^{(\beta_{0_{0ij}} + u0_{0j})}}$$

… and the ICC using a linearization approach proposed by Goldstein and colleague's (2002) as:

$$\text{ICC} = \frac{\sigma_{0j}^2 \cdot p^2(1+F)^{-2}}{p(1-p) + \sigma_{0j}^2 \cdot p^2(1+F)^{-2}}$$

… where F denote the odds ratios of the fixed effect predictions of the baseline model ($e^{\beta_{0_{0ij}}}$) and p denotes the predicted probability based on the fixed effects ($F/(1+F)$). This approach yields an advantage over conventionally used latent variable approaches for logistic models – where the first-level residual is fixed – since it is based on the mean distribution of the level 2 random effect.

A.1.2 Partially adjusted models

For our partially adjusted models, we expanded our baseline model with including additive effect for each social dimension separately. The additive effects comprise dichotomous predictors for all but one social group per dimension. The left out social group serves as the reference category. We estimate models for gender, migration background, age and education (respectively indexed: $1-4$). Since we had an equivocal model specification for all partially adjusted models, we will illustrate our model configuration based on model 1 (in which we include additive effects of gender). The partially adjusted models were configured as:

$$\begin{aligned}
\text{model:} \qquad & Y_{_{1ij}} \sim \text{Bernouli}(\pi_{_{1ij}}) \\
& \log\left(\frac{\pi_{1ij}}{1-\pi_{1ij}}\right) = \beta_{0_{1ij}} + \beta_{1_{1ij}} X_{_{1ij}} + u_{0_{1j}} \\
\text{prior:} \qquad & \beta_{0_{1ij}} \sim \text{cauchy}(-1, 4) \\
& \beta_{1_{1ij}} \sim \text{cauchy}(0, 1.5) \\
& u_{0_{1j}} \sim N(0, \sigma_{1j}^2) \\
& \sigma_{1j}^2 \sim \text{igamma}(0.01, 0.01)
\end{aligned}$$

In these models, a fixed effect of gender was included $\beta_{1_{1ij}}$[1]. This changes the interpretation of the intercept parameter $\beta_{0_{1ij}}$ to the average incidence of people who belong to the reference

[1] In the partially and fully adjusted models for SA, the prior distribution for migration background was configured as cauchy(0.5, 0.5) and cauchy(1.5, 0.5) and the constant prior for models that include migration background was configured as cauchy(-4, 0.5)

category (in this case men). With the inclusion of the additive effects, the residual variance σ^2_{1j} might have shrunken compared to the baseline model. We calculated the Proportional Change of Variances using a bootstrapped approach as:

$$\text{PCV} = \frac{1}{B}\sum_{k=1}^{B}\left(\frac{\sigma^2_{0kj} - \sigma^2_{1kj}}{\sigma^2_{0kj}}\right)$$

… where B denotes the number of bootstrap samples of which we performed 10.000. Per bootstrap one random value k is sampled from the posterior distributions of σ^2_{0j} and σ^2_{1j}. Here the PCV represents how much of the variation at the stratum-level (i.e. ICC) can be explained by the additive effect of the social dimension (in this case gender).

A.1.3 Fully adjusted models

For our fully adjusted models we included additive effects for all social dimensions that were used to construct the intersectional strata (indexed: 5). Per social dimension, dichotomous predictors were included for all social groups except the reference category. The fully adjusted model was configured as:

$$\begin{aligned}
\text{model:} \qquad\qquad & Y_{5ij} \sim \text{Bernouli}(\pi_{5ij}) \\
& \log\left(\frac{\pi_{5ij}}{1-\pi_{5ij}}\right) = \beta_{0_{5ij}} + \beta_{1_{5ij}} X_{5ij} + ... + \beta_{k_{5ij}} X_{5ij} + u_{0_{5j}} \\
\text{prior:} \qquad\qquad & \beta_{0_{5ij}} \sim \text{cauchy}(-1.5, 0.5) \\
& \beta_{1_{5ij}}, \beta_{k_{5ij}} \sim \text{cauchy}(0, 0.5) \\
& u_{0_{5j}} \sim N(0, \sigma^2_{5j}) \\
& \sigma^2_{5j} \sim \text{uniform}(0, 0.3)
\end{aligned}$$

Here $(\beta_{1_{5ij}}, \beta_{k_{5ij}})$ denote all the additive effect that were included in the model. Now, the random intercepts $u_{0_{5j}}$ capture the deviation of the additive incidence from the total predicted incidence and per intersectional stratum. To determine which stratum is relatively (dis-)advantaged, we (1) exponentiated the random intercepts to rescale them as odd ratios $\exp(u_{0_{5j}})$, next (2) we assert whether the 95% credible intervals of exponentiated random intercepts did not include 1. Based on this model we calculated the total fully adjusted incidence rates as:

$$\pi_{5ij} = \frac{e^{(\beta_{0_{5ij}} + \beta_{1_{5ij}} + \,...\, + \beta_{k_{5ij}} + u0_{5j})}}{1 + e^{(\beta_{0_{5ij}} + \beta_{1_{5ij}} + \,...\, + \beta_{k_{5ij}} + u0_{5j})}}$$

… and the PCV using a bootstrapped approach as:

$$\text{PCV} = \frac{1}{B}\sum_{k=1}^{B}\left(\frac{\sigma^2_{0kj} - \sigma^2_{5kj}}{\sigma^2_{0kj}}\right)$$

A.2 MAIHDA results

A.2.1 Variance decompositioning

Table A.1: ICC and PCV of social assistance and unemployment insurance receipt

	Gender	Migration Background	Age	Education	Full
			Social Assistance		
PCV	-0.021 (-0.406; 0.279)	0.359 (0.115; 0.546)	-0.008 (-0.382; 0.280)	0.470 (0.269; 0.627)	0.793 (0.743; 0.838)
ICC			0.113 (0.090; 0.140)		
			Unemployment Insurance		
PCV	-0.010 (-0.402; 0.299)	0.094 (-0.274; 0.363)	0.239 (-0.053; 0.475)	0.240 (-0.054; 0.474)	0.517 (0.317; 0.670)
ICC			0.041 (0.032; 0.052)		

Note: PCV: Averages of the Proportional Change of Variance, calculated using models 1 through 5 and ICC: Intra-class Correlations posterior distributions, calculated using Model 0. 95% credible interval between parentheses. N(individuals) = 45,119. (Full, i.e. all additive effects). Source: Authors' own calculation based on non-public individual level register data from the Social Statistical Datasets (SSD) of Statistics Netherlands (CBS).

For social assistance, we find that 11.3% of the variance can be attributed to differences between intersectional groups. With our partially adjusted models (indexed 1 through 4), we included dummy variables per dimension to assess how much of the between strata variation in social assistance benefit receipt can be explained by each dimension. We find that differences between migration background groups (PCV = 0.359) and differences in education (PCV = 0.470) contributed considerably to the differences in social assistance receipt between intersectional groups. There are no substantial difference in social assistance receipt between men and women (PCV = -0.021) and age-groups (PCV = 0.008). In Model 5 we included the additive effects of all social dimensions, the PCV shows that almost all the between strata variance can be explained using an additive model (PCV = 0.793). This means that although a substantial amount of the differences in social assistance receipt can be attributed to intersectional group differences, just a small fraction (20.7%) of these differences are resulting from the complex combinations of social dimension related (dis-)advantages.

For unemployment insurance, we find that 4.1% of the incidence can be attributed to between strata differences. This shows that there is less variation in unemployment insurance incidence between intersectional groups compared to social assistance. This implies that other factors contribute more to whether someone received unemployment insurance. For all partially adjusted models (Model 1 – Model 4) the PCV was not different from 0, which means that for neither social dimension the additive effects explained a substantial part of the between intersectional group differences in unemployment insurance receipt. In Model 5, the fully adjusted model, we find that 51.7% of the between stratum differences can be explained using solely additive effects. This means that even though there is limited variation between intersectional groups, a considerable fraction of this variation (48.3%) is caused by non-additive effects.

A.2.2 Predicted incidences

Table A.2: Predicted incidences per intersectional stratum for social assistance and unemployment insurance benefit receipt

				Incidences			
				Social Assistance		Unemployment Insurance	
Migration Background	Gender	Age	Education	B	95%CI	B	95%CI
Dutch	Female	Young	Academic	0.040	(0.022; 0.064)	0.169	(0.131; 0.212)
			Non-Academic	0.056	(0.033; 0.083)	0.213	(0.172; 0.258)
		Middle	Academic	0.014	(0.004; 0.028)	0.208	(0.165; 0.253)
			Non-Academic	0.114	(0.081; 0.151)	0.324	(0.276; 0.377)
		Old	Academic	0.025	(0.011; 0.045)	0.254	(0.210; 0.303)
			Non-Academic	0.085	(0.057; 0.117)	0.306	(0.256; 0.359)
	Male	Young	Academic	0.043	(0.024; 0.067)	0.130	(0.098; 0.165)
			Non-Academic	0.062	(0.039; 0.092)	0.192	(0.152; 0.236)
		Middle	Academic	0.019	(0.008; 0.036)	0.168	(0.131; 0.210)
			Non-Academic	0.106	(0.074; 0.142)	0.339	(0.288; 0.390)
		Old	Academic	0.028	(0.013; 0.048)	0.256	(0.207; 0.305)
			Non-Academic	0.053	(0.031; 0.083)	0.291	(0.239; 0.339)
Dutch Antillean 1st gen.	Female	Young	Academic	0.062	(0.038; 0.093)	0.193	(0.152; 0.238)
			Non-Academic	0.405	(0.350; 0.461)	0.243	(0.201; 0.292)
		Middle	Academic	0.095	(0.060; 0.138)	0.274	(0.221; 0.334)
			Non-Academic	0.496	(0.438; 0.556)	0.381	(0.328; 0.435)
		Old	Academic	0.101	(0.046; 0.176)	0.313	(0.227; 0.409)
			Non-Academic	0.430	(0.375; 0.485)	0.347	(0.293; 0.400)
	Male	Young	Academic	0.044	(0.022; 0.075)	0.167	(0.126; 0.215)
			Non-Academic	0.406	(0.351; 0.464)	0.322	(0.273; 0.373)
		Middle	Academic	0.065	(0.037; 0.101)	0.257	(0.204; 0.316)
			Non-Academic	0.431	(0.375; 0.485)	0.386	(0.336; 0.438)
		Old	Academic	0.127	(0.069; 0.198)	0.296	(0.215; 0.386)
			Non-Academic	0.401	(0.345; 0.454)	0.399	(0.344; 0.454)

(continued)

Migration Background	Gender	Age	Education	Incidences			
				Social Assistance		Unemployment Insurance	
				B	95%CI	B	95%CI
Dutch Antillean 2nd gen.	Female	Young	Academic	0.049	(0.029; 0.075)	0.173	(0.137; 0.215)
			Non-Academic	0.202	(0.158; 0.252)	0.222	(0.178; 0.270)
		Middle	Academic	0.039	(0.017; 0.070)	0.277	(0.218; 0.340)
			Non-Academic	0.170	(0.130; 0.215)	0.353	(0.303; 0.405)
		Old	Academic				
			Non-Academic	0.136	(0.072; 0.222)	0.321	(0.233; 0.422)
	Male	Young	Academic	0.043	(0.023; 0.067)	0.162	(0.125; 0.202)
			Non-Academic	0.169	(0.130; 0.213)	0.259	(0.216; 0.307)
		Middle	Academic	0.030	(0.012; 0.057)	0.212	(0.161; 0.270)
			Non-Academic	0.173	(0.133; 0.216)	0.359	(0.305; 0.411)
		Old	Academic				
			Non-Academic	0.147	(0.081; 0.228)	0.369	(0.275; 0.464)
Eastern European 1st gen.	Female	Young	Academic	0.062	(0.037; 0.092)	0.299	(0.247; 0.351)
			Non-Academic	0.124	(0.090; 0.160)	0.415	(0.363; 0.466)
		Middle	Academic	0.077	(0.050; 0.108)	0.380	(0.328; 0.429)
			Non-Academic	0.172	(0.131; 0.217)	0.483	(0.427; 0.540)
		Old	Academic	0.158	(0.114; 0.210)	0.300	(0.245; 0.360)
			Non-Academic	0.229	(0.182; 0.278)	0.375	(0.322; 0.430)
	Male	Young	Academic	0.056	(0.033; 0.083)	0.253	(0.206; 0.303)
			Non-Academic	0.062	(0.038; 0.089)	0.419	(0.364; 0.472)
		Middle	Academic	0.044	(0.024; 0.071)	0.451	(0.391; 0.512)
			Non-Academic	0.132	(0.097; 0.171)	0.507	(0.452; 0.561)
		Old	Academic	0.141	(0.081; 0.214)	0.407	(0.319; 0.498)
			Non-Academic	0.149	(0.112; 0.190)	0.530	(0.477; 0.585)

(continued)

				Incidences			
				Social Assistance		**Unemployment Insurance**	
Migration Background	**Gender**	**Age**	**Education**	**B**	**95%CI**	**B**	**95%CI**
Eastern European 2nd gen.	Female	Young	Academic	0.051	(0.028; 0.081)	0.181	(0.138; 0.230)
			Non-Academic	0.147	(0.112; 0.189)	0.303	(0.256; 0.356)
		Middle	Academic	0.032	(0.011; 0.064)	0.240	(0.177; 0.307)
			Non-Academic	0.160	(0.120; 0.200)	0.361	(0.310; 0.413)
		Old	Academic				
			Non-Academic	0.136	(0.101; 0.179)	0.308	(0.260; 0.363)
	Male	Young	Academic	0.056	(0.028; 0.092)	0.140	(0.098; 0.190)
			Non-Academic	0.126	(0.091; 0.167)	0.235	(0.192; 0.283)
		Middle	Academic	0.031	(0.011; 0.062)	0.190	(0.137; 0.253)
			Non-Academic	0.127	(0.091; 0.166)	0.372	(0.318; 0.424)
		Old	Academic	0.061	(0.019; 0.124)	0.284	(0.192; 0.388)
			Non-Academic	0.110	(0.078; 0.148)	0.380	(0.329; 0.434)
Moroccan 1st gen.	Female	Young	Academic	0.141	(0.100; 0.184)	0.223	(0.175; 0.275)
			Non-Academic	0.362	(0.309; 0.417)	0.278	(0.228; 0.330)
		Middle	Academic	0.305	(0.250; 0.363)	0.378	(0.323; 0.436)
			Non-Academic	0.487	(0.433; 0.545)	0.225	(0.183; 0.271)
		Old	Academic				
			Non-Academic	0.596	(0.541; 0.650)	0.121	(0.090; 0.158)
	Male	Young	Academic	0.106	(0.070; 0.148)	0.302	(0.246; 0.362)
			Non-Academic	0.376	(0.324; 0.427)	0.361	(0.307; 0.416)
		Middle	Academic	0.203	(0.161; 0.250)	0.397	(0.342; 0.450)
			Non-Academic	0.403	(0.349; 0.459)	0.375	(0.323; 0.427)
		Old	Academic	0.299	(0.207; 0.399)	0.362	(0.269; 0.459)
			Non-Academic	0.430	(0.378; 0.486)	0.370	(0.321; 0.422)

(continued)

				Incidences			
				Social Assistance		Unemployment Insurance	
Migration Background	**Gender**	**Age**	**Education**	**B**	**95%CI**	**B**	**95%CI**
Moroccan 2nd gen.	Female	Young	Academic	0.059	(0.036; 0.086)	0.210	(0.169; 0.253)
			Non-Academic	0.239	(0.190; 0.289)	0.281	(0.231; 0.335)
		Middle	Academic				
			Non-Academic	0.324	(0.272; 0.380)	0.358	(0.306; 0.414)
		Old	Academic				
			Non-Academic				
	Male	Young	Academic	0.101	(0.071; 0.137)	0.199	(0.158; 0.246)
			Non-Academic	0.350	(0.295; 0.401)	0.265	(0.221; 0.311)
		Middle	Academic				
			Non-Academic	0.360	(0.309; 0.413)	0.393	(0.341; 0.445)
		Old	Academic				
			Non-Academic				
Other 1st gen.	Female	Young	Academic	0.052	(0.031; 0.080)	0.228	(0.183; 0.276)
			Non-Academic	0.440	(0.382; 0.497)	0.203	(0.161; 0.247)
		Middle	Academic	0.153	(0.115; 0.195)	0.315	(0.268; 0.366)
			Non-Academic	0.402	(0.347; 0.457)	0.296	(0.247; 0.346)
		Old	Academic	0.192	(0.153; 0.239)	0.271	(0.225; 0.318)
			Non-Academic	0.471	(0.414; 0.522)	0.204	(0.161; 0.251)
	Male	Young	Academic	0.101	(0.070; 0.139)	0.195	(0.155; 0.242)
			Non-Academic	0.380	(0.325; 0.435)	0.256	(0.211; 0.305)
		Middle	Academic	0.263	(0.217; 0.314)	0.331	(0.279; 0.384)
			Non-Academic	0.428	(0.372; 0.485)	0.355	(0.303; 0.409)
		Old	Academic	0.297	(0.247; 0.350)	0.317	(0.270; 0.369)
			Non-Academic	0.414	(0.359; 0.472)	0.359	(0.308; 0.412)

(continued)

				Incidences			
				Social Assistance		Unemployment Insurance	
Migration Background	**Gender**	**Age**	**Education**	**B**	**95%CI**	**B**	**95%CI**
Other 2nd gen.	Female	Young	Academic	0.050	(0.029; 0.077)	0.172	(0.132; 0.214)
			Non-Academic	0.166	(0.125; 0.207)	0.293	(0.245; 0.342)
		Middle	Academic	0.016	(0.006; 0.031)	0.238	(0.194; 0.286)
			Non-Academic	0.126	(0.092; 0.166)	0.361	(0.312; 0.414)
		Old	Academic	0.025	(0.011; 0.045)	0.244	(0.198; 0.293)
			Non-Academic	0.101	(0.070; 0.135)	0.324	(0.274; 0.375)
	Male	Young	Academic	0.040	(0.022; 0.064)	0.163	(0.123; 0.204)
			Non-Academic	0.103	(0.073; 0.139)	0.229	(0.185; 0.275)
		Middle	Academic	0.028	(0.013; 0.048)	0.216	(0.170; 0.261)
			Non-Academic	0.128	(0.092; 0.164)	0.384	(0.328; 0.439)
		Old	Academic	0.049	(0.029; 0.075)	0.289	(0.245; 0.341)
			Non-Academic	0.114	(0.082; 0.151)	0.435	(0.382; 0.492)
Other European 1st gen.	Female	Young	Academic	0.034	(0.018; 0.056)	0.192	(0.151; 0.238)
			Non-Academic	0.058	(0.035; 0.087)	0.256	(0.212; 0.304)
		Middle	Academic	0.034	(0.017; 0.055)	0.369	(0.320; 0.418)
			Non-Academic	0.137	(0.100; 0.179)	0.415	(0.362; 0.473)
		Old	Academic	0.049	(0.029; 0.076)	0.274	(0.227; 0.322)
			Non-Academic	0.181	(0.139; 0.226)	0.314	(0.264; 0.366)
	Male	Young	Academic	0.038	(0.019; 0.062)	0.226	(0.184; 0.273)
			Non-Academic	0.123	(0.089; 0.162)	0.305	(0.257; 0.356)
		Middle	Academic	0.037	(0.019; 0.060)	0.421	(0.367; 0.473)
			Non-Academic	0.127	(0.091; 0.166)	0.461	(0.406; 0.518)
		Old	Academic	0.037	(0.019; 0.060)	0.371	(0.322; 0.427)
			Non-Academic	0.159	(0.122; 0.202)	0.443	(0.388; 0.496)

(continued)

				Incidences			
				Social Assistance		Unemployment Insurance	
Migration Background	Gender	Age	Education	B	95%CI	B	95%CI
Other European 2nd gen.	Female	Young	Academic	0.050	(0.028; 0.076)	0.177	(0.139; 0.219)
			Non-Academic	0.120	(0.087; 0.159)	0.254	(0.207; 0.303)
		Middle	Academic	0.025	(0.011; 0.045)	0.196	(0.156; 0.240)
			Non-Academic	0.179	(0.135; 0.224)	0.370	(0.314; 0.422)
		Old	Academic	0.031	(0.016; 0.052)	0.277	(0.228; 0.327)
			Non-Academic	0.111	(0.077; 0.147)	0.346	(0.295; 0.399)
	Male	Young	Academic	0.034	(0.017; 0.058)	0.150	(0.112; 0.191)
			Non-Academic	0.146	(0.108; 0.187)	0.243	(0.199; 0.293)
		Middle	Academic	0.031	(0.015; 0.053)	0.241	(0.198; 0.288)
			Non-Academic	0.114	(0.079; 0.151)	0.333	(0.283; 0.385)
		Old	Academic	0.043	(0.024; 0.069)	0.264	(0.216; 0.314)
			Non-Academic	0.079	(0.050; 0.109)	0.388	(0.334; 0.441)
Surinamese 1st gen.	Female	Young	Academic	0.071	(0.046; 0.101)	0.202	(0.159; 0.247)
			Non-Academic	0.290	(0.242; 0.343)	0.375	(0.320; 0.430)
		Middle	Academic	0.065	(0.041; 0.096)	0.275	(0.227; 0.325)
			Non-Academic	0.356	(0.304; 0.410)	0.416	(0.362; 0.471)
		Old	Academic	0.078	(0.046; 0.117)	0.276	(0.217; 0.336)
			Non-Academic	0.290	(0.241; 0.342)	0.336	(0.286; 0.391)
	Male	Young	Academic	0.047	(0.024; 0.080)	0.177	(0.132; 0.229)
			Non-Academic	0.289	(0.239; 0.342)	0.315	(0.265; 0.368)
		Middle	Academic	0.091	(0.062; 0.124)	0.274	(0.229; 0.325)
			Non-Academic	0.311	(0.261; 0.366)	0.419	(0.365; 0.474)
		Old	Academic	0.109	(0.075; 0.152)	0.264	(0.213; 0.320)
			Non-Academic	0.284	(0.236; 0.333)	0.410	(0.360; 0.466)

(continued)

				Incidences			
				Social Assistance		Unemployment Insurance	
Migration Background	**Gender**	**Age**	**Education**	**B**	**95%CI**	**B**	**95%CI**
Surinamese 2nd gen.	Female	Young	Academic	0.065	(0.041; 0.095)	0.260	(0.215; 0.309)
			Non-Academic	0.280	(0.232; 0.330)	0.357	(0.305; 0.412)
		Middle	Academic	0.046	(0.027; 0.072)	0.217	(0.177; 0.263)
			Non-Academic	0.212	(0.169; 0.260)	0.376	(0.324; 0.430)
		Old	Academic				
			Non-Academic	0.199	(0.151; 0.249)	0.387	(0.325; 0.446)
	Male	Young	Academic	0.056	(0.033; 0.086)	0.189	(0.149; 0.233)
			Non-Academic	0.222	(0.177; 0.269)	0.291	(0.243; 0.340)
		Middle	Academic	0.053	(0.031; 0.081)	0.221	(0.176; 0.267)
			Non-Academic	0.294	(0.244; 0.347)	0.412	(0.358; 0.464)
		Old	Academic				
			Non-Academic	0.159	(0.114; 0.210)	0.367	(0.308; 0.430)
Turkish 1st gen.	Female	Young	Academic	0.062	(0.038; 0.091)	0.269	(0.224; 0.317)
			Non-Academic	0.320	(0.269; 0.371)	0.321	(0.273; 0.371)
		Middle	Academic	0.082	(0.053; 0.117)	0.323	(0.271; 0.378)
			Non-Academic	0.408	(0.357; 0.459)	0.346	(0.294; 0.402)
		Old	Academic				
			Non-Academic	0.451	(0.398; 0.512)	0.202	(0.160; 0.244)
	Male	Young	Academic	0.059	(0.037; 0.088)	0.261	(0.215; 0.308)
			Non-Academic	0.190	(0.147; 0.238)	0.389	(0.339; 0.443)
		Middle	Academic	0.147	(0.109; 0.189)	0.341	(0.292; 0.391)
			Non-Academic	0.324	(0.272; 0.377)	0.444	(0.390; 0.496)
		Old	Academic	0.184	(0.116; 0.263)	0.507	(0.414; 0.596)
			Non-Academic	0.350	(0.298; 0.404)	0.396	(0.343; 0.452)

(continued)

Migration Background	Gender	Age	Education	Incidences: Social Assistance B	Social Assistance 95%CI	Unemployment Insurance B	Unemployment Insurance 95%CI
Turkish 2nd gen.	Female	Young	Academic	0.087	(0.059; 0.122)	0.219	(0.177; 0.265)
			Non-Academic	0.225	(0.180; 0.278)	0.326	(0.274; 0.377)
		Middle	Academic	0.040	(0.012; 0.089)	0.294	(0.209; 0.389)
			Non-Academic	0.306	(0.254; 0.358)	0.417	(0.362; 0.471)
		Old	Academic				
			Non-Academic				
	Male	Young	Academic	0.065	(0.040; 0.097)	0.150	(0.114; 0.192)
			Non-Academic	0.231	(0.187; 0.279)	0.319	(0.269; 0.372)
		Middle	Academic	0.066	(0.027; 0.124)	0.232	(0.162; 0.319)
			Non-Academic	0.268	(0.219; 0.317)	0.372	(0.321; 0.426)
		Old	Academic				
			Non-Academic				

Note: Estimated incidence per stratum of baseline models (Model 0) based on burn-in depth of 10,000 iterations and posterior distributions 10,000 iterations. 95% credible interval between parentheses. N(individuals) = 45,119. Source: Authors' own calculation based on non-public individual level register data from the Social Statistical Database (SSD) of Statistics Netherlands (CBS)

A.2.3 Intersectional effects

Table A.3: Intersectional effects (AME) for social assistance and unemployment insurance benefit receipt

				Intersectional Effects			
				Social Assistance		Unemployment Insurance	
Migration Background	**Gender**	**Age**	**Education**	**B**	**95%CI**	**B**	**95%CI**
Dutch	Female	Young	Academic	-0.138	(-0.195; -0.075)	-0.061	(-0.112; -0.006)
			Non-Academic	-0.080	(-0.089; -0.069)	-0.066	(-0.099; -0.030)
		Middle	Academic	-0.220	(-0.267; -0.165)	-0.101	(-0.155; -0.045)
			Non-Academic	-0.074	(-0.089; -0.057)	-0.064	(-0.104; -0.024)
		Old	Academic	-0.191	(-0.244; -0.131)	-0.011	(-0.068; 0.045)
			Non-Academic	-0.081	(-0.095; -0.067)	-0.043	(-0.082; -0.001)
	Male	Young	Academic	-0.104	(-0.157; -0.043)	-0.129	(-0.174; -0.080)
			Non-Academic	-0.065	(-0.075; -0.054)	-0.099	(-0.129; -0.065)
		Middle	Academic	-0.178	(-0.226; -0.119)	-0.172	(-0.223; -0.120)
			Non-Academic	-0.061	(-0.076; -0.046)	-0.075	(-0.114; -0.034)
		Old	Academic	-0.156	(-0.209; -0.096)	-0.031	(-0.087; 0.023)
			Non-Academic	-0.076	(-0.089; -0.063)	-0.075	(-0.111; -0.037)
Dutch Antillean 1st gen.	Female	Young	Academic	-0.018	(-0.083; 0.050)	0.013	(-0.039; 0.072)
			Non-Academic	0.090	(0.060; 0.120)	-0.009	(-0.046; 0.031)
		Middle	Academic	0.032	(-0.050; 0.118)	0.026	(-0.043; 0.094)
			Non-Academic	0.133	(0.098; 0.174)	0.026	(-0.017; 0.071)
		Old	Academic	0.030	(-0.076; 0.156)	0.077	(-0.018; 0.171)
			Non-Academic	0.095	(0.062; 0.131)	0.031	(-0.016; 0.080)
	Male	Young	Academic	-0.040	(-0.102; 0.034)	-0.038	(-0.100; 0.025)
			Non-Academic	0.098	(0.068; 0.130)	0.029	(-0.014; 0.078)
		Middle	Academic	-0.008	(-0.085; 0.073)	-0.013	(-0.080; 0.057)
			Non-Academic	0.106	(0.073; 0.141)	0.012	(-0.034; 0.063)
		Old	Academic	0.088	(-0.021; 0.207)	0.048	(-0.041; 0.137)
			Non-Academic	0.091	(0.061; 0.123)	0.054	(0.007; 0.101)

(continued)

Migration Background	Gender	Age	Education	Intersectional Effects: Social Assistance B	Social Assistance 95%CI	Unemployment Insurance B	Unemployment Insurance 95%CI
Dutch Antillean 2nd gen.	Female	Young	Academic	0.021	(-0.031; 0.084)	0.012	(-0.042; 0.071)
			Non-Academic	0.028	(0.011; 0.046)	-0.007	(-0.041; 0.028)
		Middle	Academic	-0.014	(-0.069; 0.057)	0.051	(-0.016; 0.123)
			Non-Academic	0.012	(-0.004; 0.030)	0.027	(-0.021; 0.072)
		Old	Academic				
			Non-Academic	0.002	(-0.018; 0.029)	0.025	(-0.035; 0.095)
	Male	Young	Academic	0.018	(-0.031; 0.077)	-0.019	(-0.070; 0.035)
			Non-Academic	0.021	(0.006; 0.037)	0.004	(-0.030; 0.041)
		Middle	Academic	-0.021	(-0.069; 0.044)	-0.037	(-0.103; 0.031)
			Non-Academic	0.019	(0.002; 0.036)	0.015	(-0.029; 0.060)
		Old	Academic				
			Non-Academic	0.009	(-0.011; 0.037)	0.045	(-0.021; 0.123)
Eastern European 1st gen.	Female	Young	Academic	0.006	(-0.059; 0.080)	0.044	(-0.010; 0.105)
			Non-Academic	-0.017	(-0.031; -0.002)	0.041	(-0.005; 0.092)
		Middle	Academic	0.027	(-0.039; 0.101)	0.032	(-0.026; 0.089)
			Non-Academic	-0.007	(-0.025; 0.012)	0.018	(-0.037; 0.075)
		Old	Academic	0.177	(0.087; 0.268)	-0.008	(-0.077; 0.060)
			Non-Academic	0.014	(-0.005; 0.034)	-0.035	(-0.081; 0.013)
	Male	Young	Academic	0.009	(-0.052; 0.075)	-0.031	(-0.086; 0.029)
			Non-Academic	-0.028	(-0.039; -0.017)	0.024	(-0.021; 0.072)
		Middle	Academic	-0.028	(-0.088; 0.041)	0.075	(0.013; 0.134)
			Non-Academic	-0.012	(-0.026; 0.004)	0.016	(-0.039; 0.074)
		Old	Academic	0.129	(0.019; 0.251)	0.072	(-0.016; 0.159)
			Non-Academic	-0.006	(-0.021; 0.011)	0.074	(0.020; 0.129)

(continued)

				Intersectional Effects			
				Social Assistance		Unemployment Insurance	
Migration Background	**Gender**	**Age**	**Education**	**B**	**95%CI**	**B**	**95%CI**
Eastern European 2nd gen.	Female	Young	Academic	-0.005	(-0.067; 0.060)	0.027	(-0.024; 0.083)
			Non-Academic	-0.004	(-0.023; 0.012)	0.055	(0.019; 0.092)
		Middle	Academic	-0.055	(-0.121; 0.027)	0.019	(-0.055; 0.100)
			Non-Academic	-0.005	(-0.026; 0.015)	0.045	(0.005; 0.089)
		Old	Academic				
			Non-Academic	-0.012	(-0.033; 0.005)	0.031	(-0.005; 0.070)
	Male	Young	Academic	0.014	(-0.055; 0.093)	-0.040	(-0.096; 0.022)
			Non-Academic	-0.004	(-0.022; 0.013)	-0.004	(-0.037; 0.029)
		Middle	Academic	-0.044	(-0.109; 0.031)	-0.052	(-0.120; 0.020)
			Non-Academic	-0.008	(-0.027; 0.009)	0.035	(-0.006; 0.080)
		Old	Academic	0.004	(-0.077; 0.110)	0.054	(-0.037; 0.150)
			Non-Academic	-0.013	(-0.032; 0.002)	0.070	(0.030; 0.115)
Moroccan 1st gen.	Female	Young	Academic	-0.070	(-0.158; 0.023)	0.010	(-0.050; 0.075)
			Non-Academic	-0.041	(-0.076; -0.003)	-0.014	(-0.056; 0.028)
		Middle	Academic	0.127	(0.044; 0.211)	0.094	(0.027; 0.156)
			Non-Academic	0.013	(-0.029; 0.059)	-0.122	(-0.164; -0.083)
		Old	Academic				
			Non-Academic	0.096	(0.049; 0.151)	-0.156	(-0.195; -0.122)
	Male	Young	Academic	-0.096	(-0.188; 0.001)	0.077	(0.014; 0.142)
			Non-Academic	-0.013	(-0.047; 0.023)	0.031	(-0.013; 0.077)
		Middle	Academic	0.038	(-0.042; 0.124)	0.088	(0.030; 0.147)
			Non-Academic	-0.013	(-0.052; 0.031)	-0.037	(-0.084; 0.012)
		Old	Academic	0.149	(0.033; 0.252)	0.080	(-0.009; 0.172)
			Non-Academic	0.005	(-0.033; 0.046)	-0.004	(-0.052; 0.046)

(continued)

				Intersectional Effects			
				Social Assistance		Unemployment Insurance	
Migration Background	**Gender**	**Age**	**Education**	**B**	**95%CI**	**B**	**95%CI**
Moroccan 2nd gen.	Female	Young	Academic	-0.013	(-0.072; 0.053)	0.045	(-0.009; 0.102)
			Non-Academic	0.019	(-0.003; 0.043)	0.025	(-0.010; 0.062)
		Middle	Academic				
			Non-Academic	0.049	(0.020; 0.078)	0.021	(-0.020; 0.063)
		Old	Academic				
			Non-Academic				
	Male	Young	Academic	0.097	(0.031; 0.168)	0.013	(-0.039; 0.068)
			Non-Academic	0.075	(0.047; 0.107)	-0.001	(-0.035; 0.035)
		Middle	Academic				
			Non-Academic	0.074	(0.043; 0.107)	0.029	(-0.017; 0.074)
		Old	Academic				
			Non-Academic				
Other 1st gen.	Female	Young	Academic	-0.204	(-0.281; -0.116)	0.009	(-0.047; 0.065)
			Non-Academic	0.026	(-0.017; 0.071)	-0.075	(-0.107; -0.042)
		Middle	Academic	-0.032	(-0.120; 0.057)	0.017	(-0.042; 0.075)
			Non-Academic	-0.010	(-0.053; 0.034)	-0.087	(-0.124; -0.044)
		Old	Academic	0.032	(-0.055; 0.125)	0.009	(-0.048; 0.066)
			Non-Academic	0.032	(-0.014; 0.080)	-0.114	(-0.145; -0.078)
	Male	Young	Academic	-0.070	(-0.165; 0.023)	-0.052	(-0.107; 0.004)
			Non-Academic	0.012	(-0.027; 0.051)	-0.056	(-0.092; -0.020)
		Middle	Academic	0.163	(0.078; 0.251)	0.006	(-0.056; 0.071)
			Non-Academic	0.026	(-0.015; 0.067)	-0.063	(-0.107; -0.021)
		Old	Academic	0.204	(0.128; 0.285)	0.036	(-0.022; 0.093)
			Non-Academic	0.019	(-0.023; 0.062)	-0.026	(-0.066; 0.020)

(continued)

Migration Background	Gender	Age	Education	Intersectional Effects: Social Assistance B	95%CI	Intersectional Effects: Unemployment Insurance B	95%CI
Other 2nd gen.	Female	Young	Academic	0.007	(-0.056; 0.073)	0.004	(-0.046; 0.058)
			Non-Academic	0.009	(-0.010; 0.030)	0.036	(0.000; 0.074)
		Middle	Academic	-0.080	(-0.130; -0.025)	0.007	(-0.049; 0.063)
			Non-Academic	-0.008	(-0.025; 0.009)	0.028	(-0.013; 0.071)
		Old	Academic	-0.057	(-0.106; -0.006)	0.049	(-0.006; 0.106)
			Non-Academic	-0.015	(-0.030; 0.001)	0.028	(-0.012; 0.071)
	Male	Young	Academic	-0.002	(-0.052; 0.059)	-0.025	(-0.073; 0.027)
			Non-Academic	-0.005	(-0.019; 0.011)	-0.022	(-0.053; 0.015)
		Middle	Academic	-0.037	(-0.085; 0.018)	-0.039	(-0.094; 0.017)
			Non-Academic	-0.001	(-0.016; 0.014)	0.028	(-0.018; 0.073)
		Old	Academic	0.013	(-0.044; 0.078)	0.079	(0.023; 0.136)
			Non-Academic	-0.005	(-0.019; 0.012)	0.096	(0.047; 0.150)
Other European 1st gen.	Female	Young	Academic	-0.053	(-0.100; 0.007)	-0.042	(-0.098; 0.014)
			Non-Academic	-0.034	(-0.043; -0.024)	-0.046	(-0.081; -0.007)
		Middle	Academic	-0.066	(-0.117; -0.008)	0.063	(0.005; 0.122)
			Non-Academic	-0.016	(-0.031; -0.000)	-0.003	(-0.055; 0.052)
		Old	Academic	-0.029	(-0.090; 0.040)	0.003	(-0.055; 0.061)
			Non-Academic	-0.000	(-0.018; 0.018)	-0.046	(-0.088; -0.003)
	Male	Young	Academic	-0.029	(-0.078; 0.032)	-0.025	(-0.080; 0.031)
			Non-Academic	-0.008	(-0.020; 0.006)	-0.029	(-0.070; 0.012)
		Middle	Academic	-0.039	(-0.092; 0.021)	0.087	(0.024; 0.146)
			Non-Academic	-0.012	(-0.026; 0.003)	0.012	(-0.039; 0.067)
		Old	Academic	-0.040	(-0.090; 0.022)	0.078	(0.019; 0.139)
			Non-Academic	-0.000	(-0.016; 0.018)	0.034	(-0.016; 0.086)

(continued)

				Intersectional Effects			
				Social Assistance		Unemployment Insurance	
Migration Background	Gender	Age	Education	B	95%CI	B	95%CI
Other European 2nd gen.	Female	Young	Academic	0.029	(-0.031; 0.093)	-0.001	(-0.053; 0.053)
			Non-Academic	0.004	(-0.012; 0.018)	0.000	(-0.033; 0.037)
		Middle	Academic	-0.035	(-0.083; 0.018)	-0.058	(-0.114; -0.003)
			Non-Academic	0.019	(0.001; 0.039)	0.021	(-0.024; 0.066)
		Old	Academic	-0.021	(-0.073; 0.033)	0.074	(0.013; 0.133)
			Non-Academic	-0.003	(-0.019; 0.012)	0.032	(-0.011; 0.076)
	Male	Young	Academic	0.004	(-0.042; 0.056)	-0.052	(-0.098; 0.001)
			Non-Academic	0.016	(0.002; 0.031)	-0.020	(-0.056; 0.017)
		Middle	Academic	-0.009	(-0.056; 0.046)	-0.027	(-0.084; 0.034)
			Non-Academic	0.003	(-0.010; 0.016)	-0.024	(-0.067; 0.020)
		Old	Academic	0.020	(-0.034; 0.079)	0.038	(-0.020; 0.097)
			Non-Academic	-0.007	(-0.019; 0.005)	0.047	(0.001; 0.096)
Surinamese 1st gen.	Female	Young	Academic	-0.063	(-0.134; 0.014)	-0.030	(-0.087; 0.030)
			Non-Academic	0.005	(-0.023; 0.034)	0.043	(-0.003; 0.091)
		Middle	Academic	-0.097	(-0.172; -0.017)	-0.034	(-0.093; 0.024)
			Non-Academic	0.024	(-0.014; 0.061)	0.000	(-0.048; 0.052)
		Old	Academic	-0.062	(-0.154; 0.034)	0.006	(-0.061; 0.079)
			Non-Academic	-0.003	(-0.039; 0.026)	-0.026	(-0.069; 0.016)
	Male	Young	Academic	-0.087	(-0.153; -0.012)	-0.079	(-0.137; -0.017)
			Non-Academic	0.017	(-0.008; 0.043)	-0.020	(-0.063; 0.027)
		Middle	Academic	-0.013	(-0.090; 0.074)	-0.060	(-0.118; 0.005)
			Non-Academic	0.018	(-0.012; 0.048)	-0.020	(-0.072; 0.030)
		Old	Academic	0.025	(-0.060; 0.110)	-0.028	(-0.092; 0.033)
			Non-Academic	0.007	(-0.023; 0.035)	0.010	(-0.035; 0.059)

(continued)

				Intersectional Effects			
				Social Assistance		Unemployment Insurance	
Migration Background	**Gender**	**Age**	**Education**	**B**	**95%CI**	**B**	**95%CI**
Surinamese 2nd gen.	Female	Young	Academic	-0.004	(-0.068; 0.067)	0.074	(0.019; 0.129)
			Non-Academic	0.034	(0.012; 0.058)	0.060	(0.017; 0.104)
		Middle	Academic	-0.061	(-0.122; 0.005)	-0.058	(-0.114; -0.002)
			Non-Academic	0.000	(-0.020; 0.021)	0.007	(-0.038; 0.053)
		Old	Academic				
			Non-Academic	-0.004	(-0.024; 0.017)	0.044	(-0.003; 0.094)
	Male	Young	Academic	-0.005	(-0.063; 0.061)	-0.028	(-0.080; 0.026)
			Non-Academic	0.018	(-0.001; 0.038)	-0.006	(-0.044; 0.032)
		Middle	Academic	-0.025	(-0.089; 0.046)	-0.077	(-0.137; -0.018)
			Non-Academic	0.042	(0.018; 0.069)	0.013	(-0.034; 0.060)
		Old	Academic				
			Non-Academic	-0.008	(-0.026; 0.010)	0.013	(-0.038; 0.064)
Turkish 1st gen.	Female	Young	Academic	-0.114	(-0.185; -0.036)	0.073	(0.014; 0.135)
			Non-Academic	0.003	(-0.026; 0.035)	0.023	(-0.018; 0.067)
		Middle	Academic	-0.089	(-0.170; -0.001)	0.046	(-0.015; 0.106)
			Non-Academic	0.037	(0.001; 0.078)	-0.027	(-0.072; 0.018)
		Old	Academic				
			Non-Academic	0.063	(0.026; 0.102)	-0.098	(-0.133; -0.062)
	Male	Young	Academic	-0.090	(-0.161; -0.016)	0.043	(-0.015; 0.102)
			Non-Academic	-0.035	(-0.058; -0.012)	0.058	(0.014; 0.102)
		Middle	Academic	0.064	(-0.021; 0.148)	0.041	(-0.018; 0.102)
			Non-Academic	0.009	(-0.021; 0.042)	0.028	(-0.021; 0.079)
		Old	Academic	0.108	(-0.009; 0.227)	0.213	(0.128; 0.298)
			Non-Academic	0.023	(-0.005; 0.055)	0.024	(-0.019; 0.071)

(continued)

				Intersectional Effects			
				Social Assistance		Unemployment Insurance	
Migration Background	**Gender**	**Age**	**Education**	**B**	**95%CI**	**B**	**95%CI**
Turkish 2nd gen.	Female	Young	Academic	0.123	(0.057; 0.195)	0.050	(-0.003; 0.106)
			Non-Academic	0.043	(0.025; 0.062)	0.050	(0.014; 0.092)
		Middle	Academic	-0.005	(-0.061; 0.076)	0.040	(-0.049; 0.135)
			Non-Academic	0.073	(0.050; 0.099)	0.060	(0.016; 0.108)
		Old	Academic				
			Non-Academic				
	Male	Young	Academic	0.079	(0.022; 0.147)	-0.053	(-0.100; 0.001)
			Non-Academic	0.049	(0.031; 0.070)	0.031	(-0.007; 0.073)
		Middle	Academic	0.040	(-0.027; 0.133)	-0.035	(-0.120; 0.055)
			Non-Academic	0.060	(0.041; 0.084)	0.004	(-0.042; 0.050)
		Old	Academic				
			Non-Academic				

Note: Estimated intersectional effects per stratum of baseline models (Model 0) based on burn-in depth of 10,000 iterations and posterior distributions 10,000 iterations. 95% credible interval between parentheses. N(individuals) = 45,119. Source: Authors' own calculation based on non-public individual level register data from the Social Statistical Database (SSD) of Statistics Netherlands (CBS)

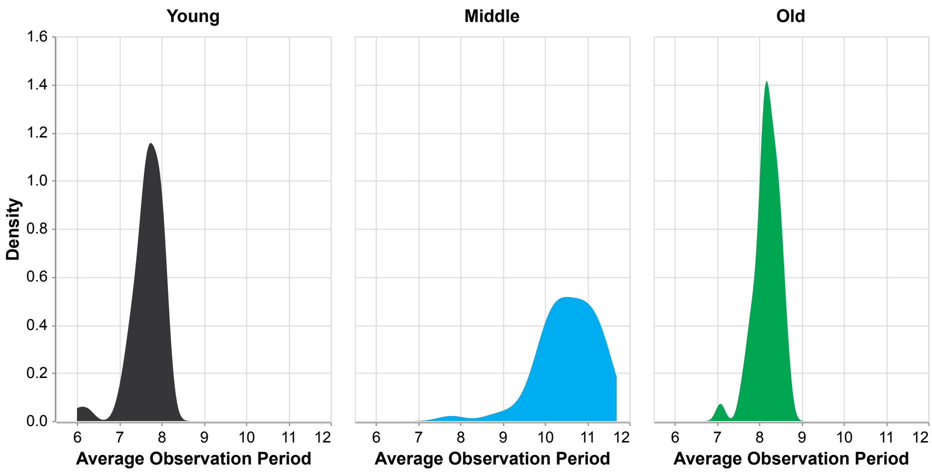
A.3 Supplementary analyses

In order to examine the relationship between the length of the observation period and the incidence of benefit receipt, we conducted two distinct analyses. One utilized individual-level data, while the other employed stratum-level data, adhering to the specified analytical sample as outlined in the methods section.

A.3.1 Variation in the length of the observation period

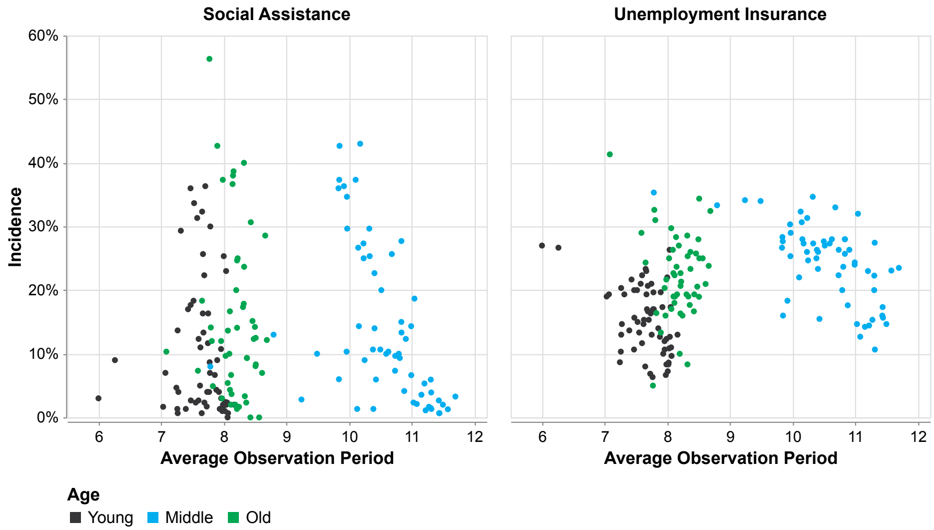
We find some variation in the average duration of the observation perioder between intersectional strata, ranging from 5.997 to 11.697 years. Fig Figure A.1 illustrates the distribution of average observation periods within strata per age group. The primary source of variation among intersectional groups arises from distinct age brackets within the age groups. Specifically, the middle-age group exhibits a maximum observation period duration of 14 years, whereas younger and older age groups have a maximum observation period of 10 years.

Noteworthy instances of brief observation periods include young individuals without an academic degree and a first-generation Eastern European migration background, with the shortest periods recorded (M = 5.997, s.d. = 2.216; M = 6.260, s.d. = 2.238 for men and women, respectively). Similarly, middle-aged first-generation Eastern European men without an academic degree show relatively short observation periods (M = 7.783, s.d. = 2.938). The brevity of their observations is understandable, given that these groups predominantly consist of labor migrants temporarily residing in the Netherlands. In theory, the shorter observation periods for these groups would



Note: Kernel density calculated on the average duration of the the observation period per stratum N(stratum) = 163.
Source: Authors' own calculation based on non-public individual level register data from the Social Statistical Database (SSD) of Statistics Netherlands (CBS)

Figure A.1: Variation in the average duration of the observation period per stratum by age



Note: Correlations between Social Assistance and Unemployment Insurance incidence and the observations period by age.
Source: Authors' own calculation based on non-public individual level register data from the Social Statistical Database (SSD) of Statistics Netherlands (CBS)

Figure A.2: Association between benefit receipt incidence and average duration of observation period

lead to a bias favoring lower incidence rates. Nevertheless, we observe middle aged individuals to have higher incidence rates of benefit receipt.

A.3.2 The association between incidence and duration of the observation period

Figure A.2, illustrates the relationship between the average duration of the observation period and the incidence rates of either social assistance or unemployment insurance. Further analysis, presented in Table A.4, corroborates this absence of association for social assistance. However, our analysis does reveal a weak association between the observation period and unemployment insurance incidence. While our initial analysis suggested a relationship between observation period duration and unemployment insurance incidence, this association becomes non-significant when controlling for age differences, see Table A.5. This implies that the observed association might be primarily driven by age rather than the duration itself. Nonetheless, the findings presented in the paper might slightly overestimate the unemployment insurance incidence amongst middle-aged individuals.

Table A.4: Regression analyses of the association between the duration of the observation period and benefit receipt incidence

	Individual Level		Stratum Level	
	Social Assistance	**Unemployment Insurance**	**Social Assistance**	**Unemployment Insurance**
Intercept	0.129 (0.107; 0.150)	0.127 (0.112; 0.141)	0.144 (0.023; 0.267)	0.076 (0.007; 0.149)
Duration	0.000 (-0.001; 0.001)	0.010 (0.009; 0.011)	-0.002 (-0.015; 0.012)	0.015 (0.007; 0.022)
Log-Likelihood	-12406.061 (-12424.877; -12389.036)	-22357.746 (-22376.611; -22340.648)	116.683 (113.515; 118.150)	211.986 (208.785; 213.519)
var(sigma strata)	0.015 (0.012; 0.018)	0.004 (0.003; 0.006)		
var(sigma)	0.101 (0.100; 0.103)	0.158 (0.156; 0.160)	0.015 (0.012; 0.019)	0.005 (0.004; 0.006)

Note:Averages of posterior distributions. 95% CI between parentheses. N(strata) = 164. **Source**: Authors' own calculation based on non-public individual level register data from the Social Statistical Datasets (SSD) of Statistics Netherlands (CBS).

Table A.5: Regression analyses of the association between the duration of the observation period and benefit receipt incidence controlled for age

	Individual Level		Stratum Level	
	Social Assistance	**Unemployment Insurance**	**Social Assistance**	**Unemployment Insurance**
Intercept	0.141 (0.110; 0.172)	0.157 (0.155; 0.159)	0.740 (0.379; 1.104)	0.789 (0.611; 0.965)
Duration	0.000 (-0.001; 0.001)	0.001 (-0.000; 0.002)	-0.057 (-0.091; -0.023)	-0.052 (-0.068; -0.035)
Age (ref. Middle)				
Young	0.015 (-0.031; 0.054)	-0.000 (-0.025; 0.025)	-0.120 (-0.214; -0.024)	-0.144 (-0.189; -0.098)
Old	-0.038 (-0.079; 0.006)	-0.065 (-0.088; -0.041)	-0.202 (-0.311; -0.091)	-0.240 (-0.292; -0.186)
Log-Likelihood	-12406.390 (-12441.790; -12376.810)	-22358.330 (-22393.720; 22326.550)	124.139 (120.065; 126.399)	252.315 (248.235; 254.608)
var(sigma strata)	0.014 (0.011; 0.018)	0.003 (0.003; 0.005)		
var(sigma)	0.101 (0.100; 0.103)	0.158 (0.156; 0.160)	0.014 (0.011; 0.017)	0.003 (0.003; 0.004)

Note:Averages of posterior distributions. 95% CI between parentheses. N(strata) = 164. **Source**: Authors' own calculation based on non-public individual level register data from the Social Statistical Datasets (SSD) of Statistics Netherlands (CBS).

Appendix B

Supplements to Chapter 3

Table B.1: Model fit measures for manifest variables

Model	Chi-Square	df	CFI	RMSEA
Financial Resources	9.210**	1	0.999	0.021
Social Capital	3.388***	1	1.000	0.000
Cultural Capital	275.915***	11	0.987	0.033
General Health	10.100**	2	0.998	0.015
Mental Well-Being	126.358***	6	0.998	0.030

Source: Authors' own calculation based on non-public individual level register data from the Social Statistical Database (SSD) provided by Statistics Netherlands (CBS) and the Longitudinal Internet studies for the Social Sciences (LISS) from CenterData.

B.1 Factor analyses

In this appendix, we describe the steps we took to perform factor analyses using the lavaan package in R. The analyses were performed on the pooled dataset prior to the analyses, comprising of all observation of all individuals. The goal of factor analysis is to explain the correlations among the observed variables by grouping them into a smaller number of latent variables, also known as factors.

In our study, we performed a confirmatory factor analysis (CFA) to identify the underlying latent variables that contributed to a set of observed variables. For most variables we specified formative models where the latent variable loaded on the observed variables. Only in the case of mental health, we allowed the observed variables to load on the latent variable, indicating a reflective model. The choice between a reflective and formative model depends on theoretical assumptions about the relationship between the observed variables and the latent variable.

We used modification indices to determine the covariances between the indicators that needed to be included in the model. The modification indices represent the difference in the chi-square statistic between the model without the specified covariance and the model with the specified covariance. We included covariances that had a modification index greater than 200, which suggests that the specified covariance should be added to the model. In preparation of the CFA for our latent variables, continuous variables were standardized. To homogenize the resulting factor scores and reduce the influence of univariate outliers, the resulting factor scores were standardized. See Table B.1 for model fit and Table B.2 for factor loadings.

Table B.2: Factor loadings for indicators used to measure the manifest variables

Name	Description	Loading	S.E.
Financial Resources			
wealth	Percentile groups of household assets, sourced from VEHTAB	1.000	0.000
inc	Percentile groups of household income, sourced from INHATAB This variable describes the household and is common to all household members.	0.797	0.034
own	... self-owned dwelling	0.635	0.015
Social Capital			
sc1_hi	The number of high educated contacts, calculated using [cs326, cs337, cs348, cs359, cs370]	1.000	0.000
sc2_f	The number of full-time employed contacts, calculated using [cs327, cs338, cs349, cs360, cs371]	2.657	1.343
sc3	The density of connection within the core-network, calculated using the sum of [cs305-cs315] as k divided by the number of possible connections in the core-network (k - (k-1))/2	5.031	2.404
Cultural Capital			
	How often did you visit these performances or concerts over the past 12 months?		
cs494	... a theatre performance	0.448	0.011
cs517	... a dance or ballet performance	0.209	0.006
cs093	... a classical concert	0.400	0.009
cs094	... an opera	0.111	0.004
	In the past 12 months, how often did you visit...		
cs101	... a museum	1.000	0.000
cs100	... an art gallery	0.678	0.011
cs099	... a film house or film festival	0.675	0.014
General Health			
	You indicated that there were periods since 2008 when you were unable to work for six consecutive weeks or longer because of health impairments. In which calendar year did this happen? If it happened in more than one year, please select all those calendar years.		
v4	... (0: no, 1: yes; indicated per year)	-0.198	0.073
ch004	How would you describe your health, generally speaking? (1: poor – 5: excellent)	1.000	0.000
bmi	BMI, calculated using ch016 (heigth) and ch017 (weight) as weight / (height/100)**2	-6.322	0.818
bmi_lo	Underweight (bmi < 18.5)	0.438	0.064
bmi_hi	Overweight (25 < bmi < 30)	-1.202	0.175
Mental Well-Being			
	The following questions are about how you felt over the past month. Please choose the answer that best describes how you felt during this past month. This past month .... (1: never – 6: continuously)		
ch011	... I felt very anxious.	-0.922	0.012
ch012	... I felt so down that nothing could cheer me up.	-1.283	0.013
ch013	... I felt calm and peaceful.	0.910	0.009
ch014	... I felt depressed and gloomy.	-1.283	0.013

ch015	... I felt happy.	1.000	0.000

Note: The factors listed in this table were constructed in separate models. Variables with a loading of 1.000 indicate that these were used to anchor the latent construct. Source: Authors' own calculation based on non-public individual level register data from the Social Statistical Database (SSD) provided by Statistics Netherlands (CBS) and the Longitudinal Internet studies for the Social Sciences (LISS) from CenterData.

B.2 Predicted incidences and intersectional effects

Table B.3: Predicted incidences and intersectional effects per intersectional stratum for benefit receipt

			Incidences		Intersectional Effects	
Migration Background	**Age**	**Gender**	**B**	**95%CI**	**B**	**95%CI**
Dutch	20<30	Female	0.052	(0.031; 0.073)	0.019	(-0.007; 0.045)
		Male	0.026	(0.000; 0.051)	-0.010	(-0.040; 0.021)
	30<40	Female	0.046	(0.028; 0.066)	0.001	(-0.023; 0.024)
		Male	0.056	(0.033; 0.078)	0.006	(-0.022; 0.033)
	40<50	Female	0.072	(0.054; 0.090)	-0.004	(-0.027; 0.019)
		Male	0.080	(0.060; 0.100)	0.001	(-0.024; 0.025)
	50<60	Female	0.063	(0.045; 0.081)	0.001	(-0.039; 0.006)
		Male	0.093	(0.072; 0.114)	0.010	(-0.017; 0.035)
Non-Western 1st gen.	20<30	Female	0.099	(0.019; 0.180)	-0.034	(-0.120; 0.050)
		Male	0.073	(-0.019; 0.165)	-0.064	(-0.161; 0.032)
	30<40	Female	0.138	(0.060; 0.217)	-0.008	(-0.092; 0.076)
		Male	0.098	(0.019; 0.179)	-0.052	(-0.135; 0.033)
	40<50	Female	0.199	(0.145; 0.254)	0.022	(-0.038; 0.084)
		Male	0.164	(0.103; 0.226)	-0.016	(-0.084; 0.052)
	50<60	Female	0.234	(0.156; 0.309)	0.054	(-0.026; 0.134)
		Male	0.226	(0.163; 0.290)	0.043	(-0.027; 0.112)
Non-Western 2nd gen.	20<30	Female	0.156	(0.102; 0.210)	0.001	(-0.063; 0.064)
		Male	0.088	(0.008; 0.172)	-0.071	(-0.160; 0.019)
	30<40	Female	0.185	(0.098; 0.274)	0.016	(-0.078; 0.112)
		Male	0.134	(0.045; 0.223)	-0.039	(-0.136; 0.054)
	40<50	Female	0.431	(0.305; 0.555)	0.232	(0.101; 0.363)
		Male	0.157	(-0.034; 0.343)	-0.046	(-0.239; 0.147)
	50<60	Female	0.205	(0.006; 0.405)	0.003	(-0.202; 0.203)
		Male	0.175	(0.024; 0.330)	-0.032	(-0.185; 0.127)
Western 1st gen.	20<30	Female	0.000	(-0.107; 0.106)	-0.047	(-0.159; 0.068)
		Male	0.104	(-0.021; 0.230)	0.053	(-0.075; 0.186)
	30<40	Female	0.057	(-0.018; 0.131)	-0.004	(-0.087; 0.078)
		Male	0.104	(0.005; 0.204)	0.040	(-0.065; 0.146)
	40<50	Female	0.073	(-0.004; 0.149)	-0.018	(-0.102; 0.066)
		Male	0.123	(0.018; 0.227)	0.029	(-0.083; 0.139)
	50<60	Female	0.074	(-0.002; 0.152)	-0.020	(-0.104; 0.064)
		Male	0.114	(-0.019; 0.241)	0.016	(-0.120; 0.146)
Western 2nd gen.	20<30	Female	0.028	(-0.050; 0.104)	-0.016	(-0.097; 0.066)
		Male	0.046	(-0.047; 0.139)	-0.001	(-0.100; 0.095)
	30<40	Female	0.063	(-0.009; 0.134)	0.006	(-0.071; 0.083)
		Male	0.036	(-0.040; 0.111)	-0.025	(-0.104; 0.055)
	40<50	Female	0.070	(-0.004; 0.143)	-0.017	(-0.097; 0.063)
		Male	0.055	(-0.029; 0.136)	-0.035	(-0.125; 0.051)
	50<60	Female	0.124	(0.052; 0.195)	0.033	(-0.045; 0.110)
		Male	0.145	(0.068; 0.222)	0.051	(-0.032; 0.134)

Note: Medians of the intersectional effects posterior distributions, 95% credible intervals between parentheses. N(strata) = 40; N(individuals) = 3,755; N(observation) = 24,572. In this table, only the intersectional effects are presented that were different from zero. Source: Authors' own calculation based on non-public individual level register data from the Social Statistical Database (SSD) provided by Statistics Netherlands (CBS) and the Longitudinal Internet studies for the Social Sciences (LISS) from CenterData.

B.3 Capital disparities and average indirect effects

Table B.4: Average additive indirect effects controlled and uncontrolled for the effects of other mediating variables

	Uncontrolled	**Controlled**
Financial Resources	-0.088 (-0.095; -0.082)	-0.083 (-0.091; -0.076)
Education	-0.022 (-0.029; -0.015)	0.002 (-0.005; 0.009)
Social Capital	-0.023 (-0.035; -0.011)	0.005 (-0.007; 0.016)
Cultural Capital	-0.013 (-0.021; -0.006)	-0.009 (-0.016; -0.001)
Language Proficiency	-0.029 (-0.057; -0.001)	0.012 (-0.015; 0.038)
General Health	-0.002 (-0.009; 0.006)	0.006 (-0.001; 0.013)
Mental Well-Being	-0.056 (-0.065; -0.046)	-0.027 (-0.037; -0.018)

Note: Average additive indirect effects per capital, 95% credible intervals between parentheses. Calculated using Models 2 and 3. Models 2 are a sequence of models, where the effect of each capital is estimated without controlling for capital effects. Model 3 is a singular model which estimates the effects of capitals simultaneously. N(strata) = 40; N(individuals) = 3,755; N(observation) = 24,572. **Source**: Authors' own calculation based on non-public individual level register data from the Social Statistical Database (SSD) provided by Statistics Netherlands (CBS) and the Longitudinal Internet studies for the Social Sciences (LISS) from CenterData.

Table B.5: Additive indirect effects of social characteristics on benefit receipt via resources

	Financial Resources	Education	Social Capital	Highbrow Cultural Capital	Language Proficiency	General Health	Mental Well-Being
Age (ref. 20-30)							
30-40	-0.027	0.001	0.001	0.000	-0.002	-0.003	0.000
	(-0.035; -0.019)	(-0.001; 0.003)	(-0.001; 0.003)	(-0.000; 0.001)	(-0.004; 0.000)	(-0.005; -0.000)	(-0.001; 0.001)
40-50	-0.033	0.000	-0.001	-0.000	-0.003	-0.004	0.000
	(-0.041; -0.025)	(-0.000; 0.001)	(-0.004; 0.001)	(-0.001; 0.000)	(-0.007; 0.000)	(-0.007; -0.002)	(-0.000; 0.001)
50-60	-0.026	-0.001	-0.002	-0.000	-0.004	-0.006	-0.001
	(-0.034; -0.019)	(-0.002; 0.001)	(-0.005; 0.002)	(-0.001; 0.000)	(-0.009; 0.000)	(-0.010; -0.004)	(-0.003; -0.000)
Gender (ref. Male)							
Female	0.002	-0.000	-0.001	-0.000	0.001	0.004	-0.000
	(-0.003; 0.007)	(-0.001; 0.000)	(-0.002; 0.001)	(-0.001; 0.000)	(-0.000; 0.002)	(0.003; 0.007)	(-0.001; 0.000)
Migration Background (ref. Dutch)							
Non-Western 1st gen.	0.019	0.001	-0.000	-0.004	-0.000	0.004	-0.003
	(0.005; 0.033)	(-0.001; 0.004)	(-0.002; 0.001)	(-0.013; 0.004)	(-0.002; 0.001)	(0.001; 0.009)	(-0.007; -0.001)
Non-Western 2nd gen.	0.011	0.000	0.000	0.000	0.000	0.005	-0.001
	(-0.000; 0.023)	(-0.000; 0.001)	(-0.001; 0.001)	(-0.001; 0.001)	(-0.001; 0.002)	(0.002; 0.009)	(-0.002; 0.001)
Western 1st gen.	0.051	-0.000	-0.001	-0.004	-0.000	0.013	0.002
	(0.039; 0.063)	(-0.001; 0.001)	(-0.003; 0.001)	(-0.014; 0.005)	(-0.001; 0.001)	(0.008; 0.018)	(0.001; 0.005)
Western 2nd gen.	0.050	-0.000	-0.000	-0.000	-0.001	0.009	0.000
	(0.036; 0.065)	(-0.001; 0.001)	(-0.002; 0.001)	(-0.002; 0.001)	(-0.002; 0.000)	(0.005; 0.015)	(-0.001; 0.002)

Note: Additive indirect effects per capital per social characteristics, 95% credible intervals between parentheses. Calculated using 3. N(strata) = 40; N(individuals) = 3,755; N(observation) = 24,572. Source: Authors' own calculation based on non-public individual level register data from the Social Statistical Database (SSD) provided by Statistics Netherlands (CBS) and the Longitudinal Internet studies for the Social Sciences (LISS) from CenterData.

Table B.6: Indirect effects of intersectional strata on benefit receipt via financial resources, cultural capital and mental well-being

Migration Background	Age	Gender	Financial Resources	Cultural Capital	Mental Well-Being
Dutch	20<30	Female	-0.005 (-0.014; 0.004)	-0.000 (-0.001; 0.001)	0.000 (-0.003; 0.003)
		Male	0.004 (-0.006; 0.014)	-0.000 (-0.001; 0.001)	-0.001 (-0.004; 0.002)
	30<40	Female	0.000 (-0.008; 0.008)	0.000 (-0.001; 0.001)	-0.000 (-0.002; 0.002)
		Male	-0.000 (-0.010; 0.009)	-0.000 (-0.001; 0.001)	0.001 (-0.002; 0.004)
	40<50	Female	-0.003 (-0.011; 0.005)	0.000 (-0.001; 0.001)	-0.001 (-0.003; 0.002)
		Male	0.004 (-0.004; 0.012)	-0.000 (-0.001; 0.001)	0.001 (-0.002; 0.004)
	50<60	Female	0.005 (-0.003; 0.012)	-0.000 (-0.002; 0.002)	0.000 (-0.002; 0.002)
		Male	-0.005 (-0.013; 0.004)	0.000 (-0.001; 0.002)	-0.000 (-0.004; 0.003)
Non-Western 1st gen.	20<30	Female	-0.000 (-0.028; 0.029)	0.001 (-0.003; 0.006)	-0.001 (-0.011; 0.010)
		Male	0.029 (-0.003; 0.063)	-0.001 (-0.005; 0.003)	-0.003 (-0.012; 0.007)
	30<40	Female	0.016 (-0.012; 0.045)	-0.001 (-0.004; 0.003)	0.001 (-0.009; 0.011)
		Male	-0.001 (-0.030; 0.028)	-0.001 (-0.004; 0.004)	-0.000 (-0.009; 0.009)
	40<50	Female	-0.007 (-0.029; 0.014)	0.000 (-0.003; 0.004)	-0.004 (-0.011; 0.003)
		Male	-0.005 (-0.027; 0.018)	-0.001 (-0.005; 0.002)	0.004 (-0.003; 0.012)
	50<60	Female	0.007 (-0.019; 0.034)	-0.001 (-0.004; 0.001)	-0.004 (-0.012; 0.005)
		Male	-0.014 (-0.037; 0.010)	0.001 (-0.001; 0.005)	0.003 (-0.003; 0.011)
Non-Western 2nd gen.	20<30	Female	-0.005 (-0.027; 0.018)	-0.001 (-0.003; 0.002)	0.002 (-0.006; 0.011)
		Male	0.014 (-0.016; 0.045)	0.004 (0.000; 0.009)	0.003 (-0.006; 0.013)
	30<40	Female	-0.011 (-0.042; 0.020)	0.000 (-0.003; 0.004)	0.001 (-0.008; 0.012)
		Male	-0.028 (-0.061; 0.006)	-0.003 (-0.007; 0.000)	-0.006 (-0.015; 0.003)
	40<50	Female	0.059 (0.015; 0.104)	0.001 (-0.003; 0.006)	0.004 (-0.008; 0.017)
		Male	0.014 (-0.045; 0.073)	0.002 (-0.004; 0.010)	-0.023 (-0.042; -0.006)
	50<60	Female	-0.004 (-0.067; 0.060)	0.004 (-0.003; 0.012)	0.010 (-0.008; 0.030)
		Male	0.003 (-0.049; 0.056)	-0.010 (-0.021; -0.002)	-0.013 (-0.029; 0.002)

(continued)

Migration Background	Age	Gender	Financial Resources	Cultural Capital	Mental Well-Being
Western 1st gen.	20<30	Female	-0.001 (-0.035; 0.035)	0.000 (-0.005; 0.005)	-0.004 (-0.015; 0.007)
		Male	0.055 (0.010; 0.101)	0.003 (-0.002; 0.008)	0.010 (-0.002; 0.024)
	30<40	Female	-0.006 (-0.033; 0.021)	0.000 (-0.004; 0.004)	0.001 (-0.006; 0.010)
		Male	0.022 (-0.014; 0.060)	0.001 (-0.004; 0.005)	-0.003 (-0.013; 0.007)
	40<50	Female	-0.001 (-0.030; 0.028)	-0.004 (-0.010; 0.002)	-0.002 (-0.009; 0.006)
		Male	-0.014 (-0.051; 0.021)	0.003 (-0.002; 0.007)	-0.002 (-0.012; 0.008)
	50<60	Female	-0.010 (-0.038; 0.017)	0.001 (-0.005; 0.006)	0.004 (-0.004; 0.012)
		Male	-0.010 (-0.054; 0.036)	0.005 (0.000; 0.011)	-0.009 (-0.022; 0.003)
Western 2nd gen.	20<30	Female	-0.001 (-0.027; 0.026)	-0.002 (-0.007; 0.001)	-0.001 (-0.009; 0.008)
		Male	-0.013 (-0.045; 0.020)	-0.000 (-0.004; 0.003)	0.002 (-0.007; 0.012)
	30<40	Female	0.014 (-0.012; 0.039)	0.001 (-0.002; 0.004)	-0.000 (-0.008; 0.008)
		Male	-0.005 (-0.032; 0.022)	-0.001 (-0.005; 0.002)	-0.007 (-0.015; 0.001)
	40<50	Female	0.009 (-0.017; 0.035)	0.002 (-0.001; 0.005)	0.002 (-0.006; 0.010)
		Male	-0.014 (-0.044; 0.016)	-0.001 (-0.005; 0.002)	0.001 (-0.007; 0.009)
	50<60	Female	0.006 (-0.019; 0.032)	0.002 (-0.001; 0.005)	0.004 (-0.003; 0.012)
		Male	-0.007 (-0.034; 0.021)	0.001 (-0.003; 0.004)	-0.001 (-0.009; 0.006)

Note: Intersectional indirect effects per intersectional stratum, 95% credible intervals between parentheses. Calculated using Model 3. N(strata) = 40; N(individuals) = 3,755; N(observation) = 24,572. Source: Authors' own calculation based on non-public individual level register data from the Social Statistical Database (SSD) provided by Statistics Netherlands (CBS) and the Longitudinal Internet studies for the Social Sciences (LISS) from CenterData.

Appendix C

Supplements to Chapter 4

C.1 Factor analyses

This appendix outlines the procedures followed to conduct factor analyses with the `lavaan` package in R. These analyses were conducted on a pooled dataset before initiating the main analyses. Factor analysis aims to identify underlying patterns among observed variables by organizing them into a smaller set of latent factors.

In our research, we employed confirmatory factor analysis (CFA) to uncover latent constructs that influenced our observed variables. For all variables, we specified formative models where the latent construct influenced the observed variables. This distinction between formative and reflective models is grounded in theoretical perspectives regarding the relationship between observed and latent variables. We utilized modification indices to identify necessary covariances among indicators within the model. Modification indices indicate the change in the chi-square statistic when a specific covariance is included and we added covariances with indices over 200, signaling their relevance. Before performing CFA on the latent variables, continuous variables were standardized and final factor scores were standardized with grand mean centering to improve consistency and mitigate univariate outlier effects. See Table C.1 for model fit statistics and Table C.2 for factor loadings.

Table C.1: Model fit measures for manifest variables

Model	Chi-Square	df	CFI	RMSEA
Economic Capital	166.131***	4	0.982	0.048
Social Capital	3.388***	1	1.000	0.000
Highbrow Cultural Capital	354.090***	23	0.988	0.026
Person Capital	1882.556***	39	0.976	0.050

Source: Authors' own calculation based on non-public individual level register data from the Social Statistical Database (SSD) provided by Statistics Netherlands (CBS) and the Longitudinal Internet studies for the Social Sciences (LISS) from CenterData.

Table C.2: Factor loadings for indicators used to measure the manifest variables

Name	Description	Loading	S.E.
Economic Capital			
wealth	Percentile groups of household wealth	1.000	0.000
inc	Percentile groups of household income	1.130	0.046
	This variable describes the household and is common to all household members.		
own	... self-owned dwelling	0.627	0.015
edu	Education in education years.	1.666	0.061
Social Capital			
sc1_hi	The number of high educated contacts	1.000	0.000
sc2_f	The number of full-time employed contacts	2.657	1.343
sc3	The density of connection within the core-network	5.031	2.404
Cultural Capital			

(continued)

Name	Description	Loading	S.E.
	How often did you visit these performances or concerts over the past 12 months?		
cs494	... a theatre performance	0.443	0.011
cs517	... a dance or ballet performance	0.200	0.005
cs093	... a classical concert	0.394	0.009
cs094	... an opera	0.108	0.004
	In the past 12 months; how often did you visit...		
cs101	... a museum	1.000	0.000
cs100	... an art gallery	0.669	0.011
cs099	... a film house or film festival	0.658	0.014
Person Capital			
	You indicated that there were periods since 2008 when you were unable to work for six consecutive weeks or longer because of health impairments. In which calendar year did this happen? If it happened in more than one year		
v4	... (0: no; 1: yes)	0.064	0.005
ch004	How would you describe your health? (1: poor; – 5: excellent)	0.534	0.009
bmi	BMI	-0.031	0.009
bmi_go	Normal weight (18.5 < bmi < 25)	0.008	0.005
bmi_hi	Overweight (25 < bmi < 30)	0.021	0.004
	The following questions are about how you felt over the past month. Please choose the answer that best describes how you felt during this past month. This past month .... (1: never – 6: continuously)		
ch011	... I felt very anxious.	-0.881	0.011
ch012	... I felt so down that nothing could cheer me up.	-0.877	0.010
ch013	... I felt calm and peaceful.	0.905	0.009
ch014	... I felt depressed and gloomy.	-0.873	0.010
ch015	... I felt happy.	1.000	0.000

Note: The factors listed in this table were constructed in separate models. Variables with a loading of 1.000 indicate that these were used to achor the latent construct. Source: Authors' own calculation based on non-public individual level register data from the Social Statistical Database (SSD) provided by Statistics Netherlands (CBS) and the Longitudinal Internet studies for the Social Sciences (LISS) from CenterData.

C.2 Random effects of capitals

Table C.3: Predicted random effects of economic capital on benefit receipt

	Predicted Effect		Random Effect	
Strata	**B**	**95%CI**	**B**	**95%CI**
Native 20<30 Female	-0.006	(-0.024; 0.013)	0.030	(0.009; 0.052)
Native 20<30 Male	-0.007	(-0.027; 0.015)	0.029	(0.006; 0.054)
Native 30<40 Female	-0.019	(-0.036; -0.002)	0.017	(-0.003; 0.038)
Native 30<40 Male	-0.034	(-0.056; -0.012)	-0.018	(-0.040; 0.006)
Native 40<50 Female	-0.046	(-0.064; -0.028)	-0.010	(-0.032; 0.011)
Native 40<50 Male	-0.054	(-0.074; -0.034)	0.002	(-0.022; 0.027)
Native 50<60 Female	-0.009	(-0.026; 0.007)	0.026	(0.005; 0.048)
Native 50<60 Male	-0.013	(-0.033; 0.006)	0.023	(-0.000; 0.045)
Non-Western 1st gen. 20<30 Female	-0.041	(-0.084; -0.000)	-0.005	(-0.047; 0.034)
Non-Western 1st gen. 20<30 Male	-0.019	(-0.060; 0.026)	0.017	(-0.026; 0.060)
Non-Western 1st gen. 30<40 Female	-0.040	(-0.085; 0.001)	-0.004	(-0.048; 0.039)
Non-Western 1st gen. 30<40 Male	-0.046	(-0.092; -0.004)	-0.011	(-0.055; 0.032)
Non-Western 1st gen. 40<50 Female	-0.068	(-0.109; -0.031)	-0.032	(-0.072; 0.004)
Non-Western 1st gen. 40<50 Male	-0.037	(-0.077; 0.000)	-0.001	(-0.040; 0.037)
Non-Western 1st gen. 50<60 Female	-0.058	(-0.104; -0.017)	-0.022	(-0.065; 0.018)
Non-Western 1st gen. 50<60 Male	-0.049	(-0.092; -0.010)	-0.013	(-0.054; 0.026)
Non-Western 2nd gen. 20<30 Female	-0.056	(-0.093; -0.020)	-0.020	(-0.057; 0.014)
Non-Western 2nd gen. 20<30 Male	-0.036	(-0.080; 0.006)	-0.000	(-0.039; 0.046)
Non-Western 2nd gen. 30<40 Female	-0.035	(-0.080; 0.009)	0.000	(-0.043; 0.046)
Non-Western 2nd gen. 30<40 Male	-0.043	(-0.088; -0.001)	-0.007	(-0.049; 0.036)
Non-Western 2nd gen. 40<50 Female	-0.068	(-0.130; -0.020)	-0.032	(-0.085; 0.018)
Non-Western 2nd gen. 40<50 Male	-0.043	(-0.098; 0.007)	-0.007	(-0.058; 0.045)
Non-Western 2nd gen. 50<60 Female	-0.046	(-0.103; 0.004)	-0.010	(-0.063; 0.039)
Non-Western 2nd gen. 50<60 Male	-0.052	(-0.110; -0.004)	-0.016	(-0.070; 0.032)
Western 1st gen. 20<30 Female	-0.024	(-0.066; 0.023)	0.012	(-0.031; 0.057)
Western 1st gen. 20<30 Male	-0.045	(-0.097; -0.000)	-0.010	(-0.056; 0.036)
Western 1st gen. 30<40 Female	-0.031	(-0.073; 0.010)	0.005	(-0.036; 0.046)
Western 1st gen. 30<40 Male	-0.029	(-0.077; 0.023)	0.007	(-0.040; 0.058)
Western 1st gen. 40<50 Female	-0.044	(-0.088; -0.004)	-0.008	(-0.050; 0.033)
Western 1st gen. 40<50 Male	-0.021	(-0.066; 0.029)	0.015	(-0.030; 0.065)
Western 1st gen. 50<60 Female	-0.020	(-0.061; 0.024)	0.016	(-0.027; 0.058)
Western 1st gen. 50<60 Male	-0.054	(-0.112; -0.006)	-0.018	(-0.068; 0.031)
Western 2nd gen. 20<30 Female	-0.017	(-0.057; 0.025)	0.018	(-0.022; 0.062)
Western 2nd gen. 20<30 Male	-0.028	(-0.072; 0.018)	0.008	(-0.035; 0.053)
Western 2nd gen. 30<40 Female	-0.035	(-0.077; 0.006)	0.001	(-0.041; 0.043)
Western 2nd gen. 30<40 Male	-0.023	(-0.065; 0.021)	0.013	(-0.027; 0.059)
Western 2nd gen. 40<50 Female	-0.024	(-0.065; 0.018)	0.011	(-0.027; 0.056)
Western 2nd gen. 40<50 Male	-0.042	(-0.089; -0.001)	-0.007	(-0.049; 0.037)
Western 2nd gen. 50<60 Female	-0.034	(-0.076; 0.008)	0.002	(-0.039; 0.041)
Western 2nd gen. 50<60 Male	-0.036	(-0.079; 0.007)	-0.000	(-0.041; 0.043)

Note: Averages of the random effect posterior distributions from Model 4, 95% credible intervals between brackets. N(individuals) = 3755, N(strata)= 40. Source: Authors' own calculation based on non-public individual level register data from the Social Statistical Database (SSD) provided by Statistics Netherlands (CBS) and the Longitudinal Internet studies for the Social Sciences (LISS) from CenterData.

Appendix D

Supplements to Chapter 5

Table D.1: Descriptive statistics of control variables per stratum

		Full Population		Sample	
Strata	**Variable**	**Value**	**sd/(range)**	**Value**	**sd/(range)**
Native Women	Age	42.471	9.878	42.130	10.088
	Education (ISCED)	4.074	(1; 9)	4.146	(2; 7)
	#children<18	0.784	(0; 15)	0.713	(0; 5)
	Socio-economic status (ISEI)	49.341	16.574	49.269	18.581
	N	1275732		300	
	Observations	11.268		10.890	
Native Men	Age	42.311	9.868	42.360	10.049
	Education (ISCED)	3.826	(1; 9)	3.692	(2; 8)
	#children<18	0.576	(0; 14)	0.607	(0; 5)
	Socio-economic status (ISEI)	48.297	16.976	46.653	16.906
	N	1315400		300	
	Observations	11.253		10.983	
First generation African Women	Age	36.586	8.271	35.969	7.643
	Education (ISCED)	3.546	(1; 9)	3.749	(1; 9)
	#children<18	0.375	(0; 12)	0.275	(0; 6)
	Socio-economic status (ISEI)	43.114	13.772	39.921	15.627
	N	31061		300	
	Observations	7.928		8.153	
First generation African Men	Age	37.648	8.763	37.456	9.073
	Education (ISCED)	3.525	(1; 9)	3.653	(1; 9)
	#children<18	0.222	(0; 14)	0.222	(0; 6)
	Socio-economic status (ISEI)	42.392	15.053	40.369	17.446
	N	37082		300	
	Observations	7.663		7.213	
First generation Asian Women	Age	38.141	8.846	38.406	8.712
	Education (ISCED)	3.819	(1; 9)	3.836	(1; 9)
	#children<18	0.324	(0; 12)	0.345	(0; 6)
	Socio-economic status (ISEI)	41.120	16.329	38.993	17.545
	N	76240		300	
	Observations	8.313		8.817	

(continued)

		Full Population		Sample	
Strata	**Variable**	**Value**	**sd/(range)**	**Value**	**sd/(range)**
First generation Asian Men	Age	39.039	9.249	38.610	9.202
	Education (ISCED)	3.810	(1; 9)	3.978	(1; 9)
	#children<18	0.319	(0; 12)	0.362	(0; 6)
	Socio-economic status (ISEI)	42.425	17.063	41.369	19.087
	N	38124		300	
	Observations	8.697		8.713	
First generation Eastern European Women	Age	37.753	9.089	37.926	9.143
	Education (ISCED)	4.424	(1; 9)	4.585	(1; 8)
	#children<18	0.286	(0; 9)	0.251	(0; 6)
	Socio-economic status (ISEI)	43.133	17.441	40.617	19.057
	N	73992		300	
	Observations	7.494		7.253	
First generation Eastern European Men	Age	37.877	8.913	37.952	9.140
	Education (ISCED)	3.851	(1; 9)	3.939	(1; 9)
	#children<18	0.184	(0; 8)	0.159	(0; 6)
	Socio-economic status (ISEI)	39.647	16.047	35.825	16.133
	N	89218		300	
	Observations	6.568		6.400	
First generation MENA Women	Age	38.137	8.849	38.120	8.625
	Education (ISCED)	3.584	(1; 9)	3.522	(1; 9)
	#children<18	0.579	(0; 11)	0.556	(0; 9)
	Socio-economic status (ISEI)	45.141	12.938	41.391	14.888
	N	35481		300	
	Observations	8.401		8.447	
First generation MENA Men	Age	39.495	8.955	39.699	9.031
	Education (ISCED)	3.542	(1; 9)	3.256	(1; 9)
	#children<18	0.342	(0; 11)	0.441	(0; 6)
	Socio-economic status (ISEI)	43.632	14.380	39.459	16.252
	N	50254		300	
	Observations	8.383		8.143	

(continued)

		Full Population		Sample	
Strata	**Variable**	**Value**	**sd/(range)**	**Value**	**sd/(range)**
First generation North American and Oceanian Women	Age	42.354	9.292	42.030	9.166
	Education (ISCED)	4.861	(1; 9)	4.889	(2; 9)
	#children<18	0.579	(0; 9)	0.535	(0; 5)
	Socio-economic status (ISEI)	52.411	15.821	50.354	17.992
	N	12700		300	
	Observations	8.514		8.333	
First generation North American and Oceanian Men	Age	41.987	9.192	41.161	8.934
	Education (ISCED)	4.771	(1; 9)	4.791	(2; 9)
	#children<18	0.362	(0; 7)	0.359	(0; 5)
	Socio-economic status (ISEI)	52.746	17.055	52.753	18.458
	N	13627		300	
	Observations	8.159		8.330	
First generation PIB Women	Age	38.908	9.568	39.459	9.854
	Education (ISCED)	3.819	(1; 9)	4.091	(1; 9)
	#children<18	0.788	(0; 12)	0.821	(0; 6)
	Socio-economic status (ISEI)	46.093	12.678	44.524	15.225
	N	17583		300	
	Observations	8.750		8.520	
First generation PIB Men	Age	39.448	9.472	39.910	9.583
	Education (ISCED)	3.891	(1; 9)	3.837	(1; 9)
	#children<18	0.532	(0; 11)	0.653	(0; 7)
	Socio-economic status (ISEI)	45.650	15.408	43.929	16.789
	N	21903		300	
	Observations	7.584		7.443	
First generation Polish Women	Age	36.699	8.866	35.639	8.355
	Education (ISCED)	4.543	(1; 9)	4.711	(2; 8)
	#children<18	0.170	(0; 6)	0.140	(0; 3)
	Socio-economic status (ISEI)	40.156	17.537	37.846	17.983
	N	34342		300	
	Observations	6.973		7.117	

(continued)

		Full Population		Sample	
Strata	**Variable**	**Value**	**sd/(range)**	**Value**	**sd/(range)**
First generation Polish Men	Age	38.367	8.592	37.694	8.342
	Education (ISCED)	3.501	(1; 9)	3.652	(1; 7)
	#children<18	0.042	(0; 5)	0.051	(0; 3)
	Socio-economic status (ISEI)	35.878	13.792	31.666	12.777
	N	75404		300	
	Observations	6.653		6.890	
First generation Scandinavian Women	Age	40.597	9.851	40.878	9.730
	Education (ISCED)	4.563	(1; 9)	4.637	(2; 8)
	#children<18	0.451	(0; 13)	0.438	(0; 4)
	Socio-economic status (ISEI)	50.808	16.445	50.867	17.623
	N	49449		300	
	Observations	7.818		7.550	
First generation Scandinavian Men	Age	40.633	9.741	40.258	9.653
	Education (ISCED)	4.160	(1; 9)	4.195	(1; 8)
	#children<18	0.276	(0; 13)	0.263	(0; 4)
	Socio-economic status (ISEI)	48.943	17.057	48.130	18.510
	N	58156		300	
	Observations	7.214		6.903	
First generation South American Women	Age	38.568	9.139	38.017	8.740
	Education (ISCED)	4.131	(1; 9)	4.113	(1; 9)
	#children<18	0.385	(0; 9)	0.402	(0; 5)
	Socio-economic status (ISEI)	43.984	16.141	41.277	18.166
	N	16106		300	
	Observations	8.524		8.580	
First generation South American Men	Age	38.825	9.575	37.470	9.237
	Education (ISCED)	4.015	(1; 9)	3.891	(1; 8)
	#children<18	0.331	(0; 8)	0.237	(0; 5)
	Socio-economic status (ISEI)	43.672	16.747	40.535	18.101
	N	12792		300	
	Observations	8.100		7.987	

(continued)

		Full Population		Sample	
Strata	**Variable**	**Value**	**sd/(range)**	**Value**	**sd/(range)**
First generation Western European Women	Age	40.593	9.404	41.061	9.390
	Education (ISCED)	5.006	(1; 9)	5.328	(1; 9)
	#children<18	0.369	(0; 12)	0.376	(0; 4)
	Socio-economic status (ISEI)	52.001	17.582	54.473	18.372
	N	34923		300	
	Observations	7.797		8.067	
First generation Western European Men	Age	41.094	9.261	41.675	9.587
	Education (ISCED)	4.670	(1; 9)	4.624	(1; 9)
	#children<18	0.233	(0; 11)	0.248	(0; 4)
	Socio-economic status (ISEI)	50.351	18.414	51.198	19.284
	N	50314		300	
	Observations	7.542		7.027	
Second generation African Women	Age	35.284	9.096	34.156	8.403
	Education (ISCED)	4.746	(2; 8)	4.667	(2; 7)
	#children<18	0.273	(0; 5)	0.199	(0; 5)
	Socio-economic status (ISEI)	52.735	16.718	51.588	18.989
	N	2018		300	
	Observations	8.222		8.170	
Second generation African Men	Age	35.218	8.962	34.328	8.535
	Education (ISCED)	4.174	(2; 8)	4.319	(2; 8)
	#children<18	0.209	(0; 5)	0.183	(0; 4)
	Socio-economic status (ISEI)	50.387	17.046	50.135	18.914
	N	2144		300	
	Observations	8.250		8.417	
Second generation Asian Women	Age	32.888	8.277	33.096	8.590
	Education (ISCED)	4.647	(2; 8)	4.638	(2; 8)
	#children<18	0.174	(0; 7)	0.178	(0; 5)
	Socio-economic status (ISEI)	51.413	17.311	50.859	18.346
	N	4682		300	
	Observations	6.820		6.810	

(continued)

Strata	Variable	Full Population Value	Full Population sd/(range)	Sample Value	Sample sd/(range)
Second generation Asian Men	Age	32.944	8.333	33.641	8.587
	Education (ISCED)	4.231	(2; 9)	4.419	(2; 8)
	#children<18	0.128	(0; 5)	0.171	(0; 4)
	Socio-economic status (ISEI)	50.033	17.282	50.467	18.490
	N	4951		300	
	Observations	6.837		7.250	
Second generation Eastern European Women	Age	38.991	9.201	38.924	9.219
	Education (ISCED)	4.179	(2; 9)	4.248	(2; 8)
	#children<18	0.434	(0; 5)	0.402	(0; 4)
	Socio-economic status (ISEI)	50.826	16.070	51.072	18.113
	N	3453		300	
	Observations	10.868		10.880	
Second generation Eastern European Men	Age	38.789	9.119	38.515	8.905
	Education (ISCED)	3.967	(1; 9)	4.015	(1; 8)
	#children<18	0.298	(0; 7)	0.291	(0; 4)
	Socio-economic status (ISEI)	50.032	16.736	48.590	18.230
	N	3714		300	
	Observations	10.750		11.017	
Second generation MENA Women	Age	31.458	6.387	32.013	7.352
	Education (ISCED)	4.026	(1; 9)	4.161	(1; 8)
	#children<18	0.069	(0; 4)	0.145	(0; 4)
	Socio-economic status (ISEI)	48.555	15.914	47.848	17.354
	N	3271		300	
	Observations	6.698		6.240	
Second generation MENA Men	Age	31.461	6.452	31.597	6.902
	Education (ISCED)	3.551	(1; 9)	3.512	(1; 8)
	#children<18	0.061	(0; 6)	0.069	(0; 3)
	Socio-economic status (ISEI)	47.134	16.140	46.869	17.909
	N	3430		300	
	Observations	6.754		6.727	

(continued)

Strata	Variable	Full Population Value	Full Population sd/(range)	Sample Value	Sample sd/(range)
Second generation North American and Oceanian Women	Age	41.341	10.963	41.350	11.051
	Education (ISCED)	4.376	(1; 9)	4.489	(2; 9)
	#children<18	0.733	(0; 7)	0.711	(0; 5)
	Socio-economic status (ISEI)	50.884	16.520	50.250	17.688
	N	8106		300	
	Observations	9.621		9.730	
Second generation North American and Oceanian Men	Age	41.431	11.092	42.315	11.062
	Education (ISCED)	4.180	(2; 9)	4.184	(2; 8)
	#children<18	0.579	(0; 6)	0.673	(0; 5)
	Socio-economic status (ISEI)	50.575	16.987	49.902	18.240
	N	8722		300	
	Observations	9.396		9.803	
Second generation PIB Women	Age	30.902	5.262	31.204	5.959
	Education (ISCED)	4.218	(1; 9)	4.376	(2; 9)
	#children<18	0.038	(0; 5)	0.052	(0; 3)
	Socio-economic status (ISEI)	50.229	15.982	50.282	18.217
	N	4407		300	
	Observations	7.814		7.927	
Second generation PIB Men	Age	30.889	5.164	31.289	5.949
	Education (ISCED)	3.836	(1; 9)	3.948	(2; 8)
	#children<18	0.022	(0; 7)	0.040	(0; 4)
	Socio-economic status (ISEI)	48.984	16.464	47.873	18.112
	N	4673		300	
	Observations	8.035		8.020	
Second generation Polish Women	Age	40.591	10.979	40.874	11.028
	Education (ISCED)	4.122	(2; 9)	3.968	(2; 8)
	#children<18	0.565	(0; 5)	0.607	(0; 4)
	Socio-economic status (ISEI)	49.869	16.381	47.472	18.296
	N	1198		300	
	Observations	9.190		9.450	

(continued)

Strata	Variable	Full Population Value	Full Population sd/(range)	Sample Value	Sample sd/(range)
Second generation Polish Men	Age	40.083	11.011	39.556	10.869
	Education (ISCED)	3.795	(1; 8)	3.856	(2; 8)
	#children<18	0.463	(0; 5)	0.424	(0; 5)
	Socio-economic status (ISEI)	48.858	16.793	47.716	17.645
	N	1384		300	
	Observations	9.027		9.210	
Second generation Scandinavian Women	Age	40.673	9.551	40.906	9.730
	Education (ISCED)	4.240	(1; 9)	4.177	(2; 9)
	#children<18	0.589	(0; 8)	0.662	(0; 5)
	Socio-economic status (ISEI)	50.529	16.543	49.162	18.156
	N	23322		300	
	Observations	11.456		10.873	
Second generation Scandinavian Men	Age	40.576	9.619	40.557	9.169
	Education (ISCED)	3.989	(1; 9)	4.094	(2; 9)
	#children<18	0.423	(0; 10)	0.380	(0; 4)
	Socio-economic status (ISEI)	49.782	17.125	49.628	19.315
	N	24960		300	
	Observations	11.232		11.653	
Second generation South American Women	Age	34.457	8.588	35.391	9.073
	Education (ISCED)	4.234	(2; 8)	4.297	(2; 8)
	#children<18	0.239	(0; 10)	0.295	(0; 7)
	Socio-economic status (ISEI)	49.064	16.233	47.889	17.734
	N	1975		300	
	Observations	7.822		8.270	
Second generation South American Men	Age	34.182	8.374	34.247	8.447
	Education (ISCED)	3.856	(2; 8)	3.834	(2; 8)
	#children<18	0.129	(0; 4)	0.152	(0; 4)
	Socio-economic status (ISEI)	48.301	16.303	45.904	17.309
	N	2148		300	
	Observations	7.962		7.957	

(continued)

Strata	Variable	Full Population		Sample	
		Value	**sd/(range)**	**Value**	**sd/(range)**
Second generation Western European Women	Age	39.084	9.231	39.079	9.247
	Education (ISCED)	4.505	(2; 9)	4.525	(2; 8)
	#children<18	0.435	(0; 9)	0.437	(0; 5)
	Socio-economic status (ISEI)	52.241	16.402	51.813	18.228
	N	15109		300	
	Observations	11.207		10.963	
Second generation Western European Men	Age	38.961	9.264	39.214	9.467
	Education (ISCED)	4.239	(1; 9)	4.074	(2; 9)
	#children<18	0.320	(0; 8)	0.385	(0; 5)
	Socio-economic status (ISEI)	51.496	17.061	49.528	18.060
	N	16219		300	
	Observations	11.160		10.983	

Table D.2: Extended summary of additive effects and random effects for social assistance receipt

	Model 1	Model 2	Model 3	Model4	Model 5
Intercept	0.059 (0.040; 0.079)	0.031 (-0.034; 0.098)	0.015 (-0.014; 0.045)	0.015 (-0.014; 0.043)	0.044 (0.026; 0.063)
Migration Background (ref. Native)					
Scandinavia		0.021 (-0.058; 0.099)	0.008 (-0.026; 0.043)	0.007 (-0.027; 0.042)	0.001 (-0.018; 0.020)
Western Europe		0.017 (-0.065; 0.099)	0.004 (-0.031; 0.039)	0.004 (-0.029; 0.039)	-0.001 (-0.020; 0.018)
Eastern Europe		0.034 (-0.045; 0.114)	0.008 (-0.028; 0.045)	0.007 (-0.027; 0.043)	-0.007 (-0.026; 0.012)
Polish		0.017 (-0.065; 0.097)	0.006 (-0.029; 0.041)	0.005 (-0.028; 0.040)	-0.002 (-0.021; 0.017)
North America and Oceania		0.010 (-0.071; 0.092)	0.002 (-0.034; 0.037)	0.001 (-0.032; 0.035)	-0.004 (-0.023; 0.014)
South America		0.056 (-0.024; 0.132)	0.022 (-0.014; 0.057)	0.021 (-0.013; 0.057)	0.010 (-0.009; 0.029)
MENA		0.127 (0.046; 0.205)	0.053 (0.017; 0.087)	0.052 (0.018; 0.086)	0.021 (0.002; 0.041)
PIB		0.037 (-0.044; 0.114)	0.011 (-0.024; 0.046)	0.010 (-0.025; 0.046)	-0.003 (-0.022; 0.016)
Asia		0.038 (-0.042; 0.123)	0.013 (-0.023; 0.049)	0.012 (-0.023; 0.045)	-0.004 (-0.022; 0.015)
Africa		0.160 (0.081; 0.239)	0.068 (0.033; 0.104)	0.067 (0.033; 0.102)	0.034 (0.015; 0.053)
Gender (ref. Male)					
Female		-0.010 (-0.039; 0.019)	-0.004 (-0.016; 0.009)	-0.004 (-0.016; 0.009)	-0.003 (-0.010; 0.003)
Generation (ref. Native and First Generation)					
Second Generation		-0.036 (-0.066; -0.006)	-0.014 (-0.027; -0.002)	-0.014 (-0.028; -0.001)	-0.003 (-0.010; 0.005)
SA (t-1)			0.627 (0.598; 0.656)	0.550 (0.429; 0.668)	0.516 (0.396; 0.633)
Interactions					

(continued)

	Model 1	**Model 2**	**Model 3**	**Model4**	**Model 5**
Female * SA (t-1)				0.000 (-0.050; 0.053)	-0.001 (-0.050; 0.049)
Generation * SA (t-1)				0.004 (-0.047; 0.057)	0.010 (-0.043; 0.064)
Scandinavia * SA (t-1)				0.077 (-0.065; 0.219)	0.071 (-0.069; 0.210)
Western Europe * SA (t-1)				0.021 (-0.121; 0.162)	0.028 (-0.116; 0.170)
Eastern Europe * SA (t-1)				0.135 (-0.012; 0.274)	0.122 (-0.024; 0.268)
North America and Oceania * SA (t-1)				0.114 (-0.032; 0.252)	0.115 (-0.026; 0.262)
South America * SA (t-1)				0.061 (-0.080; 0.199)	0.067 (-0.073; 0.210)
MENA * SA (t-1)				0.083 (-0.053; 0.228)	0.081 (-0.061; 0.225)
PIB * SA (t-1)				0.100 (-0.041; 0.241)	0.107 (-0.031; 0.251)
Asia * SA (t-1)				0.128 (-0.014; 0.270)	0.114 (-0.027; 0.257)
Africa * SA (t-1)				0.019 (-0.126; 0.162)	0.024 (-0.117; 0.175)
Control Variables					
ISCED 2					-0.009 (-0.018; 0.000)
ISCED 3					-0.033 (-0.042; -0.024)
ISCED 4					-0.026 (-0.039; -0.013)
ISCED 5					-0.039 (-0.048; -0.029)
ISCED 6					-0.045 (-0.054; -0.036)
					-0.043

(continued)

	Model 1	Model 2	Model 3	Model4	Model 5
ISCED 7					(-0.052; -0.033)
ISCED 8					-0.039 (-0.051; -0.026)
ISCED 9					0.005 (-0.009; 0.020)
ISEI					0.000 (0.000; 0.000)
ISEI miss					0.038 (0.036; 0.041)
ISCED miss					-0.026 (-0.036; -0.017)
Work related migration					-0.056 (-0.060; -0.052)
Refugee					0.021 (0.016; 0.025)
Family related migration					-0.023 (-0.028; -0.018)
Other reasons for migration					-0.048 (-0.052; -0.043)
#children <18					-0.004 (-0.005; -0.003)
Separated					0.026 (0.022; 0.030)
Single					0.014 (0.011; 0.016)
Widow					0.008 (-0.004; 0.020)
Random Effects					
sigma	0.220 (0.219; 0.221)	0.220 (0.219; 0.221)	0.174 (0.173; 0.174)	0.174 (0.173; 0.174)	0.172 (0.171; 0.172)
var(sigma) strata	0.065 (0.053; 0.081)	0.047 (0.036; 0.061)	0.020 (0.015; 0.026)	0.020 (0.015; 0.026)	0.010 (0.008; 0.014)
var(sigma) year	0.005 (0.003; 0.009)	0.005 (0.003; 0.009)	0.004 (0.002; 0.006)	0.004 (0.002; 0.006)	0.004 (0.002; 0.006)

(continued)

	Model 1	**Model 2**	**Model 3**	**Model4**	**Model 5**
var(SA (t-1)) strata			0.079 (0.062; 0.102)	0.081 (0.061; 0.108)	0.080 (0.060; 0.107)
var(SA (t-1)) year			0.022 (0.013; 0.033)	0.022 (0.013; 0.033)	0.022 (0.014; 0.033)

Note: Averages of the fixed effect posterior distributions, 95% credible intervals between parentheses. N(individuals) = 12600. Source: Authors' own calculation based on non-public individual level register data from the FD-trygd database provided by Statistics Norway (SSB).

Table D.3: Social assistance incidence rate and intersectional effect per intersectional stratum

	Incidence Rate		Intersectional Effect	
Strata	**B**	**95%CI**	**B**	**95%CI**
First generation Western European Men	0.010	(0.000; 0.020)	-0.039	(-0.090; 0.012)
First generation North American and Oceanian Women	0.014	(0.005; 0.023)	-0.017	(-0.069; 0.036)
First generation Western European Women	0.018	(0.009; 0.027)	-0.020	(-0.069; 0.031)
First generation Polish Women	0.019	(0.009; 0.028)	-0.019	(-0.071; 0.034)
Second generation North American and Oceanian Women	0.019	(0.011; 0.027)	0.023	(-0.027; 0.077)
First generation Polish Men	0.020	(0.011; 0.030)	-0.028	(-0.080; 0.024)
Second generation North American and Oceanian Men	0.020	(0.011; 0.028)	0.014	(-0.038; 0.066)
First generation North American and Oceanian Men	0.021	(0.012; 0.031)	-0.020	(-0.073; 0.032)
Native Women	0.023	(0.015; 0.030)	0.002	(-0.065; 0.066)
Second generation Western European Women	0.023	(0.014; 0.031)	0.020	(-0.029; 0.071)
Second generation Polish Men	0.027	(0.018; 0.036)	0.015	(-0.037; 0.065)
Second generation Scandinavian Men	0.027	(0.020; 0.035)	0.011	(-0.041; 0.062)
First generation Scandinavian Men	0.028	(0.019; 0.038)	-0.023	(-0.075; 0.027)
Second generation Asian Men	0.029	(0.019; 0.038)	-0.005	(-0.056; 0.047)
Native Men	0.030	(0.022; 0.038)	-0.001	(-0.068; 0.064)
First generation Scandinavian Women	0.030	(0.020; 0.040)	-0.011	(-0.061; 0.038)
Second generation PIB Women	0.030	(0.021; 0.039)	0.008	(-0.044; 0.061)
Second generation Scandinavian Women	0.031	(0.023; 0.039)	0.025	(-0.026; 0.077)
Second generation Eastern European Women	0.032	(0.025; 0.040)	0.013	(-0.039; 0.066)
Second generation Polish Women	0.032	(0.023; 0.040)	0.030	(-0.020; 0.082)
Second generation Asian Women	0.035	(0.024; 0.045)	0.011	(-0.040; 0.066)
First generation PIB Women	0.036	(0.027; 0.045)	-0.021	(-0.073; 0.030)
Second generation Eastern European Men	0.036	(0.028; 0.044)	0.007	(-0.047; 0.060)
First generation Eastern European Men	0.041	(0.031; 0.051)	-0.024	(-0.077; 0.028)
Second generation African Women	0.041	(0.032; 0.050)	-0.103	(-0.154; -0.052)
Second generation South American Women	0.043	(0.035; 0.052)	0.002	(-0.049; 0.054)
Second generation PIB Men	0.045	(0.036; 0.054)	0.013	(-0.038; 0.063)
First generation Asian Women	0.047	(0.038; 0.055)	-0.012	(-0.066; 0.039)
Second generation Western European Men	0.050	(0.042; 0.058)	0.037	(-0.013; 0.087)
First generation South American Men	0.054	(0.045; 0.063)	-0.033	(-0.084; 0.017)
First generation Eastern European Women	0.057	(0.047; 0.067)	0.002	(-0.050; 0.054)
Second generation African Men	0.057	(0.048; 0.066)	-0.097	(-0.148; -0.047)

(continued)

	Incidence Rate		Intersectional Effect	
Strata	**B**	**95%CI**	**B**	**95%CI**
First generation South American Women	0.065	(0.056; 0.074)	-0.012	(-0.064; 0.039)
First generation PIB Men	0.068	(0.059; 0.077)	0.000	(-0.051; 0.050)
First generation Asian Men	0.077	(0.068; 0.086)	0.007	(-0.046; 0.059)
Second generation MENA Women	0.079	(0.069; 0.090)	-0.032	(-0.082; 0.020)
Second generation MENA Men	0.084	(0.074; 0.094)	-0.037	(-0.088; 0.013)
Second generation South American Men	0.096	(0.087; 0.105)	0.044	(-0.007; 0.097)
First generation MENA Women	0.155	(0.146; 0.164)	0.008	(-0.043; 0.060)
First generation MENA Men	0.219	(0.210; 0.228)	0.062	(0.011; 0.113)
First generation African Women	0.283	(0.274; 0.293)	0.103	(0.053; 0.155)
First generation African Men	0.289	(0.279; 0.299)	0.098	(0.047; 0.150)

Note: Predicted incidences per intersectional stratum calculated using Model 1. Predicted intersectional effects per intersectional stratum calculated using Model 2. 95% credible intervals between parentheses. N(individuals) = 12600. Source: Authors' own calculation based on non-public individual level register data from the FD-trygd database provided by Statistics Norway (SSB).

Table D.4: Social assistance persistency rate and intersectional persistency effect per intersectional stratum

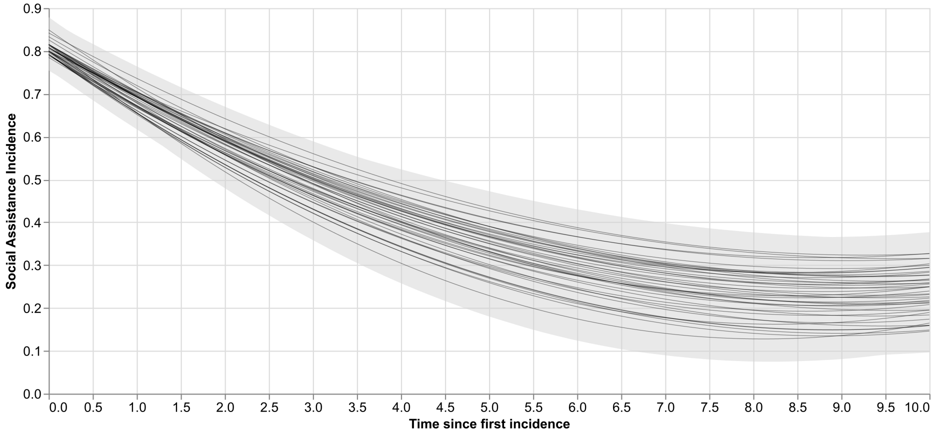
	Incidence Rate		Intersectional Effect		Controlled Intersectional Effect	
Strata	**B**	**95%CI**	**B**	**95%CI**	**B**	**95%CI**
First generation Western European Men	0.378	(0.302; 0.452)	-0.206	(-0.313; -0.104)	-0.197	(-0.303; -0.102)
Second generation Polish Men	0.471	(0.429; 0.513)	-0.125	(-0.222; -0.031)	-0.125	(-0.222; -0.034)
Native Men	0.476	(0.439; 0.513)	-0.078	(-0.195; 0.039)	-0.080	(-0.195; 0.041)
Second generation Scandinavian Women	0.505	(0.470; 0.542)	-0.072	(-0.166; 0.022)	-0.077	(-0.167; 0.011)
First generation Scandinavian Men	0.549	(0.501; 0.597)	-0.026	(-0.119; 0.068)	-0.014	(-0.108; 0.078)
Second generation South American Women	0.553	(0.517; 0.589)	-0.064	(-0.152; 0.022)	-0.057	(-0.147; 0.034)
Second generation African Women	0.579	(0.541; 0.618)	-0.051	(-0.145; 0.037)	-0.042	(-0.135; 0.049)
First generation MENA Women	0.584	(0.566; 0.602)	-0.049	(-0.138; 0.043)	-0.046	(-0.136; 0.047)
First generation South American Men	0.585	(0.553; 0.618)	-0.026	(-0.117; 0.065)	-0.021	(-0.115; 0.068)
Second generation North American and Oceanian Women	0.597	(0.549; 0.642)	-0.068	(-0.162; 0.029)	-0.072	(-0.169; 0.024)
First generation African Men	0.599	(0.579; 0.619)	-0.028	(-0.119; 0.058)	-0.031	(-0.118; 0.056)
Second generation PIB Men	0.599	(0.564; 0.635)	-0.053	(-0.147; 0.038)	-0.058	(-0.147; 0.032)
First generation Polish Women	0.605	(0.545; 0.663)	0.010	(-0.088; 0.105)	0.019	(-0.078; 0.119)
First generation Scandinavian Women	0.612	(0.570; 0.655)	0.039	(-0.051; 0.134)	0.041	(-0.050; 0.134)
First generation North American and Oceanian Men	0.613	(0.566; 0.660)	-0.048	(-0.141; 0.048)	-0.036	(-0.131; 0.060)
First generation South American Women	0.621	(0.591; 0.651)	0.009	(-0.080; 0.097)	0.004	(-0.088; 0.094)
Second generation Polish Women	0.622	(0.582; 0.661)	0.026	(-0.067; 0.119)	0.020	(-0.073; 0.111)
Second generation Eastern European Women	0.623	(0.588; 0.659)	-0.063	(-0.152; 0.028)	-0.050	(-0.141; 0.041)
Second generation PIB Women	0.626	(0.583; 0.669)	-0.027	(-0.119; 0.067)	-0.037	(-0.130; 0.054)
Native Women	0.633	(0.592; 0.674)	0.077	(-0.039; 0.192)	0.079	(-0.036; 0.197)
First generation PIB Women	0.633	(0.595; 0.672)	-0.015	(-0.106; 0.075)	-0.010	(-0.103; 0.082)
Second generation Scandinavian Men	0.636	(0.598; 0.674)	0.060	(-0.036; 0.154)	0.051	(-0.039; 0.141)
First generation Asian Women	0.639	(0.606; 0.673)	-0.037	(-0.129; 0.055)	-0.049	(-0.140; 0.046)
First generation Asian Men	0.644	(0.616; 0.672)	-0.034	(-0.124; 0.060)	-0.049	(-0.140; 0.042)
Second generation MENA Women	0.644	(0.613; 0.677)	0.007	(-0.087; 0.102)	0.012	(-0.077; 0.100)
Second generation MENA Men	0.644	(0.614; 0.674)	0.008	(-0.085; 0.099)	0.004	(-0.083; 0.091)
Second generation Western European Men	0.644	(0.614; 0.673)	0.066	(-0.028; 0.162)	0.060	(-0.034; 0.154)
Second generation Western European Women	0.648	(0.608; 0.689)	0.069	(-0.023; 0.163)	0.057	(-0.035; 0.152)
First generation Western European Women	0.649	(0.598; 0.700)	0.071	(-0.024; 0.169)	0.081	(-0.015; 0.180)
First generation Eastern European Men	0.651	(0.613; 0.690)	-0.030	(-0.122; 0.064)	-0.033	(-0.126; 0.059)
First generation African Women	0.657	(0.637; 0.676)	0.030	(-0.062; 0.117)	0.015	(-0.074; 0.104)

(continued)

	Incidence Rate		Intersectional Effect		Controlled Intersectional Effect	
Strata	**B**	**95%CI**	**B**	**95%CI**	**B**	**95%CI**
First generation MENA Men	0.668	(0.647; 0.688)	0.035	(-0.052; 0.124)	0.027	(-0.061; 0.116)
Second generation Asian Women	0.673	(0.628; 0.717)	-0.006	(-0.100; 0.088)	0.011	(-0.081; 0.105)
Second generation African Men	0.681	(0.649; 0.714)	0.051	(-0.039; 0.138)	0.056	(-0.035; 0.152)
First generation Polish Men	0.682	(0.625; 0.741)	0.088	(-0.008; 0.185)	0.088	(-0.008; 0.183)
Second generation South American Men	0.698	(0.677; 0.721)	0.083	(-0.006; 0.172)	0.073	(-0.017; 0.162)
Second generation North American and Oceanian Men	0.718	(0.671; 0.765)	0.052	(-0.041; 0.146)	0.042	(-0.055; 0.139)
First generation North American and Oceanian Women	0.721	(0.662; 0.780)	0.062	(-0.035; 0.162)	0.066	(-0.030; 0.164)
Second generation Eastern European Men	0.723	(0.689; 0.756)	0.037	(-0.056; 0.128)	0.047	(-0.046; 0.138)
First generation Eastern European Women	0.738	(0.705; 0.770)	0.055	(-0.036; 0.150)	0.039	(-0.057; 0.132)
First generation PIB Men	0.747	(0.716; 0.778)	0.098	(0.007; 0.188)	0.106	(0.015; 0.194)
Second generation Asian Men	0.753	(0.706; 0.800)	0.076	(-0.019; 0.171)	0.092	(-0.002; 0.186)

Note: Persistency effects per intersectional stratum calculated using Model 3. Intersectional persistency effects per intersectional stratum calculated using Model 4. Controlled intersectional persistency effects per intersectional stratum calculated using Model 5. 95% credible intervals between parentheses. N(individuals) = 12600. Source: Authors' own calculation based on non-public individual level register data from the FD-trygd database provided by Statistics Norway (SSB).

D.1 Robustness analyses



Note: Note: Averages predicted incidence posterior distributions, 95% credible interval of all strata as area. N(individuals) = 12600. Source: Authors' own calculation based on non-public individual level register data from the FD-trygd database provided by Statistics Norway (SSB).

Figure D.1: Social assistance incidence by year and stratum after the first incidence of social assistance receipt

Table D.5: Summary of additive effects and random effects for social assistance receipt of the linear growth curve models

	Model 3	Model 4	Model 5
Intercept	0.815 (0.775; 0.855)	0.812 (0.767; 0.857)	0.558 (0.472; 0.643)
Migration Background (ref. Native)			
Scandinavia	-0.003 (-0.035; 0.031)	-0.004 (-0.046; 0.037)	0.006 (-0.026; 0.038)
Western Europe	-0.007 (-0.040; 0.026)	-0.008 (-0.047; 0.031)	0.009 (-0.022; 0.041)
Eastern Europe	0.034 (0.001; 0.067)	0.035 (-0.007; 0.075)	0.047 (0.013; 0.081)
Poland	0.028 (-0.010; 0.067)	0.052 (0.008; 0.098)	0.086 (0.050; 0.124)
North America and Oceania	0.012 (-0.020; 0.046)	0.012 (-0.028; 0.053)	0.017 (-0.019; 0.056)
South America	0.037 (0.003; 0.071)	0.037 (-0.005; 0.079)	0.028 (-0.006; 0.067)
MENA	0.083 (0.049; 0.117)	0.087 (0.045; 0.128)	0.074 (0.038; 0.106)
PIB	0.027 (-0.007; 0.060)	0.027 (-0.015; 0.068)	0.034 (-0.004; 0.071)
Asia	0.048 (0.014; 0.084)	0.060 (0.019; 0.101)	0.058 (0.021; 0.105)
Africa	0.073 (0.038; 0.107)	0.063 (0.019; 0.104)	0.057 (0.023; 0.092)

(continued)

	Model 3	Model 4	Model 5
Gender (ref. Male)			
Female	-0.016 (-0.029; -0.003)	-0.013 (-0.029; 0.002)	-0.021 (-0.035; -0.009)
Generation (ref. Native and First Generation)			
Second Generation	-0.007 (-0.020; 0.005)	-0.009 (-0.026; 0.007)	-0.030 (-0.044; -0.016)
time	-0.129 (-0.134; -0.124)	-0.121 (-0.138; -0.103)	-0.117 (-0.129; -0.103)
time^2	0.007 (0.007; 0.008)	0.007 (0.005; 0.008)	0.006 (0.005; 0.007)
Interactions			
Scandinavia * time		-0.003 (-0.025; 0.018)	-0.001 (-0.017; 0.015)
Western Europe * time		-0.001 (-0.023; 0.021)	0.003 (-0.012; 0.016)
Eastern Europe * time		-0.002 (-0.023; 0.019)	0.002 (-0.014; 0.017)
Poland * time		-0.042 (-0.066; -0.019)	-0.042 (-0.059; -0.025)
North America and Oceania * time		-0.001 (-0.022; 0.021)	0.009 (-0.010; 0.026)
South America * time		-0.005 (-0.027; 0.018)	0.000 (-0.018; 0.016)
MENA * time		-0.008 (-0.030; 0.014)	-0.003 (-0.022; 0.013)
PIB * time		-0.002 (-0.024; 0.020)	0.006 (-0.010; 0.024)
Asia * time		-0.020 (-0.042; 0.002)	-0.008 (-0.024; 0.009)
Africa * time		0.011 (-0.012; 0.033)	0.018 (0.001; 0.034)
Female * time		-0.007 (-0.015; 0.001)	-0.006 (-0.012; 0.000)
Generation * time		0.004 (-0.004; 0.013)	0.001 (-0.005; 0.007)
Scandinavia * time^2		0.001 (-0.001; 0.002)	0.001 (-0.001; 0.002)
Western Europe * time^2		0.000 (-0.002; 0.002)	0.000 (-0.001; 0.001)
Eastern Europe * time^2		0.000 (-0.002; 0.002)	0.000 (-0.001; 0.001)
Poland * time^2		0.003 (0.001; 0.005)	0.004 (0.002; 0.005)
North America and Oceania * time^2		0.000 (-0.002; 0.002)	0.000 (-0.002; 0.001)
South America * time^2		0.000 (-0.001; 0.002)	0.001 (-0.001; 0.002)
MENA * time^2		0.000 (-0.002; 0.002)	0.000 (-0.001; 0.002)
PIB * time^2		0.000 (-0.002; 0.002)	0.000 (-0.002; 0.001)
Asia * time^2		0.001 (-0.001; 0.003)	0.001 (-0.001; 0.002)
Africa * time^2		-0.001 (-0.003; 0.001)	-0.001 (-0.002; 0.001)

(continued)

	Model 3	Model 4	Model 5
Female * time^2		0.000 (0.000; 0.001)	0.000 (0.000; 0.001)
Generation * time^2		0.000 (-0.001; 0.000)	0.000 (-0.001; 0.000)
Random Effects			
sigma	0.449 (0.447; 0.451)	0.449 (0.447; 0.451)	0.431 (0.429; 0.433)
var(sigma) strata	0.004 (0.000; 0.017)	0.013 (0.000; 0.026)	0.009 (0.000; 0.023)
var(sigma) year	0.057 (0.039; 0.084)	0.057 (0.039; 0.084)	0.042 (0.008; 0.066)
var(time^2) strata	0.001 (0.001; 0.001)	0.001 (0.000; 0.001)	0.000 (0.000; 0.001)
var(time) strata	0.014 (0.010; 0.019)	0.010 (0.005; 0.015)	0.006 (0.001; 0.011)

Note: Averages of the fixed effect posterior distributions, 95% credible intervals between parentheses. N(individuals) = 12600, N(strata). Source: Authors' own calculation based on non-public individual level register data from the FD-trygd database provided by Statistics Norway (SSB).

Nederlandstalige samenvatting

Inleiding

De verzorgingsstaat en de sociale zekerheid die zij biedt, vormen een kernonderdeel van hedendaagse Westerse samenlevingen. In enge zin gaat het om sociale verzekeringen en belastinggefinancierde regelingen die inkomenszekerheid bieden bij risico's als werkloosheid, ziekte, arbeidsongeschiktheid en ouderdom (o.a. Esping-Andersen, 1990). In bredere zin omvat de verzorgingsstaat ook beleid gericht op preventie, re-integratie en maatschappelijke participatie (o.a. Vrooman, 2009b). Vanuit maatschappelijk en begrotingsperspectief is het belangrijk om te begrijpen wie (herhaaldelijk) afhankelijk is van uitkeringen, hoe die afhankelijkheid zich ontwikkelt over de tijd en in welke mate dit samenhangt met structurele ongelijkheden op de arbeidsmarkt en in de samenleving.

Dit proefschrift richt zich op uitkeringsontvangst binnen de kern van de beroepsbevolking (25–60 jaar) in Nederland en Noorwegen, met een focus op bijstand en werkloosheidsuitkeringen. Deze uitkeringen functioneren als noodzakelijk vangnet: zij voorkomen dat mensen bij tegenslag volledig zonder inkomen komen te zitten en bieden ruimte om te herstellen of om de stap terug naar werk te zetten. Tegelijkertijd kan uitkeringsontvangst ook leiden tot langdurige afhankelijkheid en zijn er de mogelijke sociale en psychologische gevolgen van het "in" en "uit" een uitkeringssituatie bewegen. Juist omdat uitkeringsontvangst zowel een bescherming als een risico-indicator kan zijn, is het relevant om de ongelijkheden hierin te analyseren en om de onderliggende mechanismen te identificeren.

Migratie en de relatief lagere arbeidsmarktintegratie van bepaalde migrantengroepen zijn prominente thema's in het beleidsdiscours en het publieke debat. In Nederland is de kans op uitkeringsontvangst hoger onder mensen met een niet-westerse migratieachtergrond dan onder mensen met een Nederlandse achtergrond (zie o.a. CBS, 2020). Tegelijkertijd bestaan er ook verschillen naar bijvoorbeeld leeftijd, opleiding en, in bepaalde regelingen, gender. Veel bestaand onderzoek bekijkt dergelijke verschillen vooral langs één as (bijvoorbeeld alleen migratieachtergrond of alleen gender), waardoor het zicht op combinaties van kenmerken beperkt blijft. Dit proefschrift hanteert daarom een intersectioneel perspectief (ook bekend als "kruispuntdenken"), waarin sociale kenmerken zoals migratieachtergrond, opleiding, leeftijd en gender in combinatie worden bestudeerd. Zo kan worden onderzocht welke specifieke combinaties van kenmerken samenhangen met een disproportioneel verhoogde of juist verlaagde kans op uitkeringsontvangst en in welke mate die patronen sterker zijn dan wat men op basis van afzonderlijke kenmerken zou verwachten.

Een intersectioneel perspectief

Dit proefschrift bouwt voort op het intersectionaliteitsbegrip van Crenshaw (1989) en analyseert hoe overlappende sociale categorieën als gender, leeftijd, opleiding en migratieachtergrond gezamenlijk unieke gunstige of ongunstige maatschappelijke posities teweegbrengen. Het uitgangspunt is dat de invloed van sociale kenmerken niet alleen een optelsom hoeft te zijn, maar dat ze elkaar in hun werking ook kunnen versterken, afzwakken of compenseren. Als dergelijke processen systematisch in kaart worden gebracht, wordt zichtbaar bij welke specifieke sociale groepen uitkeringsgebruik onevenredig hoog of laag is en in hoeverre traditionele analyses, die de onderliggende sociale karakteristieken alleen naast elkaar in beschouwing nemen, uitkeringsontvangst onder- of overschatten.

Een intersectionele benadering is bovendien relevant omdat zij aansluit bij de dagelijkse beleidspraktijk in de sociale zekerheid: uitkeringsstelsels en arbeidsmarkten behandelen mensen niet als "alleen vrouw" of "alleen migrant", maar als personen met meerdere kenmerken tegelijk, die in de praktijk tezamen bepalen welke kansen, barrières en verplichtingen iemand ervaart. Uit de resultaten van dit proefschrift komt naar voren dat intersectionele ongelijkheden niet automatisch betekenen dat elke combinatie van nadelen altijd leidt tot versterkt nadeel. Soms blijken ongelijkheden vooral het resultaat van additieve processen (waar kenmerken vooral "naast elkaar" werken), terwijl in andere gevallen juist een specifieke combinatie van nadelen vanuit verschillende kenmerken een rol speelt.

Een gedetailleerde rapportage over kwetsbare groepen vraagt om zorgvuldige duiding: er bestaat een reëel risico dat bevindingen onbedoeld en onterecht stigma of stereotypering in de hand werken, zeker wanneer bepaalde groepen consequent als "hoog-risico" worden geprofileerd. Dit proefschrift benadrukt daarom dat uitkeringsontvangst niet enkel een individuele keuze weerspiegelt, maar vooral duidt op bredere structurele problemen (zoals uitsluiting, institutionele drempels en discriminatie). De centrale vraag is of – en voor wie – de beschermende en activerende doelen van het stelsel worden gerealiseerd en waar mogelijke blinde vlekken liggen, met name voor groepen die meerdere vormen van kwetsbaarheid combineren.

Uitkeringsontvangst en de Nederlandse en Noorse context

Nederland kent een "hybride" verzorgingsstaat met corporatistische, liberale en sociaaldemocratische elementen, waarbij in recente decennia meer nadruk is komen te liggen op activering en individuele verantwoordelijkheid. Dit proefschrift bestudeert twee regelingen die in uitvoeringslogica en doelgroep sterk verschillen. Werkloosheidsuitkeringen zijn in Nederland georganiseerd als sociale verzekering (via het UWV), met rechten die afhankelijk zijn van arbeidsverleden en eerdere premieafdracht. Dit impliceert een duidelijke koppeling tussen eerdere arbeid en toegang tot de regeling en maakt dat werkloosheidsuitkeringen vooral relevant zijn voor groepen met een sterkere arbeidsmarktbinding.

Bijstand is daarentegen een huishoudensafhankelijke uitkering, met een middelentoets waarbij inkomen én vermogen meetellen en die door gemeenten wordt uitgevoerd. Bijstand is bedoeld als laatste vangnet wanneer andere inkomensbronnen niet of niet langer voorhanden zijn, en gaat gepaard met strikte verplichtingen en tamelijk intensieve handhaving. Na de invoering van de Participatiewet in 2015 is de nadruk op activering en naleving versterkt en kunnen sancties volgen bij niet-naleving. Ook is de lokale uitvoeringspraktijk van belang: gemeenten verschillen in hoe verplichtingen worden uitgewerkt, welke tegenprestaties worden gevergd en hoe streng er wordt gehandhaafd. Dat maakt bijstand niet alleen een inkomensregeling, maar ook een institutionele omgeving die ertoe kan leiden dat cliëntgroepen verschillend worden behandeld, waardoor variatie ontstaat in de uitkomsten van de gevalsbehandeling.

Noorwegen fungeert in dit proefschrift als aanvullende context. Ook daar bestaat gemeentelijk uitgevoerde inkomensondersteuning (*sosialhjelp*), maar binnen de Noorse verzorgingsstaattraditie die relatief sterker inzet op universaliteit en minder op punitatieve activering. De vergelijking met Noorwegen is analytisch waardevol omdat zij laat zien dat intersectionele ongelijkheden niet uitsluitend "in mensen" zitten, maar mede worden gevormd door keuzes in het institutionele ontwerp: de mate waarin beleid sanctiegericht of ondersteunend is, hoe toegankelijk voorzieningen zijn en hoe sterk activering wordt gekoppeld aan controle.

Conceptueel kader: kapitaal en drie mechanismen

In dit proefschrift wordt ongelijkheid geconceptualiseerd in termen van vier typen hulpbronnen: economisch, cultureel, sociaal en persoonskapitaal (Vrooman et al., 2024). Deze brede kapitaalsbenadering vat ongelijkheid op als verschillen in "wat men heeft" (economisch), "waar men bij past" (cultureel), "wie men kent" (sociaal) en "wie men is" (persoonskapitaal). Het voordeel van deze typologie is dat zij klassieke arbeidsmarktongelijkheid (gekoppeld aan verschillen in opleiding, inkomen, werkpositie) verbindt met minder traditionele maar vaak cruciale dimensies, zoals taal en culturele competenties, netwerkbronnen, mentale en fysieke gezondheid. Hierdoor ontstaat een kader dat zowel materiële als niet-materiële ongelijkheid omvat en dat beter aansluit op het alledaagse proces waarin mensen kansen en/of hulpbronnen benutten, belemmeringen ervaren en risico's opvangen.

Vanuit dit kader worden drie mechanismen onderzocht:

1. **Verschillen in de hoeveelheid kapitaal**: bepaalde groepen beschikken gemiddeld over minder kapitaal, wat de kans op uitkeringsontvangst vergroot. Het gaat daarbij niet alleen om minder inkomen of een zwakkere arbeidsmarktpositie, maar ook om kleinere

financiële buffers, minder stabiele loopbanen, minder toegang tot bruikbare informatie en minder ondersteuning vanuit sociale netwerken. Ook persoonskapitaal speelt hierbij een rol: mentale en fysieke gezondheidsproblemen kunnen de inzetbaarheid beperken, het zoekproces naar werk ondermijnen en de kans vergroten dat mensen überhaupt in een kwetsbare positie terechtkomen. Belangrijk is dat deze tekorten niet louter individueel zijn, maar vaak structureel worden geproduceerd en verdeeld: kansen om kapitaal op te bouwen verschillen systematisch naar bijvoorbeeld migratieachtergrond, leeftijd, gender en opleidingsniveau. In intersectionele termen betekent dit dat kapitaaltekorten zich op specifieke kruispunten kunnen stapelen, waardoor bepaalde groepen niet alleen "minder" kapitaal hebben, maar disproportioneel minder - met een verhoogd risico op uitkeringsontvangst tot gevolg.

2. **Verschillen in rendement op kapitaal**: zelfs wanneer groepen over vergelijkbare hulpbronnen beschikken, levert dat niet voor iedereen dezelfde opbrengst op in termen van stabiel werk en het vermijden van uitkeringsontvangst. Economisch, cultureel, sociaal of persoonskapitaal kan in de praktijk minder effectief worden omgezet in arbeidsmarktkansen door processen als discriminatie, arbeidsmarktsegmentatie, ongelijke erkenning van diploma's of vaardigheden, stereotypering, of institutionele drempels in de werving en selectie van personeel. Dit mechanisme maakt duidelijk dat ongelijkheid niet alleen draait om toegang tot hulpbronnen, maar ook om de maatschappelijke *converteerbaarheid* ervan: dezelfde opleiding, hetzelfde netwerk of dezelfde gezondheid kan voor de ene groep wél en voor de andere groep minder leiden tot duurzame arbeidsmarktbinding. Tegelijkertijd kan rendement ook juist hoger zijn voor sommige kwetsbare groepen wanneer hulpbronnen als buffer fungeren: beperkte maar cruciale hulpbronnen kunnen daar een relatief grotere werking hebben omdat ze structurele barrières worden compenseren. Vanuit een intersectioneel perspectief is de vraag dus niet alleen óf kapitaal beschermt, *maar voor wie, onder welke omstandigheden en met welk effect.*

3. **Verschillen in de persistentie van uitkeringsgebruik**: uitkeringsontvangst kan zichzelf versterken doordat eerdere uitkeringsperiodes de kans op latere uitkeringsontvangst vergroten. Dit kan op meerdere manieren gebeuren: een uitkeringsverleden kan een negatief signaal afgeven aan werkgevers, beroepsvaardigheden kunnen gedateerd raken, netwerken kunnen krimpen en langdurige onzekerheid kan iemands mentale gezondheid en zoekintensiteit onder druk zetten. Daardoor wordt uitstroom lastiger en stapelen risico's zich op, wat leidt tot hardnekkige trajecten van terugkerend of langdurig uitkeringsgebruik. Cruciaal is dat dergelijke *feedback loops* niet voor iedereen even sterk hoeven te zijn. Voor sommige groepen zijn persistentie-effecten mogelijk structureler en hardnekkiger, juist omdat zij bij uitstroom opnieuw dezelfde barrières tegenkomen (bijvoorbeeld in de vorm van discriminatie, beperkte baanmobiliteit, of een gebrek aan stabiele werkmogelijkheden). Dit mechanisme is beleidsmatig relevant omdat het ongelijkheid kan bestendigen en verdiepen, ook wanneer initiële verschillen bij de eerste instroom relatief klein lijken: een kleine

achterstand kan via herhaalde of langdurige uitkeringsafhankelijkheid uitgroeien tot een structurele kloof.

Methodologische aanpak

De analyses volgen een kwantitatieve intersectionele benadering via MAIHDA-modellen (*Multilevel Analysis of Individual Heterogeneity and Discriminatory Accuracy*), die intersectionele groepen als hogere-niveaueenheden in een multilevelmodel behandelen (Evans et al., 2018; o.a. Merlo, 2018). In plaats van een omvangrijke lijst met interactietermen te schatten, wordt de complexiteit aangevat door individuen te "nesten" binnen intersectionele combinaties. Dit maakt het mogelijk om met veel categorieën tegelijk te werken - bijvoorbeeld combinaties van opleiding × leeftijd × gender × migratieachtergrond - zonder dat het model onhanteerbaar wordt.

Methodologisch is MAIHDA in dit proefschrift vooral relevant om twee redenen. Ten eerste helpt het om intersectionele verschillen systematisch in kaart te brengen, inclusief onzekerheid in de schattingen voor kleine groepen. Ten tweede maakt de methode onderscheid mogelijk tussen (a) verschillen die grotendeels additief zijn - dus verklaarbaar uit de som van afzonderlijke categorie-effecten-en (b) verschillen die niet-additief zijn, waarbij specifieke combinaties onverwacht hoge of lage risico's tonen. Dit onderscheid is inhoudelijk belangrijk: het zegt iets over de mate waarin ongelijkheid voortkomt uit brede structurele lijnen (zoals algemene opleidings- of migratie-effecten) versus specifieke kwetsbare kruispunten.

Het proefschrift maakt primair gebruik van longitudinale registerdata (Nederland: SSD; Noorwegen: FD-trygd); in sommige hoofdstukken aangevuld met surveydata (LISS) die aanvullende informatie bevatten over de vier kapitaalvormen. Door registerdata te combineren met survey-informatie ontstaat een sterke basis: registerdata leveren betrouwbare uitkomstmetingen over uitkeringsontvangst, terwijl surveys juist inzicht geven in hulpbronnen die registers vaak niet bevatten (bijvoorbeeld sociale netwerken of mentale gezondheid). Een belangrijk onderdeel van de aanpak is bovendien het expliciet meenemen van onzekerheid in schattingen, in het bijzonder voor intersectionele groepen die kleiner zijn en daardoor gevoeliger voor toevalsvariatie.

Samenvatting van de resultaten per hoofdstuk

Hoofdstuk 2: Intersectionaliteit en uitkeringsontvangst

In Hoofdstuk 2 onderzoek ik verschillen in bijstands- en werkloosheidsuitkeringen op de kruising van opleiding, gender, leeftijd en migratieachtergrond. De belangrijkste uitkomst is dat intersectionele ongelijkheden duidelijker zichtbaar zijn voor bijstand dan voor werkloosheidsuitkeringen. Voor bijstand blijken de verschillen echter wel grotendeels additief: migratieachtergrond, leeftijd en opleiding verklaren het grootste deel van de variatie, terwijl gender nauwelijks een rol speelt. Dit wijst erop dat de belangrijkste lijnen van ongelijkheid in bijstand relatief "breed" zijn: bepaalde groepen staan structureel dichter bij het bijstandsrisico, vooral door ongelijke arbeidsmarktposities en economische kwetsbaarheid.

Bij werkloosheidsuitkeringen is het patroon complexer. De intersectionele ongelijkheden zijn kleiner, maar combinaties van kenmerken hangen sterker samen met uitkeringsontvangst dan op basis van additiviteit alleen verwacht zou worden. Dit is inhoudelijk plausibel: werkloosheidsuitkeringen zijn gekoppeld aan arbeidsverleden en de instroom is nauwer verweven met specifieke voorliggende arbeidstrajecten. Daardoor kan dezelfde sociale categorie (bijvoorbeeld jong versus oud, of laag- versus hoogopgeleid) onder verschillende combinaties van kenmerken een andere betekenis krijgen. Het hoofdstuk laat daarmee zien dat niet bij alle uitkeringstypen sprake is van dezelfde ongelijkheidslogica en dat beleidsdiscussies over uitkeringsafhankelijkheid gebaat zijn bij onderscheid naar regeling.

Hoofdstuk 3: Kapitaaltekorten als verklaringsmechanisme

Hoofdstuk 3 richt zich op de vraag in hoeverre verschillen in economisch, sociaal, cultureel en persoonskapitaal intersectionele ongelijkheden in uitkeringsontvangst kunnen verklaren. Uit de analyses blijkt dat met name economische hulpbronnen en mentale gezondheid belangrijk zijn en culturele hulpbronnen in mindere mate. Dit betekent dat ongelijkheid in uitkeringsontvangst niet alleen samenhangt met arbeidsmarktposities in enge zin, maar ook met het bredere hulpbronnenpakket dat mensen kunnen inzetten om tegenslagen op te vangen en kansen te creëren.

Tegelijkertijd duiden de bevindingen erop dat niet alle kapitaalvormen even sterk of even onafhankelijk bijdragen. Sociale hulpbronnen en fysieke gezondheid spelen in deze analyses minder uitgesproken rollen dan verwacht, wat suggereert dat hun invloed mogelijk meer indirect is, of dat de beschikbare indicatoren bepaalde dimensies onvoldoende vangen. Een tweede kernresultaat is dat niet-additieve indirecte effecten zich vooral concentreren in een beperkt aantal intersectionele groepen: sommige groepen hebben disproportioneel grote hulpbronnentekorten, die hun uitkeringskans verhogen. Hiermee laat het hoofdstuk zien dat intersectionele ongelijkheid soms ontstaat doordat tekorten zich op specifieke kruispunten stapelen.

Hoofdstuk 4: Heterogene rendementen op kapitaal

In Hoofdstuk 4 onderzoek ik of dezelfde kapitaalvormen voor verschillende groepen een verschillend ‘rendement’ hebben in termen van minder uitkeringsontvangst. Economisch kapitaal en persoonskapitaal hangen samen met een lagere kans op uitkeringen, wat consistent is met het idee dat financiële buffers, arbeidsmarktkansen en gezondheid centrale beschermende factoren zijn. Opvallend is echter dat het effect van economisch kapitaal sterker lijkt voor sommige minder bevoorrechte groepen, terwijl meer bevoorrechte groepen relatief lage “returns on capital” hebben.

Deze bevinding ondersteunt het idee dat hulpbronnen voor sommige groepen meer als buffer fungeren: juist wanneer structurele barrières groter zijn, kan economisch kapitaal (bijvoorbeeld in termen van inkomen, stabiliteit of arbeidsmarktpositie) een doorslaggevende rol spelen in het vermijden van uitkeringsinstroom. Voor bevoorrechte groepen lijkt uitkeringsontvangst minder gevoelig voor verschillen in economisch kapitaal, mogelijk omdat zij al in meerdere opzichten beschermd zijn (bijvoorbeeld via sterkere arbeidsmarktbinding, betere sectorposities of meer institutionele navigatievaardigheden). Dit resultaat nuanceert de enigszins simplistische veronderstelling dat privilegiëring impliceert dat bevoorrechte groepen altijd meer profijt uit hun hulpbronnen halen dan anderen. Daartegenover staat dat het hoofdstuk laat zien dat ongelijkheid ook kan betekenen dat kwetsbare groepen juist méér afhankelijk zijn van hun (schaarse) hulpbronnen om uitkeringsrisico te vermijden.

Hoofdstuk 5: Persistentie van bijstand in Noorwegen

Hoofdstuk 5 bestudeert persistentie in bijstandsontvangst en de variatie daarin naar gender, migratieachtergrond en migratiegeneratie in de Noorse context. De belangrijkste bevinding is dat verschillen in zowel instroom als doorstroom vooral samenhangen met migratieachtergrond en herkomstregio, terwijl gender een kleinere rol speelt. Daarnaast blijkt dat persistentie niet uniform is: voor sommige groepen werkt eerdere bijstandsontvangst sterker door in latere bijstandontvangst, terwijl andere groepen sneller uitstromen en minder "vast" lijken te komen zitten.

Voor enkele groepen wijken persistentie-effecten duidelijk af van additieve verwachtingen: sommige groepen laten lager dan verwachte persistentie zien, terwijl andere juist meer persistent dan verwacht gebruik maken van bijstand. Dit wijst erop dat *feedback loops* niet voor iedereen even sterk werken en dat het proces van uitstroom samenhangt met uiteenlopende barrières (zoals arbeidsmarktdiscriminatie, gezondheid of institutionele drempels) en met verschillen in kansen om een uitkeringsperiode te overbruggen richting werk. De bevindingen uit dit hoofdstuk onderstrepen zodoende dat ongelijkheid in uitkeringsontvangst niet alleen gaat over wie instroomt, maar ook over wie in de bijstand blijft.

Overkoepelende conclusies

Een eerste overkoepelende conclusie is dat uitkeringsontvangst zowel additieve als niet-additieve patronen kent, afhankelijk van het type uitkering. Uit de analyse van bijstandsregelingen komen vooral additieve ongelijkheidspatronen naar voren: brede structurele verschillen naar migratieachtergrond, leeftijd en opleiding. Werkloosheidsuitkeringen vertonen vaker niet-additieve patronen, waarbij de combinatie van kenmerken ertoe doet (bijvoorbeeld wetenschappelijk opgeleide oudere vrouwen van Oost-Europese herkomst, die disproportioneel vaak WW ontvangen). Dit onderscheid is belangrijk omdat het laat zien dat intersectionele ongelijkheid geen vaste vorm heeft, maar afhankelijk is van institutionele context en de inrichting van de regeling.

Een tweede algemene conclusie is dat de drie mechanismen elk een deel van de ongelijkheid verklaren, maar op verschillende manieren en met verschillende reikwijdte voor specifieke intersectionele groepen. Kapitaaltekorten – met name in economische hulpbronnen en mentale gezondheid – verklaren een behoorlijk deel van de verschillen, maar niet volledig. Rendementen op economisch kapitaal blijken tussen groepen te verschillen en wijzen op buffering bij bepaalde kwetsbare intersecties. De analyse van persistentie laat tenslotte zien hoe uitkeringsontvangst zichzelf kan versterken, met duidelijke heterogeniteit tussen groepen. Daarmee verschuift de focus van alleen "wie ontvangt" naar "waardoor ontstaat het" en "hoe wordt het in stand gehouden". De resultaten van dit proefschrift lijken te duiden op discriminatieprocessen die uitkeringsontvangers die behoren tot specifieke intersectionele groepen belemmeren bij het opnieuw vinden en/of behouden van werk.

Beperkingen en toekomstig onderzoek

Dit onderzoek moet echter wel in de context worden gezien van de volgende vier beperkingen. Ten eerste was de operationalisatie van sommige kapitaalvormen in de register- en surveydata beperkt: niet alle relevante elementen (zoals specifieke aspecten van werkervaring, relatiekwaliteit, digitale vaardigheden of uiterlijk) waren voorhanden. Hierdoor kan het gewicht van bepaalde onderliggende mechanismen zijn onderschat. Ten tweede bieden analyses waarbij de oorzaken voorafgaan aan de mogelijke gevolgen wel zicht op temporaliteit, maar geen harde causaliteit; toekomstig onderzoek kan sterker inzetten op meer causale designs (bijvoorbeeld *fixed effects*-modellen) om beter te onderscheiden wat oorzaak en wat gevolg is. Ten derde sluiten administratieve categorieën (bijvoorbeeld genderregistratie en herkomstindelingen) niet altijd aan bij zelfidentificatie, wat met name in intersectioneel onderzoek relevant is, aangezien juist de precieze afbakening van categorieën de interpretatie van kruispunten beïnvloedt. Ten vierde is geen expliciete modellering van uitkeringsgerechtigdheid meegenomen, waardoor waargenomen uitkeringsontvangst niet één-op-één kan worden geïnterpreteerd als "behoefte" of "recht"; niet-gebruik en institutionele fricties blijven daarmee deels buiten beeld. Toekomstig onderzoek kan deze beperkingen aanpakken door rijkere metingen van kapitaal (met name sociaal en cultureel), door causale strategieën te combineren met intersectionele modellering en door meer aandacht te besteden aan de vraag waar in het proces ongelijkheid precies ontstaat: bij het instroomrisico, bij toekenning en toegang, of bij uitstroommogelijkheden.

Beleidsimplicaties

De bevindingen suggereren dat beleid baat kan hebben bij een meer gedifferentieerde benadering van groepen met specifieke intersecties van kenmerken. Veel ongelijkheden zijn additief, en daarbij kan generiek beleid vaak effectief zijn (bijvoorbeeld verbetering van arbeidsmarktkansen voor lageropgeleiden of het verlagen van financiële kwetsbaarheid). Tegelijkertijd laat dit proefschrift zien dat een aantal intersecties specifieke risico's kennen die niet volledig gedekt worden in beleid dat slechts één doelgroep of één kenmerk centraal stelt. Voor deze groepen is een fijnmaziger benadering relevant, die soelaas biedt aan de specifieke problematiek waar die intersectie mee kampt. Dit onderzoek identificeert deze groepen en geeft indicaties voor mogelijke achterliggende factoren.

Effectief beleid richt zich daarbij niet alleen op het aanvullen van tekorten in kapitalen, maar ook op het reduceren van processen die het rendement van kapitalen drukken en op begeleiden in de overgang van uitkering naar (duurzaam) werk voor groepen die persistent in een uitkeringssituatie verkeren. Concreet betekent dit: investeren in economische zekerheid en mentale gezondheid, drempels in institutionele toegang tot uitkeringen verlagen en tegelijk structurele barrières op de arbeidsmarkt (zoals discriminatie en segmentatie) expliciet adresseren. Voor groepen met hoge persistentie is bovendien beleid nodig dat uitstroom duurzaam ondersteunt: niet door uitsluitend het activeren van mensen te benadrukken, maar ook door ze te begeleiden naar het vinden van duurzaam werk.

In bredere zin laten de resultaten zien dat een intersectionele benadering van belang is voor beleid, omdat zij blootlegt waar “gemiddelde” patronen tekortschieten. Wanneer sociale kenmerken uitsluitend afzonderlijk of additief worden beschouwd, blijven sommige groepen buiten beeld. Een intersectionele beleidsbenadering doet recht aan deze diversiteit en houdt rekening met de specifieke problemen waarmee bepaalde intersectionele groepen worden geconfronteerd. Dit kan bijdragen aan een verzorgingsstaat die zowel beschermend als effectief activerend is, zonder kwetsbare groepen onevenredig te belasten of te stigmatiseren.

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Jos Slabbekoorn was born in Apeldoorn, the Netherlands, on December 19th, 1995. He obtained his bachelor's degree in Sociology in 2017. In 2020 he graduated cum laude from the research master Sociology and Social Research at the same university. Since September 2020, he has been working as a PhD-candidate at the Department of Sociology at Utrecht University and the Interuniversity Center of Social Science Theory and Methodology (ICS). He wrote his dissertation under the supervision of Prof. Dr. Cok Vrooman (UU | SCP) and Prof. Dr. Ineke Maas (UU | VU). Since February 2023, he has been a member of the editorial board of the academic journal *Mens & Maatschappij*. In the winter of 2023 he visited the Sociology Department at the University of Oslo, were he was hosted by Prof. Dr. Gunn Birkelund and Dr. Edvard Larsen. Since 2025, he has worked as a Postdoctoral Researcher at Radboud University, Nijmegen and the Interuniversity Center of Social Science Theory and Methodology (ICS), on two projects: (a) about paternity leave usage among men and (b) structural inequalities in scientific collaboration networks.

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In contemporary welfare states, social insurance and means-tested benefits play a vital role in providing income security against unemployment, illness, and other risks, yet considerable inequalities in benefit receipt persist. While research has long documented how gender, age, and migration background each influence welfare dependency, the ways in which these characteristics combine to create multiplicative disadvantages remain poorly understood. Therefore, this dissertation employs a quantitative intersectional framework—using administrative and longitudinal survey data from the Netherlands and Norway—to map which intersections of gender, migration background, and age exhibit disproportionately high or low rates of social assistance and unemployment insurance receipt. It further investigates three capital-based mechanisms—resource deficits, unequal returns on resources, and "Matthew effects" in benefit persistency—to uncover the structural processes driving these intersectional disparities.

Jos Slabbekoorn *(1995) obtained a bachelor's degree in Sociology (2017) and a research master's degree in Sociology and Social Research (cum laude, 2020) at Utrecht University. He conducted the present study as part of his PhD at the Department of Sociology at Utrecht University and the Interuniversity Centre for Social Science Theory and Methodology (ICS). Since February 2023, he has served on the editorial board of Mens & Maatschappij. Currently, he has been a Postdoctoral Researcher at Radboud University Nijmegen and ICS.*