Essays on poverty and labor market integration for refugees

Lukas Hobi

Inauguraldissertation zur Erlangung der Würde eines

Doctor rerum oeconomicarum

der Wirtschafts- und Sozialwissenschaftlichen Fakultät

der Universität Bern

Bern, 4. Juni 2023

Original document saved on the web server of the University Library of Bern

This work is licensed under a Creative Commons Attribution 4.0 International license. To see the license go to https://creativecommons.org/licenses/by/4.0/ or write to Creative Commons, 171 Second Street, Suite 300, San Francisco, California 94105, USA.

Copyright Notice

This work is licensed under a Creative Commons Attribution 4.0 International license.
https://creativecommons.org/licenses/by/4.0/

You are free to:

Share — copy and redistribute the material in any medium or format for any purpose, even commercially.

Adapt — remix, transform, and build upon the material for any purpose, even commercially.

The licensor cannot revoke these freedoms as long as you follow the license terms.

Under the following terms:

Attribution — You must give appropriate credit , provide a link to the license, and indicate if changes were made . You may do so in any reasonable manner, but not in any way that suggests the licensor endorses you or your use.

No additional restrictions — You may not apply legal terms or technological measures that legally restrict others from doing anything the license permits.

Notices:

You do not have to comply with the license for elements of the material in the public domain or where your use is permitted by an applicable exception or limitation.

No warranties are given. The license may not give you all of the permissions necessary for your intended use. For example, other rights such as publicity, privacy, or moral rights may limit how you use the material.

The detailed license agreement can be found at:
https://creativecommons.org/licenses/by/4.0/legalcode.en

The faculty accepted this work as dissertation on September 21st, 2023 at the request of the advisors Prof. Dr. Michael Gerfin and Prof. Dr. Zachary J. Parolin, without wishing to comment on the views expressed therein.

Preface

I would like to thank my supervisor Michael Gerfin for his support, pragmatism and encouragement during my thesis. And for showing me that event-study plots and Diff-in-Diff make for a great combination. I would also like to thank Zach Parolin for the co-supervision of this PhD thesis.

This thesis also benefited from helpful comments received at the Social Outcomes Conference in Oxford, the RC28 Conference in London and the doctoral colloquium at the Bern University of Applied Sciences.

I would also like to thank Lisa Schlittler, Debra Hevenstone, Oliver Hümbelin, Dorian Kessler, Ben Jann, Wojtek Przepiorka, Alec Fraser, Rudi Farys, Robert Fluder for support, tipps, feedback. And for reminding me of the importance of bringing the thesis to a close.

Contents

List of tables and figures

Introduction

The first part of this thesis is dedicated to the study of poverty. In many countries, it is difficult to study subnational poverty patterns, as official statistics often rely on surveys with limited ability to disaggregate regionally. This is a drawback because the social and economic structure varies within countries, which has a significant impact on poverty. To address poverty, it is therefore important to further understand urban / rural differences. In this context, administrative data-based approaches offer new opportunities. Chapter 1 contributes to the field of territorial poverty studies by using linked tax data to examine poverty in a large political district in Switzerland with 1 million inhabitants and rural and urban parts. We measure poverty using income and financial reserves (asset-based poverty) and examine poverty in urban and rural areas. By doing so we can compare the social structure of the poor in detail. We then use random forest based variable importance analysis to see whether the importance of poverty risks factors differs in urban and rural parts. We can show that poor people in rural areas are more likely to be of retirement age compared to the urban parts. Among the workforce, the share of poor is larger for those who work in agriculture compared to those working in industry or the service sector. In urban areas, the poor are more often freelancers and people of foreign origin. Despite on where they live, people with no or little education, single parents, and people working in gastronomy / tourism are disproportionately often poor. With respect to risk factors, we find that the general opportunity structure like density of workplaces or aggravated access in mountain areas seem to be of minor importance compared to risk factors that relate to the immediate social situation. Low attachment to the labor market is by far the most important characteristic predicting poverty on the household level. However, the sector of occupation is of big importance too. Since the possibilities to engage in a specific occupation are linked to the regional opportunity structure, this result fosters the argument that territorial opportunities matter.

It is also important to understand poverty as a dynamic phenomenon and observe it over multiple periods, since short, long, or recurring poverty episodes have diverse implications for the persons experiencing them and the policies to address them. Chapter 2 contributes to the longitudinal poverty literature by analyzing the same dataset for the years 2012 – 2015. We again measure both income poverty and asset-based poverty. Exploring the data for the 2012 income poor cohort graphically, we find that asset-based poverty is the more dynamic state, with many exits to non-poverty over the observed four years, whereas exits from income poverty to non-poverty are rarer. Poor persons of working age and children generally lack financial reserves but escape poverty more frequently. While poor pensioners usually have financial assets but are less likely to escape poverty. We use dynamic linear panel data models to measure how the social benefit system, labor market participation, and asset consumption influence poverty status and to estimate poverty persistence. An increase of the wage of a household's main or secondary earner reduces the probability of being poor the most, while pensions and incomes from real estate are also important to reduce poverty for pensioners. We find that poverty in Switzerland is a persistent phenomenon, with the probability of being income poor in the current year increasing by 21.7 percentage points for the working age population and children (29.1 percentage points for pensioners) and the probability of being asset-based poor in the current year increasing by 19 percentage points for the working age population and children (30.5 percentage points for pensioners) if an individual has been income or asset-based poor in the previous year.

The last part of this thesis is dedicated to labor market integration for refugees in Switzerland, which is closely tied to poverty. Chapters 1 and 2 show that a strong labor market attachment is important to protect against poverty regardless of area or even life cycle. This is even more so for refugees. Refugees usually cannot fall back on an array of social insurances, like natives can. Given that they have fled their origin country and sought refuge in a host country, refugees are also unlikely to possess financial reserves. Yet, compared to native job seekers, refugees face several additional barriers, e.g., lacking knowledge of the local language, trauma or discrimination to name a few. Given these difficulties it is interesting to know which strategies work best to ensure a rapid and durable labor market integration of refugees.

In Chapter 3 we look at two Swiss active labor market programs (ALMPs) targeted at refugees. Both programs are offered by the same ALMP provider. While the first program targets all client skill levels, the second program targets only “mid- to high-skilled” clients. This introduces a skill-split between the two programs, whereas in the period preceding the second program’s introduction (i.e., the pre-period) all client skill levels were served in the first program. The first program is characterized by a lower caseload per job coach relative to the pre-period, while the second program is characterized by richer funding and more flexibility regarding the use of program funds relative to the pre-period. To assess the impact of the two different program strategies we link program data to administrative data on employment and earnings. We use balancing to replicate “high-skilled” and “low-skilled” client groups in the pre-period. We then use event-study analysis and difference-in-differences estimation to study how clients in the two programs performed in terms of employment rate and income relative to their skill-level counterparts in the pre-period. In our event-study analysis, we find that the additional resources helped improve labor market outcomes on both ALMPs. However, we find larger effects for the lowered mean caseload for the job coaches working with the ”lower-skilled” refugees than for the richer funding and more flexible use of funds on the program working with the ”higher-skilled” refugees. Effects take hold sooner following program entry for the ”lower-skilled” group. We find a statistically significant difference-in-differences estimate only for the employment rate for the “lower-skilled” group which increased by 9.4 percentage points in the short-run.

Chapter 1

Rich cities, poor countryside?

Social structure of the poor and poverty risks in urban and rural places in an affluent country

Oliver Hümbelin, Lukas Hobi, and Robert Fluder

1.1 Introduction

Ending poverty is a priority for the global community and the top objective in the Sustainable Development Goals (SDGs). Good data is key on this journey to combat poverty. As pointed out by A. B. Atkinson (2019: 105): "we will not be able to reach our goal unless we have data to show whether or not people are actually lifting themselves out of poverty. Collecting good data is one of the most powerful tools to end poverty." This statement could be seen as less important for European countries, which all have national statistics that allow to observe and study the development of poverty. Indeed, the data infrastructure in Europe is quite good compared to many other parts of the world, but most countries lack the options to disaggregate their statistics on relevant subnational levels. Therefore, estimating regional poverty rates, given the current data resources, is a difficult task (Copus et al. 2015). At the same time, there is a substantial amount of literature highlighting the importance of regional aspects of poverty or place-based-approaches to poverty that are likely important in a diverse region such as

Europe (Madanipour and Weck 2015; Bentley and Pugalis 2014; Madanipour, Shucksmith, and Talbot 2015; Copus et al. 2015). To develop the adequate poverty policies necessary to achieve the poverty goals of the agenda by 2030 and beyond, it is crucial to understand how regional economic structure, and places in general, contribute to people living below the poverty line (Zhou und Liu 2022).

Our study contributes to this discussion in two ways. First, from the perspective of using data to improve the knowledge of poverty in wealthy countries, this study demonstrates how linked administrative data can be used to investigate poverty. While the use of administrative data to develop policies is not new (Hotz et al. 1998), novel ways to apply them have emerged. Of special importance for distributional studies are tax data (Hümbelin and Farys 2016). This kind of data is indispensable for inequality studies, particularly in regards to top-incomes (Piketty 2014; Alvaredo et al. 2013), but it also has hurdles, and simultaneously huge potential, when studying the lower part of the distribution. We linked tax data to other administrative data and survey data to overcome these hurdles and to build a rich dataset that allows to study poverty. Throughout this paper, we refer to poverty as having insufficient financial resources to meet the national line of minimal livelihood. We acknowledge that poverty, especially in affluent countries, must be broadly understood through concepts such as social exclusion (Madanipour, Shucksmith, and Talbot 2015), multidimensional poverty (Alkire and Apablaza 2016) and nonmonetary indicators (A. B. Atkinson 2019). However, it is still common to operationalize poverty by measuring financial resources (UN 2017). This has the advantage of measuring poverty in a conceptional, clear manner, and many studies show that the lack of financial resources is at the core of poverty. As Switzerland is one of the few countries that levy taxes on wealth, our data includes detailed information on this factor. Thus, we can measure poverty by assessing the financial situation of a household by its income and its wealth (Brandolini, Magri, and Smeeding 2010). Furthermore, because households are geocoded to identify residential municipalities and the data cover the population region-wide, this has great potential for the study of regional differences.

Second, the current study respectively investigates poverty on subnational levels for small areas by performing a case study for the canton of Bern in Switzerland. It is a region with 1 million inhabitants, 352 municipalities and with large urban and rural areas. This can delineate poverty patterns within and between urban and rural areas in a comparatively prosperous region of the world. These results are relevant to other parts of Europe because the structural change of the economy that leads to different outcomes for cities and the countryside can be found there likewise. Economic life in cities increasingly happens in the service and knowledge-oriented tertiary sector, while the importance of primary and partly secondary sector economic activities, like agricultural and industrial work, declined but is still present in the countryside. Recently, with the strong impact of digitalization on the economy, ICT-driven economic advances seem to result in strong economic growth, especially in urban areas. Meanwhile rural areas are struggling to attract high-skill workers, and the rift between regions deepens (Eckert, Ganapati, and Walsh 2019). Since solid data for small area regional analysis is still scarce, it is not well studied to what extent these macro-level changes translate to poverty risks from a regional perspective. To gain more insight into the differences and similarities of poverty between urban and rural parts, we analyze the following research questions:

(1) Are people living in cities or the countryside more at risk of becoming poor?
(2) Are different social groups poor in cities versus the countryside?
(3) How important is the opportunity structure with respect to the risk of being poor?
(4) Have commonly known poverty risk factors been judged as equally important in urban and rural locations?

To answer these questions, we first demonstrate how our study complements the literature on regional poverty in affluent countries (section 2). We then describe the data and the indicators used to measure poverty and related risk factors and present our strategy for analysis (section 3). Section 4 presents the results on how the social structure of the poor differs in cities and the countryside. The analysis is extended with a random forest based variable importance risks assessment for individual and regional characteristics. This approach is also used to assess differences in poverty risk factors for cities versus the countryside.

1.2 Theory

Poverty in affluent countries and the role of a spatial approach to poverty

Between economic opportunities and welfare mitigation. To understand the reasons behind poverty, it is necessary to distinguish between micro- and macro-level factors as well as the interaction between the two levels (Sidney 2009). Some studies point out that individual and/or household level characteristics, including employment status, educational level, citizenship, health status, and the civil state, are strongly associated with the risk of becoming poor (R. Atkinson and Da Voudi 2000; A. B. Atkinson et al. 2004). Some argue that differences across race, citizenship, gender or age groups may relate to discrimination within a society (Tilly 1999; Hümbelin and Fritschi 2018). However, whether these characteristics lead to poverty is strongly shaped by the macro-level context such as economic change, shifts in the demands of the labour market, and alterations in social security provision by the state, especially the scope of and access to social benefits.

On the one hand, researchers investigate structural re-configurations across Europe since the 1970s (Andreotti, Mingione, and Polizzi 2012). Deindustrialization, the upheaval of the global economy, technological change and its impact on local labour markets have undoubtedly changed which occupations are profitable. In this vein, it seems that technological change dampened median wage income growth and increased polarization of the wage distribution and skill premiums in several high-income countries (Katz and Autor 1999; Katz and Margo 2014). As Eckert, Ganapati, and Walsh

(2019) argue, these developments led to a new urban bias in economic growth that bears the risk of exacerbating the divide between cities and the countryside.

On the other hand, researchers point out that the level of *decommodification, state redistribution or, more generally, the social protection scheme and its ameliorative interventions* shape how well and who is protected by social security (Esping-Andersen 1999; Vandecasteele 2015). While all Western welfare states currently provide social security, they struggle to adapt to new social risks (Bonoli 2007) such as precarious employment, long-term unemployment, and working poverty (Crettaz 2013). At the same time, Causa and Hermansen (2020) found that the redistributive effect declined on average from 1995 to 2014 and across most of the OECD-countries. As suggested by the growing literature on non-take-up of social benefits, this tightening of welfare tools also negatively impacted the poor's access to social benefits (Eurofound 2015; Hernanz et al. 2004; Lucas et al. 2021).

Relevance of places. While there is a lively discourse on the role of macro-level factors as described above, other research focuses on regional patterns of poverty. According to Zhou and Liu (2022) and the geography of poverty it is essential to understand the spatial pattern of poverty. It is acknowledged that this approach has the potential to deepen our understanding on how (and why) people in rich countries get poor (Bentley and Pugalis 2014; Madanipour and Weck 2015), and it offers a promising link between the micro- and the macro-level. It is, however, also commonly known that estimating regional poverty rates, given the available data, is a challenging task (see Copus et al. 2015). Thus, empirical studies following the local environmental approach are still scarce, and a holistic theory combing macro-, meso- and micro-level dynamics still needs to be developed. To that end, the following paragraphs synthesize the literature to highlight what is needed to further that goal.

A recent report from the World Bank noted that people in the bottom 40 percent of the income distribution disproportionally often live in rural areas (World Bank 2020). Worldwide rurality seems to be an area with a heightened poverty risk. But is this true for a generally prosperous region like Europe? Michálek und Výbošťok (2019) recently studied the development across all 28 EU member states and found that in general economic growth helped to decrease poverty but in most EU countries, only a minority benefited from economic growth resulting in increased inequality and often an increase of poverty. According to the authors it is therefore crucial to understand the unequal distribution of wealth within countries to allow tackling poverty. In this regard understanding regional differences might deliver key elements for policy makers. Indeed urbanity, or rurality, are often associated with poverty in different ways. According to the European Commission (2010), poverty is more common in densely populated areas than in less populated counterparts in the EU-15 countries. This "urban exclusion" is mainly an effect of the segregation of the poor who tend to live gathered in affordable neighborhoods (Madanipour 2015; Foulkes and Schafft 2010). However, there is also poverty in rural places (Bertolini, Montanari, and Peragine 2008). This is mostly attributed to sectoral change stemming from technological progress and a decline of employment opportunities in specific areas. This might be a decline of the industrial sector (Bennett, Beynon, and Hudson 2000) or the agricultural sector (Shucksmith and Schafft 2012). While some leave the area, others remain trapped by their lack of opportunity and mobility. All in all, it seems that change in economic structure does not translate in a simple way to changes in poverty risks in cities and the countryside. The reasons behind this paradigm must be clarified to determine whether poverty risks differ in cities and the countryside.

Blank (2005) offers a promising way to further develop the relationship between macro- and micro-levels by introducing clear statements on how regional features might influence poverty risks:

1. One key role is played by the *natural environment*. It defines accessibility or ease of travel from a specific location. Moreover, climate and natural resources define possible economic activities. After all, cities were established with a favorable initial situation with respect to their natural environment.

Accordingly, Liu et. al (2021) found that accessibility of a region plays a major role in identifying poor regions in China.
2. The *economic structure* refers to the labour demand generated by the local economy. Is it an industrial or agricultural area? Or is labour demand about specialized tech or services? This influences job opportunities, income growth, or the risk of having unsteady revenues.
3. *Public institutions* are those organizations operating within an area to ensure its functioning. They include general infrastructure, such as the police or the educational system, as well as institutions providing public assistance programs. These institutions represent the welfare regime and are – together with the economic structure – part of the opportunity structure of inhabitants of a specific region. More recently, Baker (2020) showed that politics and more specifically power resources are a major source of regional inequalities and argued that this is the main reason why the south of the US is poorer than other regions.
4. *Social norms or expectations* are shaped by local institutions and commonly shared behavior and experiences. They set an informal bound of rules and are often a component of the discussion of welfare stigma usage (Moffitt 1983). More isolated and rural communities may have stronger social norms. These norms and general trust in the form of social capital can be a resource or an obstacle to overcome poverty as Harrison, Montgomery, and Jeanty (2019) argue finding that social capital and poverty are strongly correlated in US counties.
5. The last factor refers to *demographic characteristics*. Locations with only low skilled workers often have high shares of poor people. While demographic characteristics are easily measured, they provide limited causal information. However, because they are correlated with specific behavioral issues, they provide useful signals about what types of policies are needed and useful.

So far, it has been demonstrated that labor market characteristics are essential, that these characteristics are shaped by the regional economic structure, and that this structure is influenced by the natural environment in turn. Moreover, social security instruments are relevant, and accessibility can differ across regions due to differences in public institutions and social norms. While these concepts help highlight areas that need further attention, it is not conclusively clarified which characteristics of local labor markets and occupation structure are associated with high poverty risks or which groups protected by social security are threatened to fall through the safety net. Copus et al. (2015) offered further insights into what type of regional economic structure is associated with increased poverty risk by estimating regional at-risk-of-poverty rates for 20 European countries. They also performed a correlation analysis to identify potential socio-economic drivers of poverty, where they synthesize several theoretical strands of regional poverty drivers. Their results showed a strong correlation between at-risk-of-poverty rates and the unemployment rate as well as employment shares in elementary occupations like cleaners or agricultural tasks. They also found evidence to suggest that welfare regimes moderate these risks. However, correlated macro-indexes can be difficult to interpret since they bear the risk of ecological fallacy. Further studies combing rich individual and contextual features may be a promising way to further our understanding.

Despite these studies, it remains unclear how important, if at all, the spatial poverty approach is, and, which aspect is most relevant. This question must be addressed by further research. Therefore, we combine an inductive and deductive research approach to find regional patterns in the data based on characteristics already identified in the general poverty literature. To gain an initial understanding, we study demographic profiles of the poor in cities and the countryside. Next, we assess poverty risk factors on the individual and at the level of the opportunity structure to unravel which features of the opportunity structure are important compared to the individual level. Finally, we study if commonly known risk factors are associated with similar poverty risk importance across regions.

Poverty and the welfare state in Switzerland. To understand the following results, it is important to know where Switzerland is placed regarding its poverty prevalence and protection. Although Switzerland is one of the richest countries worldwide, a considerable part of the population lives with an income below the national poverty line. Official statistics collected by the SDG country report show (Swiss Confederation 2018) that poverty rates in Switzerland rose slightly recently. In 2016, 7.5 percent of Switzerland's permanent resident population – around 615,000 people – were affected by income poverty. According to official numbers, poverty rates are particularly high for retirees as well as non-European immigrants, people with low education levels, single parents, and for people living in a household with poor or no access to the labor market (FSO 2020).

Concerning the welfare regime in the terminology of Esping-Andersen (1990), Switzerland is classified today as a rather classic Western European welfare state with mixed elements (Armingeon 2001). Yet, Ebbinghaus (2012) points out that a nationwide classification falls short, because Switzerland is organized in a federal way with great autonomy at the level of cantons, which are the main substate divisions in Switzerland. Armingeon, Bertozzi, and Bonoli (2004) classify all Swiss cantons according to the principles of Esping-Andersen, showing heterogeneity regarding taxation and the instruments addressing poverty.[1] While social insurances addressing unemployment, old age, disability, or maternity are regulated nationwide, the instruments addressing poverty differ. While social assistance, the last safety net, is guided by national recommendations, cantons can adjust as they see fit. For further means-tested benefits, like health-premium subsidies and family supplementary benefits, the scope of action of the cantons is large. Finally, access to social benefits is organized on communal levels, which can provide more or less support and information (Hümbelin 2019). Since poverty policies are strongly driven by cantons, it is a known deficit that cantonal or even communal poverty rates are unavailable.

[1] The canton we use for our empirical analysis is the canton of Bern. It is described as a canton with liberal and conservative welfare elements. In contrast to other cantons, it has no special poverty instruments other than the ones defined by national law.

1.3 Data and methods

Measuring poverty using linked tax data

Many European poverty studies and official statistics on poverty use survey data, e.g., the European Union Statistics on Income and Living Conditions. However, survey data insufficiently represent the low income population (Korinek, Mistiaen, and Ravallion 2006; Häder, Häder, and Kühne 2012), which can only partly be corrected with statistical weights. In contrast, tax data provide a more reliable approach to study the financial situation. For our analyses, we use linked fiscal and administrative data called WiSiER data (Wanner 2019) for the year 2015 for the canton of Bern[2] - a large canton of Switzerland with a mix of urban and rural parts, representing the situation in Switzerland quite well. The restrictions of the dataset, and definitions of main variables, closely follow Fluder et al. (2020). The data with complete information represents 89 percent of the permanent population (N = 910'346 persons, 428,709 households).[3] We define households as people sharing the same residential unit, based on the register of buildings and apartments. As means-tested benefits are not taxable, tax data do not contain them. Therefore, we link information of social benefits to our data (i.e., social assistance, reduction of health insurance premiums, supplementary benefits to old-age, survivor's and the disability insurance). Our linked tax data allows us to reliably assess financial poverty. Moreover, the nearly complete representation of the population permits detailed analyses on the level of socioeconomic groups and small-scale spatial regions.

For our analyses, we measure poverty as a lack of financial resources. A first indicator measures income poverty - referring to the social subsistence level of Switzerland and the official absolute poverty line. Accordingly, a

[2]To date it is not possible to obtain tax data for all Swiss Cantons because of legal reasons.

[3]Individuals with incomplete information are excluded. This includes persons living in collective households such as nursing homes, persons with missing household data, or those who are not taxed under the regular procedures, such as pending tax cases or foreigners who are taxed in other ways.

household is poor when its expenses for the minimum needs (as set by national standards, see BKSE 2020; Schweizerische Konferenz für Sozialhilfe 2015) outweighs its total income, including social transfers from insurances and other benefits. However, this indicator incompletely describes the financial situation since households may have financial reserves to supplement their resources from income. Thus, we build a second indicator using an asset-based poverty measurement approach (Brandolini, Magri, and Smeeding 2010; UN 2017). According to this indicator, a household is poor if it does not have sufficient income to finance the daily needs and does not have enough reserves to cover the needs for 12 months. Since household members generally share resources, we assess poverty at the household level. However, the unit of analysis is the individual.

To assess poverty risk of individuals from different social groups and in different social situations, we need information beyond those on financial resources. We build these variables only partly from the register data, and we use further information from the structural survey, a large survey complementing register data in Switzerland. Since the structural survey is a sample survey, this information is available only for a subsample of the dataset. Therefore, for analyses using the structural survey (especially the variable importance analysis), the sample is reduced from 910,346 to 106,850[4] observations. The subsample differs from the overall population in its main characteristics to some extent. Thus, we balanced our subsample using e-balance[5] (Athey and Imbens 2017; Hainmueller 2012) to achieve a representation of the overall population with respect to the distribution of age groups, gender, nationality, marital status, household type and income classes. Furthermore, we linked information on level of individuals with municipality profiles from the FSO for the year 2015 (FSO 2015) to gain information for several measures of the opportunity structure as described in the next section.

[4]Using data pooled over the years 2010 - 2016 for the structural survey (Wanner 2019).

[5]All computations were done in R (R Core Team, 2021). Ebalance was calculated using the package *ebal* version 0.1-6 (Hainmueller 2012).

Poverty risk factors and the opportunity structure

We distinguish between three groups of characteristics with potential influence on individual poverty risk as shown in table 1.1. For the social structural analysis, we distinguish between features of social groups and social situation. Our third set of variables measures the opportunity structure. A detailed table including descriptive statistics can be found in the Appendix.

Table 1.1: Indicators used by group of variables.

Social Groups	**Social Situation**		**Opportunity structure (municipality level)**	
Indicator name	Indicator name	*Description*	Indicator name	*Description*
Age groups	Civil state		Density of workplaces	*Workplaces by population*
Citizenship	Education	*Highest completed education.*	Economic Sector of Workplaces	*Dominant activity in primary, secondary or tertiary sector*
Sex	Employment status hh	*Dependent or independently working, non-working or retired.*	Employees by economic sector	*Dominant activity in primary, secondary or tertiary sector*
	Health status	*Degree of disability according to social insurance agencies.*	Language	*Dominant language spoken*
	Household size		Mountain area	
	Household type		Percentage of unemployed	
	Number of employed hh members		Political leaning	*Share of votes for social party minus share of votes for popular party.*
	Sector of occupation		Population share of employed	
			Urbanity	*Cities, Agglomerations and Municipalities on the countryside*

To differentiate between social groups we use age groups, sex, and citizenship. These characteristics mostly remain stable throughout one's lifetime as age groups refers to cohorts with a common historical-biographical background and citizenship influenced by birthplace. Drawing on Tilly (1999), we argue that an effect related to these characteristics can indicate discrimination. To represent different social situations people live in, we use a set of variables often found in the literature to study poverty risks. These variables include education, household type, civil state, sector of occupation, health status / degree of disability, employment status, number of employed household members and household size. These factors describe the immediate social situation, e.g. access to the labor market or skills (education, sector of occupation), and they can be addressed by poverty interventions (Nielsen, Sørensen, und Taber 2008).

Following Blank (2005) and Copus et al. (2015), we identify different aspects of the opportunity structure. To capture accessibility of a region by its natural environment, we distinguish mountain and non-mountain areas. To address the economic structure, we use variables dividing regions based on predominantly agricultural, industrial, and service activities. We also delineate based on reported employees and on workplaces. Additionally, we measure the regional performance of the labor market based on the density of workplaces and the population share of employed and unemployed. Finally, we include indicators measuring public and community institutions and social norms. We use political leaning as a proxy for both dimensions. Since local welfare provision is organized by local communities and welfare ideologies strongly differ by right and left wing ideologies (Roosma, Oorschot, and Gelissen 2016), it is reasonable to build an indicator capturing the political leaning of a municipality based on parliamentary voting. Moreover, we built an indicator of the predominant language. Since language regions depict different cultures and traditions that represent one of the dimensions of the political cleavage system in Switzerland (Linder, Zürcher, and Bolliger 2008), we substitute part of the different institutional and normative settings with this variable.

As a general proxy for spatial differences, we use the urbanity variable based on official classification of municipalities. It classifies every municipality as either a city, being in the agglomeration, or the countryside. This last variable is also used in the empirical part to distinguish urban and rural parts.

Determining variable importance using random forest

Similarly to Liu et al. (2021) we use random forest to assess the importance of a variable empirically. Random forest is a machine-learning approach increasingly gaining attention in applied economics that combines large sets of classification and regression trees (Athey 2019; Nosratabadi et al. 2020). Random forest has the advantage of accounting for non-linear relationships and interactions in the data without the need to explicitly know and specify them (Molina and Garip 2019; Athey and Imbens 2017). Since we study individual, household and contextual characteristics which are expected to interact with each other, this is an important feature. Finally, random forest allows to relatively quantify the importance of a variable. Importance in this context refers to an increase in the probability of correctly identifying poor people that can be attributed to a specific variable.

Since continuous variables could gain more consideration in the variable importance analysis than categorical variables (Strobl and Zeileis 2008), we recoded all our regressors as categorical variables. We started with a basic model that fitted a logit regression with asset-based poverty and income poverty as binary outcomes and included all independent variables. By running a variance inflation factor analysis (O'brien 2007), we ensured that collinear factors were excluded (Tables 1.7 and 1.8 in the Appendix). We then fitted a random forest model with income poverty and asset-based poverty as binary outcomes and included all independent variables. Covariates were tested to find the best covariate to split the data into two portions, minimizing the number of wrongly classified observations, until only a small number of observations was left at the endpoints ("leaves"). To balance the high sensitivity of trees to small changes in the data, random forest combines a large number of trees to a "forest." To achieve a decorrelated set of trees, two random components are present in the algorithm: 1) each tree is fit to a randomly resampled part of the original data where each subsample is taken with replacement, and 2) for each split, only a random subset of the covariates is tested.[6]

[6] Random forest models were calculated using the package *ranger* version 0.12.1 (Wright

Although the model has difficulty correctly classifying the poor, it has good overall performance, with only 4.12 percent overall classification error rate for income poverty and 2.67 percent for asset-based poverty.

Table 1.2: Confusion matrices for random forest models.

Confusion matrix for rf model on asset-based poverty

	--TRUE--	--TRUE--	
Classified =	0	1	class. error-rate
0	101'134	277	0.27
1	2'515	509	83.17
overall			2.67

Confusion matrix for rf model on income poverty

	--TRUE--	--TRUE--	
Classified =	0	1	class. error-rate
0	99'450	439	0.44
1	3'865	670	85.23
overall			4.12

Since variable importance is a relative measure depending on how well an indicator can be predicted and asset-based poverty can be predicted better than income poverty, variable importance will be lower for asset-based poverty. To enable comparisons across the two indicators, we standardized variable importance by dividing the variable importance of each regressor by the total variable importance of all regressors in each model.

1.4 Results

Social structure of the poor in cities, agglomerations and in the countryside

First, we observe how the population of the poor differs by comparing them to the overall population (dashed line). We begin with the characteristics we use to distinguish social groups (Figure 1.3). To determine the spatial dimension, we divide the analysis by the population living in cities, the countryside and

and Ziegler 2017). In our analysis we used 500 trees (num.trees) for each random forest model. We used the (rounded down) square root of the number of covariates to try at each split (mtry) in our analysis.

agglomerations. The analysis is done using the income and the asset-based poverty measure. Data-visualizations demonstrate the general patterns. Related numbers and further analysis showing population shares and poverty rates by urbanity for all variables can be found in Hümbelin et al. (2021).

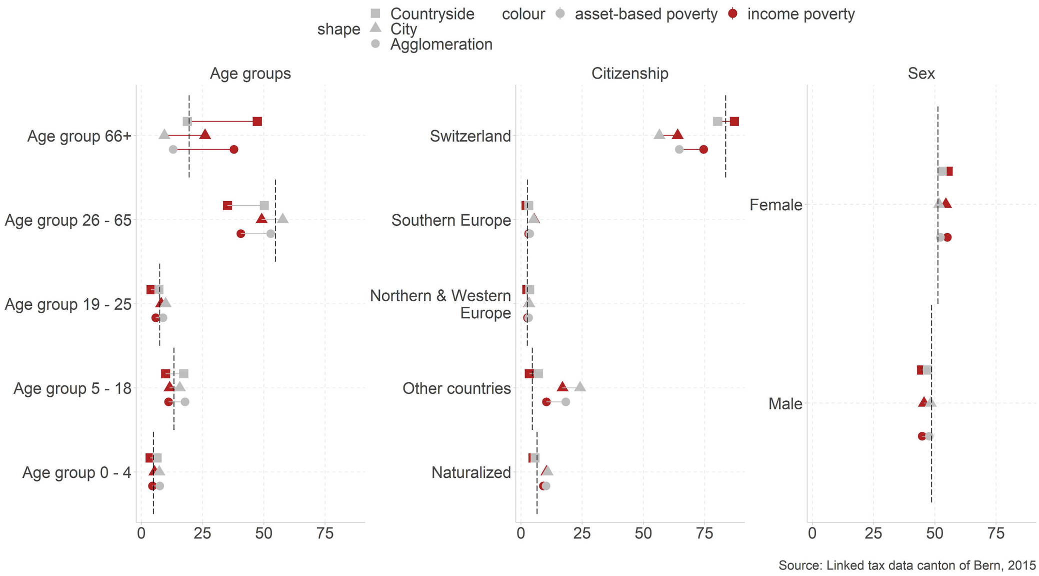

Figure 1.3: Social structure by social groups.

Note: The figure shows the composition of the poor by age group, nationality, and gender for the poor living in urban, metropolitan, and rural areas. The dashed line shows the composition of the total population.

From a *methodical perspective*, we observe that results differ if we use the income or the asset-based poverty measure. Differences are very strong regarding age groups, but they are also present for citizenship. Especially, the share of poor retirees drops significantly when switching from income poverty (38.9% of all poor) to the asset-based poverty indicator (13.9%). Since pension plans in Switzerland partially rely on private savings and people have the option to get capital from their occupational pensions instead of a rent, it is integral to the Swiss pension plan that retirees in Switzerland partly live off their financial reserves. It is therefore not surprising that less retirees fall below the asset-based poverty line when including financial reserves. Regarding citizenship, results demonstrate that Swiss citizens are better able to build financial reserves than foreign citizens from countries other than South, North, or Western Europe.

Regarding *spatial dimensions*, specific patterns can be identified. First, the share of poor retirees and poor Swiss people in general is higher in the countryside than in other regions. Second, poor people of working age and foreigners are found more often in cities and agglomerations than in the countryside. However, the associated increased poverty risk is not found among all migration groups. There are hardly any differences between foreigners from Northern and Western Europe and Swiss nationals. Migrants from Southern Europe are, by contrast, overrepresented among the poor in cities and migrants from other countries are overrepresented among the poor in cities and agglomerations. Among this latter group are many migrants from former Yugoslavia who immigrated to Switzerland in the 1990s, but also from numerous other Asian, American or African nations. Surprisingly, naturalized people are overrepresented among the poor meaning that this group still has an increased risk of becoming poor, but it is significantly reduced compared to foreigners that have not (yet) obtained a Swiss passport. Previous literature focused more on within-country migration movements, e.g. from rural to urban parts and how this influences poverty rates (c.f. Foulkes and Schafft 2010). The elevated prevalence of income and asset-based poverty for migrants from outside of Northern, Western and Southern Europe and naturalized citizens is however novel.

From an overall perspective, we find the following interesting patterns. Gender differences are rather small. While women are over-proportionately more often poor than men (55.5% female) regarding income poverty, these differences get smaller when including assets, although a difference remains (52.3%). Regarding age groups, we identify a dramatic shift of the poverty profile. When assessing poverty with the classic income poverty measure, retirees dominate the numbers. In contrast, assessing poverty while including financial reserves changes the focus to children and families. Then, these groups are disproportionately often poor and lack financial reserves to handle episodes of income poverty. This is possibly a consequence of people using any financial reserves for the purchase of housing in the phase of starting a family. Financial reserves in later phases of life are therefore more common.

We also show differences regarding several characteristics that define the social situation (Figure 1.4). When focusing on the asset-based poverty measure as a lead indicator, we find many overall patterns that are in line with the poverty literature. Poor tend to be more often singles in 1 person- (16.6% in the poverty population vs 8.1% in the overall population) or monoparental-households (30.9% vs 17.8%). They are slightly over-proportionally more often divorced or separated (10.6% vs 8.4%). They tend to have lower education (no compulsory education: 7.1% vs 3.1%), and they are more often not or weakly attached to the labor market (non-working: 40.5% vs 5.7%). We also see differences regarding the sector of occupation - which links the individual situation and the opportunity structure. Overall, we see that poor work comparatively less often in administration (23.6% vs 29.1%), industries (10.2% vs 15.5%), and finances (2.4% vs 4.2%) and more often in the gastronomy (28.1% vs 22.3%). Regarding health status, we observe no striking anomalies, signifying that those qualifying for a disability rent are not disproportionally often among the poor. However, we cannot show how health status affects poverty risks beyond disability status.

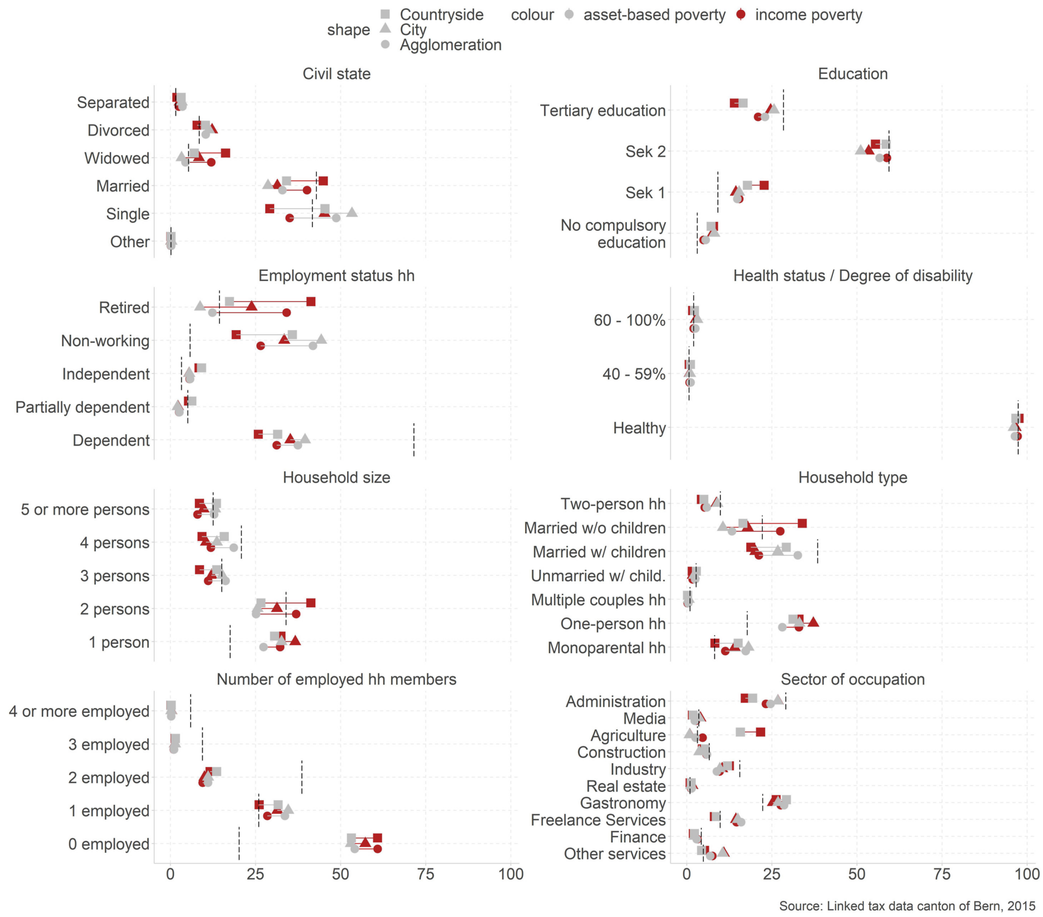

Figure 1.4: Social structure by social situation.

Note: The figure shows the composition of the poor across civil state, education, employment status, health status / degree of disability, household size, household type, number of employed household members and sector of occupation for poor living in cities, agglomerations and in the countryside. The dashed line shows the composition of the total population.

While these patterns are supported regarding the spatial dimension, we observed some interesting spatial differences. In the countryside, we more often find poor widowed, retirees and people with low education. We also see more poor that are working independently or in the agricultural industry. In cities, the poor are more often singles. In agglomerations, married with children are disproportionally often poor. Non-working poor are also more dominant in cities. Regarding the sector of occupation, poor are over-proportionally often freelancers and working in small services like hairdressers or private household helpers.

From the *methodical perspective*, we see again the big change between income and asset-based poverty assessment for retirees (34.5% income base vs 12.9% asset-based). We also see a shift for civil state. While the drop of the share of poor for widowed probably mirrors the situation of retirees, there is also a shift regarding married and single persons. This shift may refer to different life stages and possibilities to accumulate financial reserves.

Relevance of the opportunity structure

Moving forward, we evaluate the importance of different variables to distinguish the relevance of the characteristics for social groups, social situation and the opportunity structure. We show results for all social group, social situation, and the opportunity structure characteristics separately as well as a model including all variables.

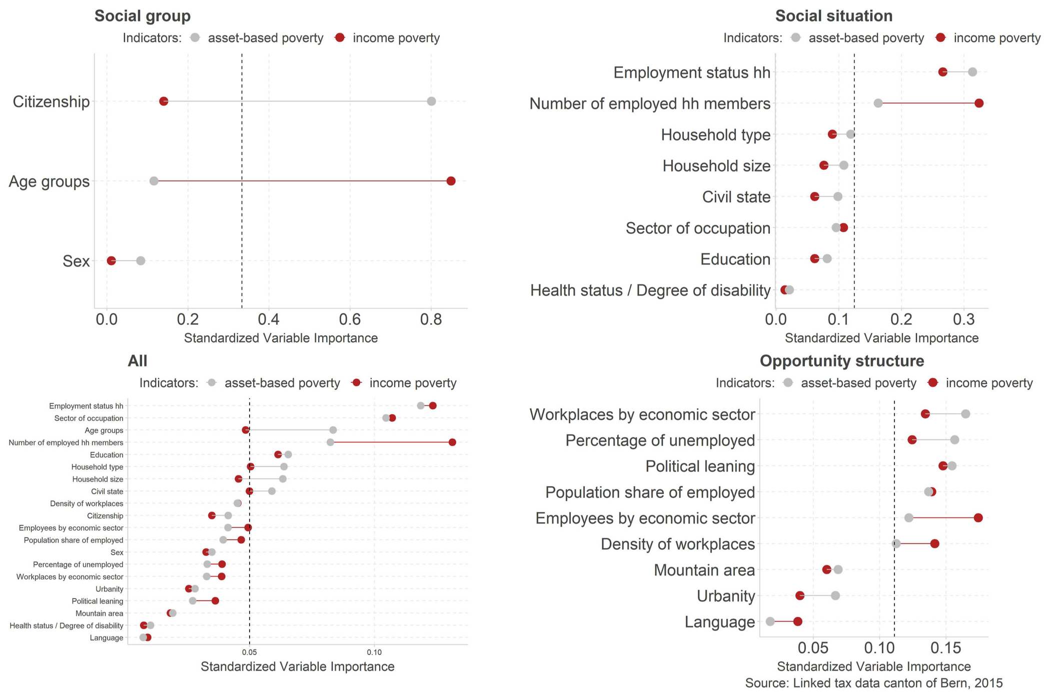

Figure 1.5: Variable importance by social group, social situation, and opportunity structure.

Note: The figure shows standardized variable importance to predict poverty derived from random forest models. The dashed line represents average variable importance across all variables. Variables are ordered by importance to predict asset-based poverty.

Overall, the variables capturing the social situation are the most important when predicting poverty. The ranking is led by characteristics that measure a household's attachment to the labor market, closely followed by the variable that measures the sector of occupation. While this last variable is less important in the analysis covering only characteristics of the social situation, it gains importance in the full model because of its interaction with the variables measuring the opportunity structure. At the same time, it can be seen in the full model that all variables measuring the opportunity structure on the level of municipalities are clearly less important for predicting poverty, suggesting that the opportunity structure is less important compared to the social situation. Among the social group variables, the age group is the most dominant variable (in the full model) while gender and citizenship are of minor importance if other variables are included in the model.

While the share of poor based on the asset-based poverty measure is slightly higher in cities compared to poverty rates in agglomerations and in the countryside[7], the mere differentiation of these three types of urbanity has comparatively low predicting power to identify poverty (see urbanity). Among the characteristics that measure the opportunity structure, those that stand for economic structure are more important than the variables measuring accessibility (mountain area) and the institutional and normative context (political leaning and language).

Regional differences of poverty risk factors importance

To determine if poverty risk factors vary by regions, we ran three separate random forest models for people living in cities, agglomerations, and in the countryside.

Results in Figure 1.6 suggest that the importance of poverty risk factors is rather constant across regions. Irrespective of where people live, the employment status, the number of household members that are active in gainful employment and the sector of occupation, remain the most important to predict poverty. Similarly, characteristics of the social groups, such as sex and citizenship but with the exception of age group, are of subordinate importance in all regions. Poverty at different life stages ranks higher generally, but it seems to be a topic that is of special relevance in the countryside, where the importance of the age groups variable takes second place. Finally, the opportunity structure seems to have comparatively lower importance in all three urbanity types.

[7] The income-based poverty rate is highest in the countryside 11.5%, followed by cities 10.4% and agglomerations 8.2%. With the asset-based poverty indicator the ranking changes to the following: 7.0% cities, 5.0% countryside and 4.4% agglomerations.

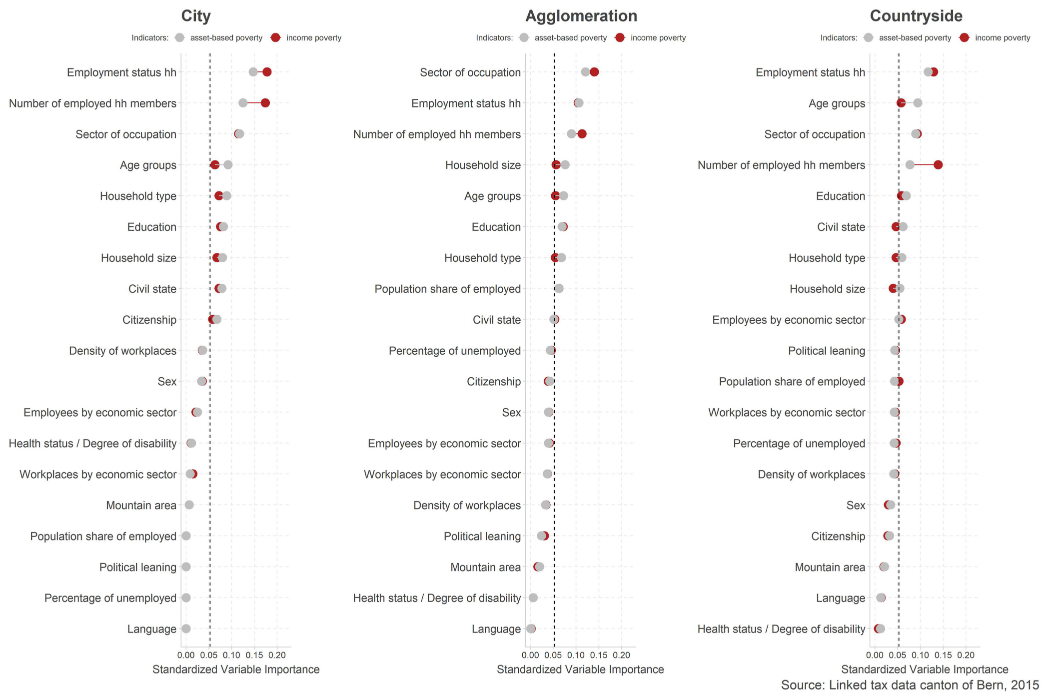

Figure 1.6: Importance of poverty risk factors in cities, agglomerations and in the countryside.
Note: The figure shows standardized variable importance to predict poverty derived from random forest models. The dashed line represents average variable importance across all variables. Variables are ordered by importance to predict asset-based poverty.

1.5 Conclusion

Following theories referring to the economic change that favors urban areas with its service and tech-based economies (Eckert, Ganapati, and Walsh 2019), it might be assumed that poverty occurs mainly in disconnected areas on the countryside (Shucksmith und Schafft 2012). This is not true, at least in Switzerland in our area of study. Even though income poverty is more prevalent in the countryside, leading to higher income poverty rates in rural parts compared to cities, this is a methodical artifact. Since we can construct an asset-based poverty measure accounting for household incomes and financial reserves, we can show that some defined as poor based on income do not qualify once the wealth situation is taken into consideration. This affects regional poverty rates through the different social structure in cities and in the countryside. On the one hand, the share of income poor with financial reserves is higher among self-employed and Swiss citizens. These groups are disproportionally more often present in the countryside. On the other hand, income poverty without financial reserves is more common among people with poor access to the labor market and foreigners from outside of Europe. These groups again are relatively more prevalent in cities. In the end, if we assess poverty rates with the asset-based approach, we find that rates are highest in cities (7.0%), then the countryside (5.0%), and they are lowest in the agglomerations (4.4%). Still poor people live in cities and in rural parts alike. As our study shows, there are several ways in which a place-based approach to poverty leads to a better understanding of how regional opportunities link to poverty.

While our study confirms general findings in the poverty literature like that the poor disproportionally often have low education or are single parents (A. B. Atkinson et al. 2004) or that they are working in unsteady occupations with seasonal fluctuations like gastronomy or tourism, our analysis is also able to show that poverty has different faces in cities and in rural parts:

1. In *rural parts*, the poor are more often likely to be retirees. Although the number of poor retirees drop drastically if financial reserves are accounted for, poor retirees are more prevalent in rural compared to urban parts. As retirees are equally present in urban and rural parts, this is a result of an increased risk of being poor, as the age specific poverty rates for individuals above 66 shows: in cities 4.2% are poor while 6.6% are in the countryside. We assume that the non-take-up of social benefits that is more prevalent in rural regions (Hümbelin 2019) plays a part in explaining this difference. Keeping in mind that our asset-based measure is constructed to give a general sense of the importance of financial reserves and includes reserves for only one year, it can be assumed that more retirees are at risk of poverty. Further studies should make use of the asset-based poverty approach and take a closer look at the financial reserves of retirees. It could be estimated if retirees' reserves

are sufficient to maintain a standard of living above the poverty line until they reach the usual life expectancy. Thus, it could be assessed how many are at risk of old-age poverty. A second noticeable group of poor in rural parts are those who work in agriculture. Although Switzerland is known as a country with comprehensive subsidies for the agricultural sector, not every farmer is able to adapt to the changing conditions of global markets. It seems that some of this group are threatened to be left behind as part of economic and societal change, as already made clear by Shucksmith and Schafft (2012).

2. In *urban parts*, other groups are disproportionally often among the poor. Freelancers, cultural professionals, and people working in small personal services like housekeepers can more often be found among the poor. While the new tech-based economy leads to innovations and hubs mainly in cities (Eckert, Ganapati, and Walsh 2019), this does not necessarily imply that everyone profits from these developments. It also illustrates that freelancers take higher risks and, therefore, possibly slip more often below the poverty line compared to occupations with more consistent working conditions like those working in industries, finances, or administration. Also, a special phenomenon of cities is the greater portion of poor foreigners. This group is clearly more often present in cities than in rural parts. 44.5% of the poor in cities are non-Swiss, while in the countryside only 19.7% of the poor are foreigners (22.5% is the overall share of non-Swiss inhabitants). However, not every region of origin bears a heightened risk of poverty. Foreigners with a background outside of Europe are by far more strongly affected than foreigners from European neighbor countries. Foreigners from the northern or western part of Europe are not excessively represented among the poor. This highlights that global migration in a wealthy country like Switzerland is associated with different poverty risks for different groups of foreigners. Highly qualified migrants from countries with a similar cultural background as Switzerland do not necessarily experience heightened poverty risks, unlike migrants with a background outside of Europe without professional training or skills that do not necessarily fit the demands of the Swiss labor market. The heightened poverty prevalence we discover suggests that these groups can

struggle to take a foothold even if they are allowed to stay in Switzerland. Since we measure poverty based on incomes post all means-tested benefits, this result also reflects that these groups encounter hurdles to apply for social assistance. Indeed, the receipt of social assistance can become a reason for a withdrawal of the residence permit, which has the effect that these groups are incentivized to not apply for social assistance and makes them an especially vulnerable group.

All in all, our study confirms previous findings showing that activity in basic occupations like cleaning or agricultural tasks are associated with higher risks of poverty (Copus et al. 2015). Furthermore, it presents findings that raise attention for others risk groups as well. Freelancers, cultural professionals, and foreigners, that are mainly found in urban areas are also confronted with an increased poverty risk. Poor retirees seem to be a specificity of rural parts. Based on these findings, it is recommended to study the living conditions of those groups in detail and to ensure poverty programs are set up to address their specific situations. In rural parts, it should be ensured that there are counseling programs addressing the situation of retirees and farmers. Poverty policies in cities should have a special focus on people with unsteady working conditions such as freelancers and those engaged in small personal services. Additionally, special programs should be tailored to reach out to foreigners with a non-European background.

Our machine-learning based risk-factor assessment suggests that the immediate social situation, such as not having access to gainful employment and the sector of occupation, are the most dominant factors predicting poverty. Other characteristics of the social situation, like household type, marital status, and education, are also important to predict poverty. Overall, the social situation variables outperform the characteristics that describe social groups, such as citizenship[8] and gender, except for age groups. In

[8]This is not a contradiction to the findings above. Since the results of the risk factor analysis assess the importance of a single factor in the context of all variables at hand, the result here just identifies the dominant factors. Since some groups of foreigners are disproportionally often among those not having sufficient access to labor market, the result

that case, it also ranks highly in the importance ordering, especially in the rural part. It seems that poverty at different life stages, especially in the countryside, is a topic worth further research. Finally, all characteristics that relate to the opportunity structure have lower predictive power compared to the social situation and social groups. This does not necessarily mean that factors like accessibility (Liu et al. 2021), social norms, local economic structure, and local institutions (Blank 2005) do not play any role. On the contrary, we believe such factors are crucial elements in a holistic approach to addressing and theorizing about poverty. Although the region we study is quite heterogenous with respect to regional economic structure, urbanity, and political orientation, it is still a well-developed area with solid infrastructure that allows people to commute within the area. Basic coverage of social service institutions is also provided. Moreover, since we study the situation in one canton, the basic welfare regulations are constant across the whole region. To gain more insights with respect to the relevance of the opportunity structure, we recommend comparative studies between different regions of the same country, comparative studies between different countries or studies with a longitudinal approach that enables researchers to study changes in the opportunity structure.

Our detailed analysis of the social structure of the poor as well as the risk factor analysis provide valuable insights into which spatial dimensions relate to the poverty phenomena in an affluent country. Furthermore, it lays the groundwork for further causal analysis that can delve into the "why" behind the observed patterns.

of the risk factor assessment signifies that it is the access to the labor market that affects the poverty risk, not citizenship.

Appendix

Table 1.7: Population shares by indicator (N = 910'346).

Indicator name | *Desc.*	**Indicator categories**	**Pop. shares**	**Source | *Theme***
Age groups	0 – 4; 5 – 18; 19 – 25; 26 – 65; 66+.	4.9% 13.3% 7.5% 54.7% 19.5%	Statpop *Social Groups*
Citizenship *Naturalized if country of origin is not Switzerland but nationality is.*	Switzerland; Northern & Western Europe; Southern Europe; Other Countries; Naturalized.	83.5% 2.6% 2.7% 4.6% 6.6%	Statpop *Social Groups*
Sex	Female; Male.	51.4% 48.7%	Statpop *Social Groups*
Civil state	Single; Married; Widowed; Divorced; Separated; Other.	41.7% 42.9% 5.3% 8.4% 1.6% 0.2%	Statpop *Social Situation*
Education *Highest completed education.*	No compulsory education; Sek 1; Sek 2; Tertiary education. Data not available.	3.1% 9.1% 59.4% 28.4% 66.7%	Structural Survey *Social Situation*
Employment status hh*	Dependent; Partially independent; Independent; Non-working; Retired.	71.5% 5.1% 3.2% 5.7% 14.4%	Fiscal data *Social Situation*
Health status *Degree of disability.*	Healthy; 40 – 59%; 60 – 100%.	97.4% 0.7% 2%	OASI data *Social Situation*
Household size	1 person; 2 persons; 3 persons; 4 persons; 5 or more persons.	17.5% 34% 15.1% 20.9% 12.6%	Statpop *Social Situation*

Household type	One-person hh; Married w/o children; Two-person hh; Monoparental hh; Married w/ children; Unmarried w/ children; Multiple couples hh.	17.8% 22.2% 9.8% 8.1% 38.5% 2.7% 0.9%	Statpop *Social Situation*
Number of employed hh members	0 employed; 1 employed; 2 employed; 3 employed; 4 or more employed.	20.2% 25.9% 38.6% 9.4% 5.9%	Fiscal data *Social Situation*
Sector of occupation	Agriculture; Industry; Construction; Gastronomy; Media; Finance; Real estate; Freelance services; Administration; Other services. Data not available.	3.1% 15.5% 6.6% 22.3% 3.5% 4.2% 0.9% 9.8% 29.1% 4.9% 88.2%	Structural Survey *Social Situation*

** Dependent if share of indep. hh earned inc.* < 0.2. *Partially dependent if* < 0.8. *Independent if* $>= 0.8$. *Non-working if no hh earned inc. and no member age* $>= 65$. *Retired if no hh earned inc. and min.* 1 *member age* $>= 65$.

Table 1.8: Pop. shares by indicator – Opportunity structure (N = 910’346, Data source = Munic. profiles).

Indicator name | *Desc.*	**Indicator categories**	**Pop. shares**	**Distribution**
Density of workplaces* *Ratio of workplaces over population.*	1st quartile [0.040 – 0.064]; 2nd quartile [0.064 – 0.078]; 3rd quartile [0.078 – 0.102]; 4th quartile [0.102 – 0.275].	31% 32.9% 16.4% 19.8%	Min: 0.040; Max: 0.275. Median: 0.074.
Economic Sector of Workplaces *If share of workplaces in sector higher than in median of communities.*	Predominantly agricultural; Pre. agricultural and industrial; Pre. industrial; Pre. agricultural and services; Pre. industrial and services; Pre. services.	7.3% 9% 2.3% 1.3% 26.5% 53.6%	
Employees by economic sector *If share of employees in sector higher than in median of communities.*	Predominantly agricultural; Pre. agricultural and industrial; Pre. industrial; Pre. agricultural and services; Pre. industrial and services; Pre. services.	4.8% 7.2% 7.0% 4.2% 43.5% 33.4%	
Language	German; French.	94.8% 5.2%	
Mountain area	Non mountain area; Mountain area.	77.6% 22.4%	
Percentage of unemployed*	1st quartile [0.3% – 0.9%]; 2nd quartile [0.9% – 1.3%]; 3rd quartile [1.3% – 1.8%]; 4th quartile [1.8% – 9.5%].	5.1% 15.6% 28.1% 51.2%	Min: 0.3%; Max: 9.5%. Median: 1.3%.
Political leaning* *Share of votes for social party minus share of votes for popular party.*	Right; Center-right; Middle; Center-left; Missing.	8.6% 11% 18.8% 61.6% 0.2%	Min: -83.7%; Max: 21.9%. Median: -12.9%.
Population share of employed* *Ratio of employed over population.*	1st quartile [0.101 – 0.261]; 2nd quartile [0.261 – 0.364]; 3rd quartile [0.365 – 0.491]; 4th quartile [0.494 – 2.235].	11.2% 13.9% 21.4% 53.5%	Min: 0.101; Max: 2.235. Median: 0.396.
Urbanity *Based on official classification.*	City; Agglomeration; Countryside.	25.7% 35.8% 38.5%	

** If share is <= 1st quartile / median / 3rd quartile of municipalities or higher.*

Table 1.9: Variance inflation factor analysis for logit model on asset-based poverty*.

Indicator name	GVIF	Degrees of freedom (Df)	Adjusted GVIF**	Indicator name	GVIF	Degrees of freedom (Df)	Adjusted GVIF**
Age groups	10.5	3	1.48	Sector of occupation	1.46	9	1.02
Citizenship	1.28	4	1.03	Density of workplaces	7.92	3	1.41
Sex	1.27	1	1.13	Economic sector of workplaces	16.6	5	1.32
Civil state	9.88	5	1.26	Employees by economic sector	17.3	5	1.33
Education	2.45	3	1.16	Language	2.45	1	1.57
Employment status hh	43.3	4	1.6	Mountain area	2.53	1	1.59
Health status / Degree of disability	1.03	2	1.01	Percentage of unemployed	4.92	3	1.3
Household size	495.39	4	2.17	Political leaning	5.89	3	1.34
Household type	1307.91	6	1.82	Population share of employed	3.08	3	1.21
Number of employed hh members	70.8	4	1.7	Urbanity	11.4	2	1.84

** All variables were kept in the set of regressors, since no variable exceeded the upper bound of 2.23 for the adjusted GVIF, which is a commonly used rule of thumb for categorical variables.* $** = GVIF^{(1/(2*Df))}$.

Table 1.10: Variance inflation factor analysis for logit model on income poverty*.

Indicator name	GVIF	Degrees of freedom (Df)	Adjusted GVIF**	Indicator name	GVIF	Degrees of freedom (Df)	Adjusted GVIF**
Age groups	16.4	3	1.59	Sector of occupation	1.71	9	1.03
Citizenship	1.39	4	1.04	Density of workplaces	8.99	3	1.44
Sex	1.22	1	1.11	Economic sector of workplaces	21.8	5	1.36
Civil state	9.22	5	1.25	Employees by economic sector	21.6	5	1.36
Education	1.97	3	1.12	Language	2.83	1	1.68
Employment status hh	79.1	4	1.73	Mountain area	2.79	1	1.67
Health status / Degree of disability	1.05	2	1.01	Percentage of unemployed	5.5	3	1.33
Household size	292.42	4	2.03	Political leaning	6.91	3	1.38
Household type	952.50	6	1.77	Population share of employed	3.33	3	1.22
Number of employed hh members	30.1	4	1.53	Urbanity	13.6	2	1.92

** All variables were kept in the set of regressors, since no variable exceeded the upper bound of 2.23 for the adjusted GVIF, which is a commonly used rule of thumb for categorical variables.* $** = GVIF^{(1/(2*Df))}$.

Chapter 2

Caught in the slough

Poverty persistence in Switzerland

2.1 Introduction

Being poor can have negative social (Mood and Jonsson 2016) and employment (Biewen 2009) consequences. It can cause negative psychological health consequences and stigma, e.g. due to being dependent on social assistance (Ali et al. 2018), as well as negative physical health consequences. Poverty may translate into debt, if e.g. a drop in income or a hike in expenses makes it difficult to finance current expenses (Pressman and Scott 2009b; 2009a). Thus, while being poor is a consequence of negative economic, social or health conditions, it can further deteriorate circumstances to prolong or cause future poverty. The consequences of poverty may be more severe, the longer a poverty episode lasts. Likewise, chances of escaping poverty decrease the longer a person stays poor (Devicienti et al. 2014), and exits from poverty may not be durable.

A larger share of the population is affected by poverty if it is measured longitudinally rather than in the cross-section (Layte and Whelan 2003), since a larger share of the population experiences short poverty episodes (Jarvis and Jenkins 1997) which may not be captured if we look at one specific year. This also implies that social security systems such as unemployment insurance or social benefits support a larger share of the population over the years than can be observed in a cross-sectional perspective. Short, long, or recurring poverty episodes also require different countermeasures (Finnie and Sweetman 2003). Whereas short poverty periods may be addressed with large-scale, less intensive measures to bridge financial needs, long or recurring poverty periods require more tailored and intensive measures (Mood 2015). Policies to address poverty should take effect early during a person's poverty episode and should also prevent falling back into poverty (Devicienti et al. 2014), which becomes less likely, the longer a person stays out of poverty.

In this article we use linked fiscal and administrative data for a large political district in Switzerland for the years 2012 to 2015 to study longitudinal poverty. We measure income poverty and asset-based poverty, which affects a sub-group of the income poor that lack financial reserves to cover expenses for the span of one year (or another defined time-period). We graphically explore poverty flows for the 2012 income poor cohort and find that asset-based poverty is the more dynamic state, with many exits to non-poverty over the observed four years, whereas exits from income poverty to non-poverty are less frequent. The dynamics are very different by age. Poor persons in working age and children generally lack financial reserves. However, more than half of the cases manage to escape poverty over the observed period. Poor pensioners on the other hand usually have financial reserves. However, only a fraction manages to escape poverty over the observed four years. We use dynamic linear panel data models to measure how labor market participation, the social benefit system and asset consumption influence poverty status and to estimate poverty persistence. An increase in the labor market income of the main or secondary earner in the household reduces the probability of being poor the most, while pensions and incomes from real estate are also important to reduce poverty for pensioners. We find that poverty is a persistent phenomenon, with the probability of being income poor in the current year increasing by 21.7 percentage points for the working age population and children (29.1 percentage points for pensioners) and the probability of being asset-based poor in the current year increasing by 19 percentage points for the working age population and children (30.5 percentage points for pensioners) if an individual has been income or asset-based poor in the previous year.

The remainder of this article is organized as follows: Section 2 reviews the literature on poverty dynamics and poverty persistence and gives details on the studied institutional context. Section 3 describes the data and methods used. Section 4 shows results on poverty flows. Section 5 presents results on labor market attachment, social benefit use, asset consumption and poverty persistence. Section 6 concludes.

2.2 Review of the literature

Risk groups and factors

Although poverty is a substantial phenomenon in many countries[1], it may go largely unnoticed, since it is not directly observable by individuals (c.f. Andriopoulou and Tsakloglou 2011a). Not all sociodemographic groups face an equal risk of long poverty spells. Risks of prolonged poverty trajectories are reported for women (Oxley et al. 2000; Oris et al. 2017), households headed by (single) women (Stevens 1994; Stevens, Ann Huff 1999; Devicienti 2011), children (Vaalavuo 2015; Leu et al. 1997; Andriopoulou and Tsakloglou 2011b; Devicienti 2011; Devicienti et al. 2014), households headed by young and elderly individuals (Andriopoulou and Tsakloglou 2011b; Devicienti et al. 2014) and for older persons (Jarvis and Jenkins 1997; Devicienti 2011), especially shortly before retirement (Bound et al. 1991) and with ongoing age (Smith et al. 2007; Salzgeber et al. 2010). Household type and civil state can be important predictors of prolonged poverty trajectories too (Finnie and Sweetman 2003; Budowski et al. 2002; Gutjahr and Heeb 2016), with couples with children, single parents, young persons, persons living alone (Fouarge and Layte 2005) and widows (Bound et al. 1991) reported as being at risk more frequently. A lack of education is often reported as an important risk of prolonged poverty trajectories too (Crandall and Weber 2004; Budowski et al., 2002; Gabriel et al. 2015; Oris

[1]The EU average at-risk-of-poverty rate was 16.9% in 2017 with values ranging from 9.1% to 25.7% for individual countries, c.f. Archive:Income poverty statistics - Statistics Explained (europa.eu), last visited on 04.06.2023.

et al. 2017; Salzgeber et al. 2010; Hümbelin and Fritschi 2018; Stevens, Ann Huff 1999; Andriopoulou and Tsakloglou 2011b; Layte and Whelan 2002; Devicienti 2011; Devicienti et al. 2014; Vaalavuo and Sirniö 2022).

Further important factors for poverty dynamics reported in the literature include: Changes in the household heads' income (Jenkins 2000), changes in secondary earners' income (Andriopoulou and Tsakloglou 2011b; Devicienti et al. 2014), changes in non-labor income (including benefits) and changes in household composition (Bane and Ellwood 1986). Similarly, short employment spells and part-time work are less effective ways to escape poverty and may instead lead to in-work poverty (Vaalavuo and Sirniö 2022).

The Swiss context

Despite its wealth and well-functioning labor market, poverty is a prevalent phenomenon in Switzerland[2,3]. The Swiss social welfare system consists of social insurances (old-age and survivor's insurance (OASI), occupational benefits, disability insurance, unemployment insurance, health and accident insurance, income compensation allowance in the event of service or maternity, family allowances) and means-tested social insurances (supplementary benefits and premium reductions) on the federal level to cover against social risks. These are complemented by further means-tested measures on the cantonal (e.g., maintenance advances) and communal level. By far the most important means-tested social insurance is social assistance, which is subsidiary to the other means-tested insurances, i.e., a claim to social assistance can be made only if needs cannot be covered through other means-tested social insurances. Financial reserves also need to be depleted below a certain threshold before a claim to social assistance can be made.

The OASI, disability insurance and supplementary benefits together are

[2]8.7% of the permanently resident population living in private households in Switzerland was income poor in 2021, c.f. Poverty | Federal Statistical Office (admin.ch), last visited on 04.06.2023.

[3]The at-risk-of-poverty rate for Switzerland was 15.5% in 2017, below the EU average of 16.9%, c.f. Archive:Income poverty statistics - Statistics Explained (europa.eu), last visited on 04.06.2023.

also called the 1st pillar and are compulsory. The occupational benefits are also called the 2nd pillar and are compulsory for employees. An important 3rd pillar is private provision which is not compulsory.

Research questions

Many studies focus on income poverty due to a lack of reliable data on financial assets. The role of financial reserves for poverty dynamics is therefore not well studied. This is a significant blind spot in the literature since financial reserves serve to bridge periods of insufficient income. And in the Swiss welfare system and many other countries wealth must be depleted below a certain threshold before a claim to social benefits can be made. In the absence of financial reserves, there is the risk of running into debt, if income is insufficient to cover expenses over a long enough period (Pressman and Scott 2009b; 2009a). Using the information in the fiscal data we calculate asset-based poverty (Brandolini et al. 2010) and study the role of financial reserves for poverty dynamics alongside income poverty. We formulate the following two research questions:

(1) Are income poverty and asset-based poverty transient or persistent phenomena? Is income or asset-based poverty more persistent, i.e., is it easier to escape from income poverty or asset-based poverty?
(2) How do the social benefit system, labor market attachment and asset consumption play together to protect against poverty? Which is most important to escape poverty?

2.3 Data and methods

Measuring longitudinal poverty using linked fiscal and administrative data

We measure poverty as a lack of financial resources. Although there is consensus in the literature that poverty should be measured as a multidimensional concept (c.f. Alkire and Apablaza 2016), poverty defined as a lack of financial resources has the advantage of being measurable in a conceptionally clear manner as well as being a key-figure for social policy and in the welfare literature. Since Switzerland is one of the few countries that levy taxes on income and wealth, the interplay of income and wealth over time can be studied with Swiss fiscal data.

We use linked fiscal and administrative data collected as part of the research project "Inequality and poverty in Switzerland"[4] funded by the Swiss National Science Foundation. Fiscal data was linked to the population register and the social assistance register. The linked data allow to reliably assess a household's financial resources and financial poverty. A first indicator measures income poverty. It refers to the social subsistence level of Switzerland, which is the official absolute poverty line and, given that a household's financial reserves are sufficiently low, indicates the threshold that qualifies for social assistance. A household is poor if its expenses for the minimum needs (as set by the national standards, c.f. BKSE 2020; Schweizerische Konferenz für Sozialhilfe 2015), rent and health insurance premia outweigh its total income including social transfers from insurances or other benefits. A second indicator measures asset-based poverty (c.f. Brandolini et al. 2010; UN 2017). According to this indicator a household is poor if it is income poor and at the same time does not have enough financial reserves to cover expenses for the social subsistence level for a defined time-period, which we define as one year for our study. The asset-based poor are therefore always income poor. They are a subgroup of the income poor, characterized by a more severe form of poverty (lack of income and financial reserves). Although our unit of analysis is the individual, we assess poverty at the household level since household members generally share resources[5]. Details on data preparation can be found in Hümbelin et al. 2022.

[4]c.f. Inequality and poverty in Switzerland – Collaborative research project of the Institute of Sociology, University of Bern and the Department of Social Work, Bern University of Applied Sciences (unibe.ch), last visited on 04.06.2023.

[5]This corresponds to how income poverty is calculated in Swiss official statistics (c.f. FSO 2012).

In this article we apply the logic of asset-based poverty to the non-poor with sufficient financial reserves to cover expenses for the social subsistence level for one year to allow a closer look at poverty dynamics. This yields the groups: non-poor and non-poor with assets, where the latter are a subgroup of the non-poor characterized by a more consolidated form of financial security (sufficient income and financial reserves)[6]. Distinguishing these groups may seem less relevant, since our focus is on poverty persistence and neither of these groups are poor. But the distinction helps our graphical analysis, to confirm whether poor exit into non-poverty with or without assets. The two groups are also substantively different in that the non-poor with assets are better protected against becoming asset-based poor than the non-poor in general are, although they are not necessarily better protected against income poverty.

We use data for the years 2012 to 2015 for the canton of Bern[7], which is a large political district in Switzerland and accounts for roughly 12% of the Swiss population[8]. The canton of Bern is mainly German-speaking but includes French-speaking communes and has a mix of urban and rural municipalities. It is average in terms of the share of its population which is dependent on social assistance[9]. Our data can therefore be thought of as being broadly representative for Switzerland. Our merged sample over the four years contains 910'346 individuals. 125'765 individuals are dropped from the sample, because they cannot be observed in all four years, likely

[6]We thank participants at the 2022 RC28 conference in London for pointing out this important subgroup.

[7]To date it is not possible to obtain fiscal data for all Swiss Cantons because of legal and administrative reasons.

[8]The permanent resident population of the canton of Bern by the end of 2021 was 1'047'473 individuals, c.f Bevölkerungsstand und -struktur, last visited on 04.06.2023. The permanent resident population in Switzerland at the end of 2021 was 8'738'791 individuals, c.f. https://www.bfs.admin.ch/bfs/de/home/statistiken/bevoelkerung.html, last visited on 04.06.2023.

[9]With a social assistance rate of 9.9% the canton of Bern was slightly above the Swiss average of 9.5% in 2020, c.f. https://de.statista.com/statistik/daten/studie/942766/umfrage/sozialhilfequote-in-der-schweiz-nach-kantonen/, last visited on 04.06.2023.

because they moved away from the canton or because they were born or died within the time frame. Our main sample for the analysis contains 784'581 individuals as a result. In section 4 we study poverty flows with a focus on the 2012 income poor cohort. The sample used in that section contains only 73'231 individuals (i.e., 9.3% of the individuals in the main sample, which corresponds to the 2012 income poverty rate).

Fiscal data are less susceptible to issues of non-response, recall bias or panel attrition than survey data (c.f. Hümbelin and Farys 2016; Mood 2015), which makes them an interesting data source for longitudinal studies. To illustrate this, we compare our data to results on poverty dynamics in Swiss official statistics on the national level which are based on the "Statistics on Income and Living Conditions"[10] (SILC) in Table 2.1. Swiss official statistics find income poverty to be a short-term state for a large part of the concerned individuals[11]. Like the official statistics, we find that more persons are income poor in at least one of the four observed years, rather than in exactly one year as would be observed in a cross-sectional perspective. However, we find more persistence for income poverty in our data. Our shares are lower than the official statistics for being income poor in exactly one or two years, but they are higher for being income poor in exactly three or all four years, as well as being income poor in at least one year. Our share for being income poor in all four years (4.5%) even exceeds our shares for being income poor in exactly two (3.1%) or three years (2.2%), which we do not see for income poverty in official statistics or asset-based poverty in our data.

[10] c.f. https://www.bfs.admin.ch/bfs/en/home/statistics/economic-social-situation-population/surveys/silc.html, last visited on 04.06.2023.

[11] From 2017 to 2020, 16.3% of the Swiss population was income poor at least once, while 3.2% were income poor in 2 years and 1.9% were income poor in 4 years. During the same period, 27.2% of the Swiss population was at-risk-of-poverty at least once, whereas values for other European countries range from 15.4% to 39.3%. 4.5% of the Swiss population was at-risk-of-poverty in 4 years, whereas values for other European countries range from 2.5% to 13.8%, c.f. Dynamics of poverty | Federal Statistical Office (admin.ch), last visited on 04.06.2023.

Table 2.1: Income and asset-based poverty in 2012 – 2015, in % of the population.

	Income poor	Asset-based poor	Income poor, FSO
In at least one year	16.2	9.4	13.6
In exactly 1 year	6.5	4.7	7.7
In exactly 2 years	3.1	2.1	3.7
In exactly 3 years	2.2	1.3	1.1
In all 4 years	4.5	1.3	1.1

Source: WiSiER-data canton of Bern, 2012 - 2015, calculations inequalities and ≪Dynamik der Armut: Armutsindikatoren im Zeitraum von vier Jahren, nach Anzahl Jahren - 2014-2020 | Tabelle | Bundesamt für Statistik (admin.ch)≫. C.f. Dynamics of poverty | Federal Statistical Office (admin.ch) for the most recent years.

Analytical strategy

To answer our research questions, we explore flows from income or asset-based poverty out to non-poverty and backflows into poverty graphically through alluvial charts. We then calculate dynamic linear panel data models to describe the roles of the social welfare system, labor market attachment and asset consumption for poverty status and to measure poverty persistence. Following Vaalavuo and Sirniö 2022 we calculate linear probability models, rather than logistic regression models, since estimates from the former can be more readily compared across models with different regressors and over different spans of years (Mood 2010). We consider the following model (Muck 2022a):

$$y_{it} = \alpha * y_{i(t-1)} + \beta' x_{it} + \mu_i + \epsilon_{it}, \tag{2.1}$$

where y_{it} is individual i's income or asset-based poverty status in year t, measured as a binary variable, $y_{i(t-1)}$ is i's income or asset-based poverty status in the previous year. x_{it} is a $k * it$ matrix of financial variables in logs which measure receipts from social insurances, labor market participation and asset consumption. We also include the financial amount of a household's basic needs, gross rent and health insurance premia, which allows us to control for varying household compositions. μ_i is an individual-specific effect and ϵ_{it} is an error-term.

Dynamic linear panel data models are difficult to estimate since the presence of the lagged dependent variable $y_{i(t-1)}$ in the equation introduces a bias due to the correlation of the lagged dependent variable with the error-term ϵ_{it}. This bias is large when there are few time-periods t but many observed individuals i (as is the case with our data) which is known as "Nickell's bias" in the literature (Nickell 1981). Looking at Fixed-effects regression models (FE) and Pooled Ordinary least squares regression models (OLS) side-by-side is nevertheless useful, since the FE estimate is likely to be biased downwards, while the Pooled OLS estimate is likely to be biased upwards (Bond 2002). In other words, the FE and Pooled OLS estimators should bracket the true estimate for the lagged dependent variable.

Following this idea, our first specification is an FE model[12] for the years 2012 – 2015. This approach controls for any observed and unobserved time-invariant characteristics. However, time-varying unobserved characteristics (such as a change in health, a change of jobs or job loss) may still bias our results. By subtracting averages of observations across time, the FE estimator can be written as (Muck 2022a):

$$y_{it} - \hat{y}_i = \alpha * (y_{i(t-1)} - \hat{y}_{i(-1)}) + \beta'(x_{it} - \hat{x}_i) + (\epsilon_{it} + \hat{\epsilon}_i),$$

where $\hat{y}_i$, $\hat{x}_i$ and $\hat{\epsilon}_i$ are averages across time and $\hat{y}_{i(-1)}$ is the average of the lagged income or asset-based poverty status. Subtracting the averages cancels the individual-specific effect. Our second specification is a Pooled OLS model. It takes the form (Muck 2022b):

$$y_{it} = \alpha * y_{i(t-1)} + \beta' x_{it} + u_{it},$$

where instead of μ_i and ϵ_{it} we have an error-term u_{it}. The Pooled

[12] Calculations were done in the statistical software "R". We used the *plm* package version 2.6-2 to calculate Fixed-effects, Pooled OLS and system GMM models (c.f. Croissant und Millo 2008).

OLS model does not differentiate for an individual-specific effect. Our last specification is a System Generalized method of moments model (GMM) estimator. It is based on the first-difference (FD) estimator, which is obtained by subtracting (Muck 2022a):

$$y_{i(t-1)} = \alpha * y_{i(t-2)} + \beta' x_{i(t-1)} + \mu_i + \epsilon_{i(t-1)},$$

from (2.1), thereby giving:

$$y_{it} - y_{i(t-1)} = \alpha * (y_{i(t-1)} - y_{i(t-2)}) + \beta'(x_{it} - x_{i(t-1)}) + (\epsilon_{it} - \epsilon_{i(t-1)}).$$

Like the above estimators, the FD estimator is biased since $y_{i(t-1)}$ is correlated with $\epsilon_{i(t-1)}$. The System GMM estimator resolves this bias by using the twice lagged difference of the dependent variable $(y_{i(t-2)} - y_{i(t-3)})$ as an instrument for $(y_{i(t-1)} - y_{i(t-2)})$ and should provide consistent estimates which can be confronted to the FE and Pooled OLS estimates (Bond 2002). In our case, the panel data allows us to calculate the System GMM estimator for the most recent year (2015) including the lagged dependent variable for the previous year (2014), but no further as we do not have any instruments further back in the data.

2.4 Poverty flows

For the following analysis we focus on the 2012 income poor cohort (N = 73'231). We plot their flows from income poverty or asset-based poverty out to non-poverty and non-poverty with assets over the 2012 to 2015 period, as well as backflows into poverty following 2013. We also plot the 2012 income poverty and asset-based poverty rates for the respective population for reference, which are 9.3% and 4.8% respectively in the 2012 overall population.

In figure 2.2 we see that roughly half of the income poor population is also asset-based poor (51.1%) in 2012. The flows from the asset-based poor to the non-poor are bigger each year, than the flows from the income poor but not asset-based poor to the non-poor. Moving to 2013, 31.7% of the 2012 income poor cohort have become non-poor, most of which have been asset-based poor the year before. However, the income poor but not asset-based poor make up the largest share of those who exit to non-poverty with assets. This is also due to the definition of the states of poverty and non-poverty. Income poor will move out to non-poor with assets if household incomes exceed expenses while their financial reserves are left unchanged, whereas asset-based poor will move out to non-poor without assets. Each year a fraction of the income poor becomes asset-based poor too, whereas a similar amount of asset-based poor become income poor but not asset-based poor.

Moving from 2013 onwards there is a bigger backflow from non-poverty to the asset-based poor each year, than there is from non-poverty to people that are only income poor but not asset-based poor. Most of the backflow into asset-based poverty stems from the non-poor without assets, whereas most of the backflow to people that are income-poor but not asset-based poor stems from the non-poor with assets, which again is also due to the definition of the poverty and non-poverty states. There is also a dynamic from non-poor without assets to non-poor with assets and vice-versa, the latter being slightly larger, since the group of non-poor without assets is also bigger to begin with starting in 2013. The flows between poverty and non-poverty are larger than the flows between the two states of poverty or between the two states of non-poverty. And the flows from poverty out to non-poverty are larger than the backflows into poverty. As a result, more people continue to exit poverty over the years, although this decrease is much weaker than the one from 2012 to 2013. Moving to 2014 38.5% of the 2012 income poor cohort have become non-poor and moving to 2015 this further increases to 42%.

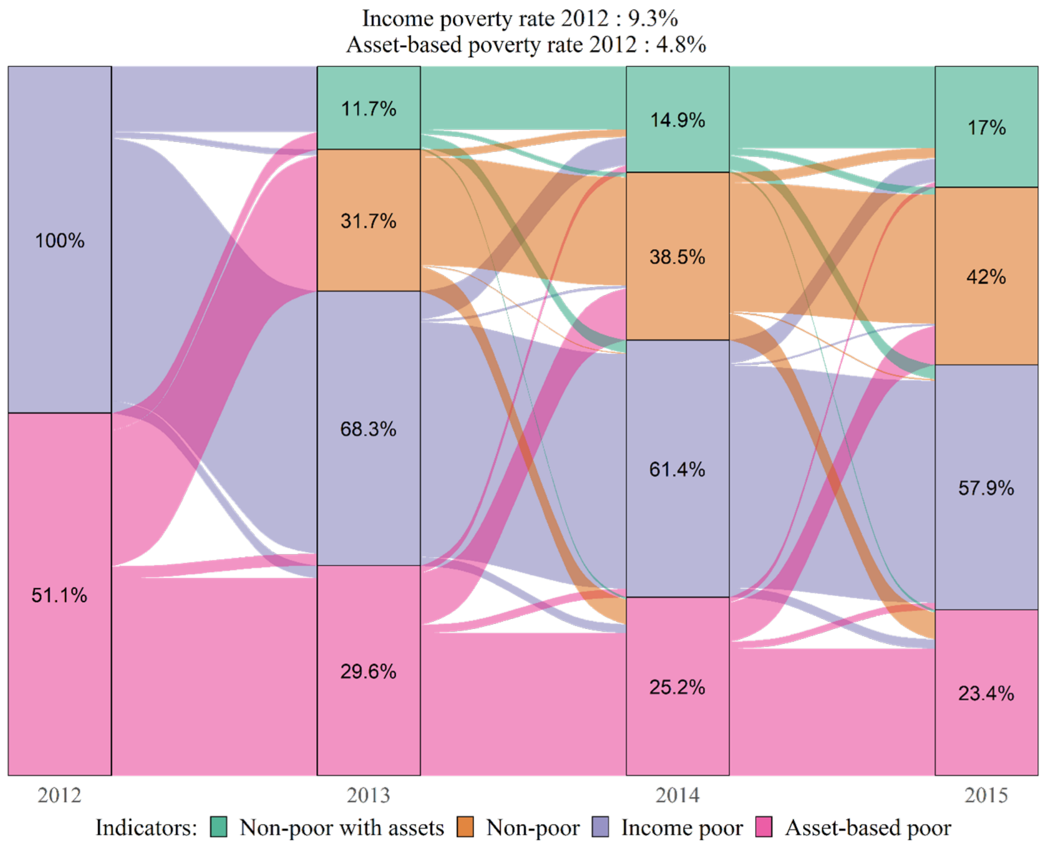

Figure 2.2: Poverty flows for the income poor population 2012.
Note: Since asset-based poor are a subgroup of income poor, they are contained in the % for income poor. The same applies to non-poor with assets as a subgroup of non-poor. E.g. in 2013, 31.7% of the 2012 income poor population were non-poor, 20% were non-poor without assets and 11.7% were non-poor with assets. The % of the non-poor and income poor sums up to 100%. Source: WiSiER-data canton of Bern, 2012 - 2015, calculations inequalities

Over the four years, more than half of the asset-based poor have escaped poverty, decreasing from 51.1% to 23.4% in 2015. Less than half of the income poor have escaped poverty over the four years, decreasing from 100% down to 57.9%. This indicates that asset-based poverty is the easier poverty state to escape from. This seems counterintuitive, since escaping from asset-based poverty should be harder due to the added lack of financial reserves, than escaping from income poverty. But it can be explained, if we consider that asset-based poor are able to get help in the form of social assistance due to the lack of financial reserves and that they may be under more pressure to do so. Whereas income poor may postpone reaching out for help and are unable to make a claim to social benefits.

Since we expect theses dynamics to differ for different phases in the life course, we present alluvial charts for persons aged 26 to 65 and pensioners. In figure 2.3 we see that for the population in retirement age although many are income poor (18.4% in 2012) only few are also asset-based poor (3.5%). This is to be expected since the old-age security system in Switzerland is based on old age pensions (old-age and survivor's insurance, occupational pension) and self-prevention in the form of financial assets. Private savings are rewarded with tax benefits, and regarding occupational pension plans when retirement age is reached there is a choice of whether the pension assets take the form of a rent or are in part paid out. Therefore, most retirees possess financial reserves to cover a 12-months period in case of insufficient income.

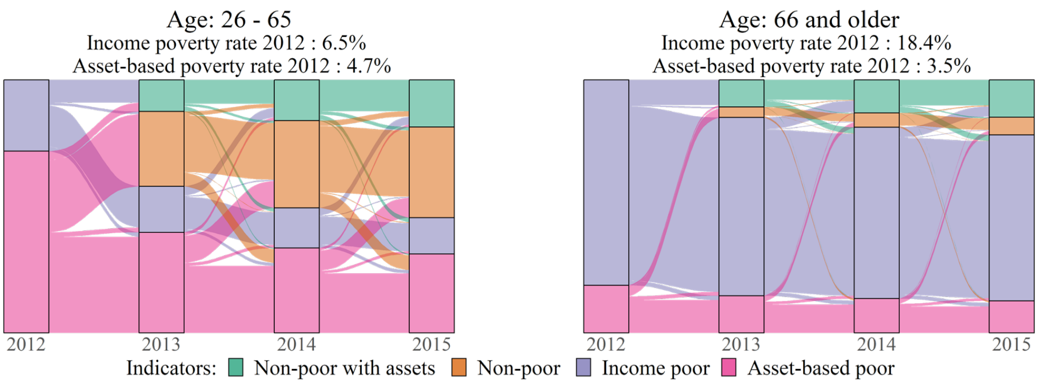

Figure 2.3: Poverty flows for the income poor population 2012 for persons aged 26 - 65 and pensioners.
Source: WiSiER-data canton of Bern, 2012 - 2015, calculations inequalities

For persons aged 26 to 65 the income poverty rate is lower but also closer to the asset-based poverty rate. Many are at a stage in life where they have not yet accumulated financial reserves to cover expenses for a 12-months period in case of insufficient income.

We also see that the flows out from poverty are much stronger for persons aged 26 to 65. Most of them escape poverty over the four years, whereas only a fraction of the population in retirement age does so. Although it is unlikely for the population in retirement age to be asset-based poor, it is more difficult for them to escape from income poverty, than for younger age groups, which live in households that are more strongly attached to the labor market.

Following this descriptive analysis we move on to assess the importance of the welfare system, labor market attachment and asset consumption for an escape from poverty and to measure poverty persistence.

2.5 Poverty persistence

The section on poverty flows has shown that the poverty dynamics are very different for pensioners and persons aged 26 to 65. For this reason, our analysis is carried out separately for the population in working age and children on the one hand and pensioners on the other. For each group, we present FE, Pooled OLS and system GMM models for income and asset-based poverty. Since our financial control variables run the risk of collinearity or even being colliders (e.g. main earner's income and taxes), we start out with models containing only the income or asset-based poverty status for the previous period as regressors to check that the estimate for the lagged dependent variable remains stable when moving to the full model.

Working age population and children

Table 2.4: Linear probability models for income poverty (0 / 1) with lagged income poverty status for working age population and children.

	Fixed effects	Pooled OLS	System GMM
Income-based poverty, t - 1	-0.149***	0.599***	0.276***
	(0.001)	(0.001)	(0.003)
Observations	1,882,339	1,882,339	649,104
R^2	0.022	0.324	
Adjusted R^2	-0.479	0.324	
F Statistic	28,416.880*** (df = 1; 1244026)	1,044,182.000*** (df = 1; 1882338)	
Note:		*p<0.1; **p<0.05; ***p<0.01	

Table 2.5: Linear probability models for asset-based poverty (0 / 1) with lagged asset-based poverty status for working age population and children.

	Fixed effects	Pooled OLS	System GMM
Asset-based poverty, t - 1	-0.155***	0.556***	0.250***
	(0.001)	(0.001)	(0.003)
Observations	1,882,339	1,882,339	649,104
R^2	0.025	0.290	
Adjusted R^2	-0.476	0.290	
F Statistic	31,331.630*** (df = 1; 1244026)	858,716.000*** (df = 1; 1882338)	
Note:		*p<0.1; **p<0.05; ***p<0.01	

The FE estimates for income and asset-based poverty persistence are negative and suggest that past poverty status should decrease chances of poverty in the current period. This runs counter common understanding of the phenomenon and suggests that the FE estimate is biased downwards as expected, due to "Nickell's bias". The Pooled OLS estimates suggest strong poverty persistence, with poverty in the previous period increasing the probability to be poor again in the current period by 59.9 percentage points for income poverty and 55.6 percentage points for asset-based poverty. As the Pooled OLS estimates are likely to be biased upwards, we prefer the system GMM estimates, which lie between the FE and Pooled OLS estimates. They suggest an increase of the probability to be poor in the current period by 27.6 and 25 percentage points for income and asses-based poverty respectively, due to poverty in the previous period.

Since the FE estimates are not reasonable and the Pooled OLS estimates are likely biased upwards, we only pursue the System GMM estimates for the full models.

Table 2.6: Linear probability models for income and asset-based poverty (0 / 1) with financial variables in logs and lagged income and asset-based poverty status for working age population and children.

	System GMM: Income poverty	System GMM: Asset-based poverty
Log of 1st earner's wages	-0.455***	-0.089***
	(0.069)	(0.014)
Log of 2nd earner's wages	-0.204***	-0.064***
	(0.028)	(0.005)
Log of income from real estate	0.034***	0.039***
	(0.001)	(0.0004)
Log of income from private transfers	-0.002***	-0.002***
	(0.0001)	(0.00005)
Log of stipends	0.008***	0.014***
	(0.002)	(0.002)
Log of supplementary benefits	-0.028***	-0.022***
	(0.0003)	(0.0003)
Log of social assistance	-0.009***	-0.005***
	(0.0002)	(0.0002)
Log of premium reductions	0.001***	0.0001**
	(0.0001)	(0.0001)
Log of maintenance advances	0.024***	0.025***
	(0.006)	(0.006)
Log of canton-specific aid	-0.006***	-0.003
	(0.002)	(0.002)
Log of social assistance for refugees	-0.039***	-0.037***
	(0.001)	(0.001)
Log of taxes	-0.048***	-0.039***
	(0.0005)	(0.0003)
Log of payments from private transfers	-0.003	0.001
	(0.004)	(0.004)
Log of liquidities	-0.003***	-0.009***
	(0.0001)	(0.0001)
Log of household basic needs	0.069***	0.044***
	(0.005)	(0.004)
Log of gross rent	-0.118***	-0.065***
	(0.007)	(0.005)
Log of health insurance premia	-0.001***	-0.002***
	(0.0002)	(0.0002)
Income-based poverty, t - 1	0.217***	
	(0.004)	
Asset-based poverty, t - 1		0.190***
		(0.003)
Observations	649,104	649,104
Note:		*p<0.1; **p<0.05; ***p<0.01

The estimates for poverty poversistence are smaller than in the models containing only the lagged dependent variable. Past poverty status increases the probability to be poor again in the current period by 21.7 percentage points for income-poverty and by 19 percentage points for asset-based poverty. Besides the estimates for the lagged dependent variables, the largest estimates are found for an increase in a household's main or secondary earner's income. Keeping in mind that these are "lin-log models", with the dependent (and lagged dependent) variables measured as dummy variables and the regressors measured in logs, a 1 percentage point increase of the income of a household's main earner reduces the probability to be income poor by approximately 0.5 percentage points and the probability to be asset-based poor by approximately 0.1 percentage points. It makes sense that the effect of an increase in income is greater on income poverty rather than asset-based poverty, where it is more direct. We also notice some peculiarities in the model, with both the estimates for an increase in taxes and a household's gross rent having a negative sign. Although these are expenses for a household, they also denote wealthier households. We move on to look at the respective models for pensioners.

Pensioners

Table 2.7: Linear probability models for income poverty (0 / 1) with lagged income poverty status for pensioners.

	Fixed effects	Pooled OLS	System GMM
Income-based poverty, t – 1	-0.095***	0.878***	0.433***
	(0.002)	(0.001)	(0.007)
Observations	438,899	438,899	167,902
R^2	0.009	0.696	
Adjusted R^2	-0.544	0.696	
F Statistic	2,489.687*** (df = 1; 281705)	1,333,407.000*** (df = 1; 438898)	

Note: *p<0.1; **p<0.05; ***p<0.01

Table 2.8: Linear probability models for asset-based poverty (0 / 1) with lagged asset-based poverty status for pensioners.

	Fixed effects	Pooled OLS	System GMM
Asset-based poverty, t – 1	-0.087***	0.718***	0.427***
	(0.002)	(0.001)	(0.010)
Observations	438,899	438,899	167,902
R^2	0.007	0.485	
Adjusted R^2	-0.547	0.485	
F Statistic	2,007.669*** (df = 1; 281705)	438,662.200*** (df = 1; 438898)	
Note:			*p<0.1; **p<0.05; ***p<0.01

The FE estimates for income and asset-based poverty persistence are again negative and not reasonable. The Pooled OLS estimates suggest very strong poverty persistence, with poverty in the previous period increasing the probability to be poor again in the current period by 87.8 percentage points for income poverty and 71.8 percentage points for asset-based poverty. The System GMM estimates suggest an increase of the probability to be poor in the current period by 43.3 and 42.7 percentage points for income and asses-based poverty respectively, due to poverty in the previous period. We notice how both the Pooled OLS and System GMM estimates are larger than for the younger age group, which is to be expected, since pensioners are less strongly attached to the labor market and therefore, if they are poor, are more likely to remain poor.

Table 2.9: Linear probability models for income and asset-based poverty (0 / 1) with financial variables in logs and lagged income and asset-based poverty status for pensioners.

	System GMM: Income poverty	System GMM: Asset-based poverty
Log of 1st earner's wages	-2.070***	-0.334***
	(0.225)	(0.040)
Log of 2nd earner's wages	-1.488***	-0.379***
	(0.112)	(0.027)
Log of income from real estate	-0.130***	0.019***
	(0.002)	(0.001)
Log of income from private transfers	-0.017***	-0.004***
	(0.0004)	(0.0002)
Log of OASI	-0.363***	-0.206***
	(0.010)	(0.005)
Log of pensions, 2nd pillar	-0.265***	-0.017***
	(0.003)	(0.001)
Log of pensions, 3rd pillar	-0.029***	0.006***
	(0.002)	(0.001)
Log of pensions, other	-0.160***	-0.020***
	(0.004)	(0.001)
Log of supplementary benefits	-0.046***	-0.016***
	(0.0005)	(0.0003)
Log of social assistance	-0.019***	-0.007***
	(0.001)	(0.001)
Log of premium reductions	0.016***	0.007***
	(0.0003)	(0.0002)
Log of canton-specific aid	-0.008***	-0.007***
	(0.001)	(0.001)
Log of taxes	-0.016***	-0.008***
	(0.001)	(0.0004)
Log of payments from private transfers	0.130	-0.011
	(0.225)	(0.032)
Log of liquidities	0.011***	-0.014***
	(0.0002)	(0.0003)
Log of household basic needs	0.623***	0.238***
	(0.033)	(0.011)
Log of gross rent	-0.901***	-0.291***
	(0.048)	(0.015)
Log of health insurance premia	0.013*	0.012***
	(0.007)	(0.003)
Income-based poverty, t - 1	0.291***	
	(0.006)	
Asset-based poverty, t - 1		0.305***
		(0.010)
Observations	167,902	167,902
Note:		*p<0.1; **p<0.05; ***p<0.01

Again estimates for poverty poversistence are smaller than in the models containing only the lagged dependent variable, but larger than for the younger group. For pensioners past poverty status increases the probability to be poor again in the current period by 29.1 percentage points for income-poverty and by 30.5 percentage points for asset-based poverty. Besides the estimates for the lagged dependent variables, the largest estimates are again found for an increase in a household's main or secondary earner's income. An increase of the income of a household's main earner by 1 percentage point reduces the probability to be income poor by approximately 2.1 percentage points and the probability to be asset-based poor by approximately 0.3 percentage points. We notice that this effect of an increase in the main earner's income on income poverty is much larger than for the younger group. It is unusual for pensioners to have a labor market income, which generally makes them likely to be income poor. But pensioners that do have a labor market income are much less likely to be income poor, respectively. Continuing in the order of magnitude, an increase of a household's gross rent decreases the probability to be income or asset-based poor, again denoting wealthier households. While an increase in a household's basic needs increases the probabilty to be income or asset-based poor. We also notice the importance of the OASI, other pensions and incomes from real estate to reduce the probability of being income or asset-based poor for pensioners.

2.6 Conclusion

To answer our research question (1), we conclude that generally asset-based poverty is the more dynamic state and easier to escape from than income poverty. We have seen this in initial descriptive statistics showing that a larger share of the population is income poor in all four observed years rather than in exactly two or three years, which we do not find for asset-based poverty. Alluvial charts show that in the 2012 income poor population a larger share of the asset-based poor escapes asset-based poverty than the respective share for the income poor. Our analytical results confirm this, with the exception of the estimate for asset-based poverty persistence for pensioners (0.305), which is larger than the respective estimate for income poverty persistence (0.291).

The finding that asset-based poverty is the more dynamic state and easier to escape from than income poverty may have much to do with the benefit system in Switzerland which requires depletion of financial assets below a certain threshold before a claim to social assistance can be made. This may require persons and households which are unable to leave income poverty out of their own resources, to first enter asset-based poverty before leaving poverty.

To answer our research question (2), we conclude that poverty, especially income poverty, is persistent. Only 57.9% of the 2012 income poor population escape income poverty over the observed four years. The surest way out of income or asset-based poverty is a household's strong attachment to the labor market. The importance of labor market attachment to avoid income and asset-based poverty is consistent with the literature and is also found for results with the same data in a cross-sectional perspective (c.f. Hümbelin et al. 2022). For pensioners, we also notice the importance of the OASI, other pensions and incomes from real estate to reduce the probability of being income or asset-based poor.

Although we observe many individuals in the data we used, the time-series is quite short and comprises only four years. Drawing on data from the social security earnings records (SSER[13]), which are available from 1981 (c.f. Kalambaden and Martınez 2021), would considerably lengthen the time-series. A longer time-series would decrease the "Nickell's bias" which our FE estimates have suffered from. Strictly speaking, the SSER data would not allow us to study poverty persistence. But they would allow us to study low-income persistence and the persistence of low-income into poverty with further lags. This could be an interesting exercise to better understand low-income dynamics and the importance of low-income trajectories for poverty.

[13]https://www.zas.admin.ch/zas/en/home/services-en-ligne/particuliers/extrait-du-compte-individuel.html, last visited on 04.06.2023.

Chapter 3

Low caseload vs. rich funding

A case study of two labor market programs

3.1 Introduction

A rapid integration for refugees into the labor market is important for refugees as well as their host country. From a government perspective, economically independent refugees reduce the costs of welfare expenditure and increase tax revenue. The “Integration Agenda Switzerland” lists vocational education of young refugees and the labor market integration of adult refugees as two of five targets, alongside targets on local language proficiency and familiarization with local customs and contacts with the local population[1]. From the perspective of individual refugees, economic independence is often the only alternative to dependence on social assistance, since usually no other safety net is available.

It is interesting to know, which strategies work best for a rapid labor market integration for refugees. In this study we look at two Swiss active labor market programs (ALMPs) targeted at refugees. Both programs are offered by the same ALMP provider. While the first program targets all client skill levels, the second program targets only “mid- to high-skilled” clients. This introduces a skill-split between the two programs, whereas in the period

[1]c.f. https://www.sem.admin.ch/sem/de/home/integration-einbuergerung/integrationsfoerderung/kantonale-programme/integrationsagenda.html, last visited on 04.06.2023.

preceding the second program's introduction (i.e., the pre-period) all client skill levels were served in the first program.

The first program is characterized by a lower caseload per job coach relative to the pre-period, while the second program is characterized by richer funding and more flexibility regarding the use of program funds relative to the pre-period. To assess the impact of the two different program strategies we link program data to administrative data on employment and earnings. We use balancing to replicate "high-skilled" and "low-skilled" client groups in the pre-period. We then use event-study analysis and difference-in-differences estimation to study how clients in the two programs performed in terms of employment rate and income relative to their skill-level counterparts in the pre-period.

In our event-study analysis, we find that the additional resources helped improve labor market outcomes on both ALMPs. However, we find larger effects for the lowered mean caseload for the job coaches working with the "lower-skilled" refugees than for the richer funding and more flexible use of funds on the program working with the "higher-skilled" refugees. Effects also take hold sooner following program entry for the "lower-skilled" group. We find a statistically significant difference-in-differences estimate only for the employment rate for the "lower-skilled" group which increased by 9.4 percentage points in the short-run.

The remainder of this article is organized as follows: Section 2 reviews the literature on labor market integration for refugees. Section 3 describes the background and program details and states our research questions. Section 4 details the data and methods used. Section 5 presents results on employment rate and income, discusses the results and compares them to previous results for the studied groups. Section 6 concludes.

3.2 Labor market integration for refugees

Active labor market programs (ALMPs) are programs aimed at improving the labor market outcomes for a target population – usually an unemployed population with the aim of rapid and durable (re)integration into the labor market. With the exception of direct employment programs in the public sector (Kluve 2010; Gerfin and Lechner 2002), the literature generally reports positive labor market effects for ALMPs (Card et al. 2010; Focacci 2020; Goller et al. 2021), with more favorable results reported for programs with wage subsidies (Kluve 2010; Behncke et al. 2006; Gerfin and Lechner 2002). ALMPs are reported to be more effective for long-term unemployed (Lalive et al. 2011; Gerfin et al. 2005) and women (Card et al. 2018; van Ours et al. 2000; Greenberg et al. 2003).

The intensity of monitoring of the job search effort as well as warning and enforcement of sanctions may be further important aspects contributing to an ALMPs efficiency (Lalive et al. 2005; Huber et al. 2017; Kluve 2010; Behncke et al. 2010). These may in turn be influenced by the caseload of case workers, with lower caseload allowing for more intensive support and monitoring of the job search effort and more intensive enforcement of sanctions (Hainmueller et al. 2016). Finally, in a meta-analysis Greenberg et al. (2003) report no evidence that more expensive training programs perform better.

There may be several barriers that make labor market integration of immigrants more challenging than the labor market (re)integration of native job seekers. Proficiency in the local language (Lochmann et al. 2019; Auer 2018) plays an important role for finding a job. It may be difficult to have a foreign degree accredited in the host country (Bennet-AbuAyyash et al. 2009). And individuals may be subject to discrimination based on their ethnic background (Zschirnt and Ruedin 2016).

While people that immigrate for labor market reasons may be able to return to their origin country if they cannot establish economic independence, this is usually not possible for refugees. Networks can improve chances for finding a job and upon arrival in the host country the size of that network may depend on how strongly the ethnic group to which one belongs is represented locally (Martén et al. 2019). Networks also grow over time and therefore depend on the time since arrival in the host country (Cheung and Phillimore 2014). Given that refugees have fled from conflict, (mental) health problems and trauma may be another barrier to labor market integration and the journey from the origin country to the host country may also entail a deterioration of human capital (Brell et al. 2020).

Even within the refugee population there is a hierarchy. Asylum seekers are put at a disadvantage. There are restrictions on mobility and the possibility to work. The longer the asylum process takes, the later an integration into the labor market can occur. Therefore, while the time since arrival in the host country should positively affect labor market integration, through enlarged networks and improved proficiency in the local language, the duration spent in the asylum process negatively affects labor market integration and may discourage individuals (Hainmueller et al. 2016). Persons with a temporary residence permit may also still face higher restrictions regarding family reunification, housing and mobility (c.f. Bertrand 2019) relative to recognized refugees and their "temporary" status may discourage hiring.

Wage subsidies are reported as an effective ALMP instrument also for immigrant populations (Butschek and Walter 2014). The same is true for intensive counselling for immigrants (Joona and Nekby 2012). And job search assistance may be effective for lower-educated refugees (Battisti et al. 2019).

In the next section we give information about the background and program details, before formulating our research questions.

3.3 Background and program details

We study a Swiss provider that has offered ALMP for refugees under a Pay-for-services[2] (PFS) contract for many years. In August 2015 a Social Impact Bond (SIB) program is introduced at the same provider in parallel with the continued PFS program and financed by the same public administration funder. The SIB program also offers ALMP for refugees but targets only "mid- to high-skilled" clients. Referrals to the SIB come from the PFS program or other social service providers in the region. Candidates for the

[2]Please note that in this article "PFS" always refers to "Pay for services", unlike "Pay for success" which refers to performance-based-contracts.

SIB program participate in a 10-day work-readiness trial in metal working. Less work-ready clients can be moved to the PFS program during the work-readiness trial or after starting in the SIB program (c.f. Hevenstone et al. 2023b). We refer to the period preceding the SIB program's introduction as the "pre-period," whereas we refer to the period following the SIB program's introduction as the "post-period" for the remainder of the article.

SIBs are a format of performance-based-contracts involving a service provider, a public administration party, an investor and an evaluator that measures performance upon which the investor's return on investment paid by the public administration is contingent (c.f. Hevenstone et al. 2023a; Fraser et al. 2018). Payment under a SIB is based on outcomes to incentivize greater performance, rather than being based on time and effort as in a PFS contract. Note however that in the studied case contract incentives to the provider and investor were relatively weak, compared to other SIB contracts. The SIB program could offer wage subsidies. This was abandoned early on in the program, however, and the related contract target was removed since wage subsidies saw no application in practice, which is contrary to the dominating view in the ALMP literature (c.f. Kluve 2010; Behncke et al. 2006; Gerfin and Lechner 2002). Lastly, the SIB program operated under a "first place, then train" principle. In a quasi-experiment Arendt (2022) reports mixed results for work-first policies for refugees in Denmark, although men find work more quickly in the short-run.

The SIB had richer funding and more flexibility regarding the use of program funds (c.f. Hevenstone et al. 2023b). Whereas the PFS program expanded the number of job coaches on the program (or increased their job percentages) in the post-period which led to a lower caseload, while the available funding on the program increased at a slower rate. We calculate the mean available funding per client and the mean caseload per 100% job on each program based on provider accounting information. Although these are not actual amounts spent on each client or actual time spent with each client, this can give us an image of the overall financial and personal resources available on the programs. We use the respective level on the PFS program in 2015 as the reference period. The SIB program was subjected to a client take-up stop starting in August 2019 leading to substantially higher mean available funding per client and lower mean caseload per 100% job for 2019. Program information for 2019 is not used for the analysis.

Table 3.1: Mean available funding per client and mean caseload per 100% job.

	Mean available funding per client (PFS 2015 = 100%)		**Mean caseload per 100% job (PFS 2015 = 100%)**	
	PFS	**SIB**	**PFS**	**SIB**
2013	134%	-	-	-
2014	94%	-	96%	-
2015	100%	140%	100%	244%
2016	114%	267%	81%	85%
2017	153%	226%	54%	81%
2018	134%	198%	64%	86%
2019	*163%*	*452%*	*51%*	*38%*

Note: Based on provider accounting information and own calculations. Client take-up stop on the SIB program starting in August 2019 leads to substantially higher available funding and lower caseload on the SIB in 2019. While there is a substantially higher caseload on the SIB in its introduction year in 2015. Program information for 2019 is not used for the analysis.

Looking at client characteristics in the SIB and PFS programs in the post-period (c.f. Table 3.6), we find that clients in the SIB program are more skilled in terms of German level and education. They have been staying in Switzerland on average for one year longer at their respective time entering the program. There also seems to be a male bias in the SIB program, which may be due to the work-readiness trial in metal working.

If we compare the client pool of the SIB and PFS program in the post-period to the client pool of the PFS program in the pre-period (c.f. Table 3.7), we notice that client characteristics have stayed roughly stable between the two periods, with an overall increase in male participants and a reduction in clients with no concluded compulsory education. We also notice that data quality improved significantly in the post-period, which is mostly due to reporting requirements on the SIB contract.

Looking at assignment to services we find no evidence of participants in the SIB receiving greater assistance than PFS clients during the post-period (c.f. Table 3.8). Rather clients in the PFS program had more conversations with their job coaches, which is in line with the lower mean caseload on the PFS program, and were assigned to computer and job search courses more frequently. However, from qualitative interviews with job coaches on either program (c.f. Hevenstone et al. 2023b) we know that the SIB program could finance external courses and that language courses on the SIB program were more intensive in terms of class size, cost, and frequency. Conversations with their job coaches were also longer. As such, we refrain from drawing a conclusive assessment of the assistance situation with our available data. Overall, however, we are confident that we can replicate the skill-levels in the SIB and PFS program during the post-period in the pre-period and contrast them to their skill-level counterparts. We formulate the following two research questions:

(1) How does the lower mean caseload per 100% job impact the employment rate and income of the "low-skilled" group?
(2) How does the richer funding and greater flexibility regarding the use of program funds impact the employment rate and income of the "high-skilled" group?

We expect that the lower caseload has a positive impact on the clients in the PFS program due to a greater capacity for intensive support and monitoring of the job search effort (c.f. Hainmueller et al. 2016). For the SIB program, our expectations are mixed. Richer funding should not by itself have an impact on employment outcomes according to the meta-analysis by Greenberg et al. (2003). The SIB program could however draw on external courses. The greater funding could therefore counteract the lower personal resources. Being that this is a predominantly male client group the "first place, then train" principle may also help clients find work more quickly, at least in the short-run. We detail the data and methods used for the analysis in the next section.

3.4 Data and methods

We use individual data from the ALMP provider (client characteristics and services offered) for the 2010 to 2018 period and two administrative datasets: (1) social assistance statistics[3] and (2) social security earnings records (SSER[4]), which contain social assistance and employment data for the 2008 to 2018 period and link them via the unique social security number in Switzerland (the AHV13). The PFS program served other persons dependent on social assistance alongside refugees, but only refugees are included in our data. Refugees that have lived in Switzerland long enough to obtain a settlement permit (C) are excluded from the analysis.

We refer to clients served in the SIB program as the "high-skilled" group and to clients served in the PFS contract in the post-period as the "low-skilled" group. We balance clients in the pre-period to the SIB program and to the PFS program in the post-period using ebalance[5] (c.f. Hainmueller 2012). Our balancing is based on age at program entry, years since arrival in Switzerland, gender, immigration status, region of origin, highest concluded education, marital status, social benefit history (2 years), employment history (2 years) and earnings history (2 years). We do not balance on German level since we would lose many observations due to missings. It would also be useful to balance individuals on the duration of the asylum process, but we do not have this information. In this way we obtain a "high-skilled" group and a "low-skilled" group in the pre-period which we can confront to clients in the post-period.

[3]Recipients of social benefits | Federal Statistical Office (admin.ch), last visited on 04.06.2023.

[4]https://www.zas.admin.ch/zas/en/home/services-en-ligne/particuliers/extrait-du-compte-individuel.html, last visited on 04.06.2023.

[5]All computations were done in R (R Core Team 2023).

Table 3.2: Four compared groups.

	Pre-period	Post-period
"Low-skilled"	**"Low-skilled" PFS pre-period**	**PFS**
"High-skilled"	**"High-skilled" PFS pre-period**	**SIB**

We present covariate balance checks for the "low-skilled" and "high-skilled" groups in the Appendix (c.f. Tables 3.9 and 3.10). Since important differences remain after balancing, results need to be interpreted with caution.

Following (Miller et al. 2021) our empirical strategy looks at changes in the employment rate and monthly income for clients in the ALMP programs. We run our analysis for clients in the SIB program and their skill-level counterparts in the pre-period and for clients in the PFS program in the post-period and their skill-level counterparts in the pre-period separately. We estimate this using event-study models that allow us to assess the evolution of relative outcomes while controlling for fixed differences between groups and yearly trends over time. We estimate:

$$Y_{igt} = Post_g * \sum_{y=-4,\ y\neq 0}^{2} \beta_y * I(t_s - t_s^* = y) + \beta_{year} + \beta_g + \epsilon_{igt}. \tag{3.1}$$

Our data is constructed at the individual (i) by months since program entry (t) level. Each individual belongs to a program group (g). Y_{igt} refers to individual i in group g's employment status or monthly income at time t. The variable $Post_g$ equals 1 if individual i was an ALMP participant in the post-period, and zero otherwise. Indicator variables $I(t_s - t_s^* = y)$ measure the time relative to the semester that an individual entered an ALMP program in the post-period, and are zero in all semesters for all ALMP participants in the pre-period. The omitted category is $y = 0$, which spans the months -4 to 1 to program entry. Therefore, each estimate of β_y provides the change in outcomes for ALMP participants in the post-period relative to ALMP participants in the pre-period during semester y, as measured from the semester of program entry. If employment rates and monthly incomes for ALMP participants in the post- and pre-period were trending similarly prior to program entry, we expect that estimated coefficients associated with event times $y = -4$ to $y = -1$ will be small and not statistically significant. β_g denotes group fixed effects. β_{year} denotes calendar year fixed effects, which account for general trends in labor market outcomes for all individuals in our sample, including gradually longer durations since arrival in Switzerland. We estimate equation (3.1) with a linear model for monthly income and a linear probability model for employment status and report standard errors that are clustered at the individual level.

In addition to the event study analyses, we also present difference-in-differences (DiD) estimates as a summary of the effect across all semesters following program entry. These are estimated using the same equation except that the event-study indicators are replaced with a single variable denoting the time-period following the semester of program entry, yielding $Post_g * Post_s$. This indicator turns on starting in the semester following the semester of program entry for ALMP participants in the post-period. For the DiD regressions we also drop the group fixed effects and include age at program entry, duration since arrival, gender, highest concluded education, immigration status, region of origin, and marital status as regressors.

For both the event-study analyses and the DiD regression models we restrict the sample to clients that are observable from -28 to 13 months since program entry. Since we omit the semester containing the four months prior to program entry for our event-study analyses, results are not prone to Ashenfelter's dip (c.f. Abadie 2005). We exclude months -4 to 0 to program entry for our DiD regression models for the same reason.

Table 3.3: Description of selected variables.

Variables	**Operationalization and measurement**
Dependent variables	
Monthly income	A client's monthly income (in CHF).
Proportion employed	Client is employed in a given month = 1.
Independent variables	
Post_g	Being a participant in the PFS program in the pre-period from 2010 up to July 2015 = 0, Being a participant in either the SIB program or the PFS program in the post-period from August 2015 up to 2018 = 1.
Post_s	= 1 for the semesters following program entry and 0 otherwise.
Control variables: Demographic background	
Age at program entry	Age at entry into the program (in years).
Duration since arrival in CH	Duration since arrival in Switzerland (in years).
Gender	A simple classification of an individual's biological gender according to population register data: Male = 1, Female = 0.
Education	Highest concluded education measured in levels: Compulsory education not concluded, Compulsory education concluded, Higher education.

3.5 Results

Labor market outcomes

Our event-study analyses for the “low-skilled” groups show that trends for the employment rates and mean incomes were similar in the semesters prior to program entry as estimates associated with the event times from -4 to -0 are small and not statistically significant. In the semesters following program entry estimates associated with event times 1 and 2 become larger and turn statistically significant. This suggests that the PFS group in the post-period found work more quickly and had higher monthly incomes relative to their pre-period skill-level counterpart due to the lower caseload for job coaches on the program. For our difference-in-differences models, only the estimate for proportion employed is significant. It suggests that chances of finding a job improved by 9.4 percentage points in the short-run for PFS participants in the post-period relative to “low-skilled” PFS participants in the pre-period.

Table 3.4: Event-study analysis and difference-in-differences estimates for "low-skilled" groups.

	Event-study: Proportion employed (0 / 1)	Event-study: Mean income (CHF)	DiD: Proportion employed (0 / 1)	DiD: Mean income (CHF)
Event time (semesters): -4	-0.000	51.123		
	(0.028)	(61.268)		
Event time (semesters): -3	0.003	63.594		
	(0.025)	(54.996)		
Event time (semesters): -2	-0.005	52.620		
	(0.023)	(47.286)		
Event time (semesters): -1	-0.008	23.655		
	(0.014)	(26.367)		
Event time (semesters): 1	0.098 ***	215.372 ***		
	(0.025)	(61.589)		
Event time (semesters): 2	0.256 ***	546.245 ***		
	(0.042)	(108.337)		
pfs_post x post			0.094 *	160.402
			(0.041)	(106.982)
N x Months since program entry	15'859	15'859	13'969	13'969
R2	0.076	0.070	0.107	0.091

*** p < 0.001; ** p < 0.01; * p < 0.05.

Our event-study analyses for the "high-skilled" groups also show that trends for the employment rates and mean incomes were similar in the semesters prior to program entry as estimates associated with the event times from -4 to -0 are not statistically significant. In the semesters following program entry estimates associated with event times 1 and 2 become larger, but they turn statistically significant only during the 2^{nd} semester following program entry. Neither of our difference-in-differences estimates is statistically significant. This suggests that while the richer funding and more flexible use of program funds may have helped clients in the SIB program find work more quickly and have higher monthly incomes than "high-skilled" clients in the pre-period, these effects were weaker than the ones found for the "low-skilled" group due to the lower caseload. The effects took hold at a later event time, despite the "first place, then train" principle.

Table 3.5: Event-study analysis and difference-in-differences estimates for "high-skilled" groups.

	Event-study: Proportion employed (0 / 1)	Event-study: Mean income (CHF)	DiD: Proportion employed (0 / 1)	DiD: Mean income (CHF)
Event time (semesters): -4	-0.054	-32.425		
	(0.063)	(100.867)		
Event time (semesters): -3	-0.059	-58.972		
	(0.055)	(85.160)		
Event time (semesters): -2	-0.017	-8.528		
	(0.047)	(79.573)		
Event time (semesters): -1	0.002	68.295		
	(0.036)	(72.778)		
Event time (semesters): 1	0.050	172.470		
	(0.040)	(97.026)		
Event time (semesters): 2	0.138 *	535.196 ***		
	(0.056)	(142.966)		
sib x post			0.011	180.111
			(0.080)	(174.044)
N x Months since program entry	13’577	13’577	11’957	11’957
R2	0.051	0.088	0.096	0.131

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

To summarize, additional resources seem to have improved labor market outcomes on both ALMPs. We find larger effects for the lowered mean caseload for the job coaches working with the "lower-skilled" refugees than for the richer funding and more flexible use of funds on the program working with the "higher-skilled" refugees.

Comparison to earlier estimates

Guggisberg et al. 2021 is the evaluation of the SIB program on which payment to the SIB investor was contingent. They use the same linked dataset as this article for the SIB clients and the PFS clients in the post-period. These groups therefore coincide with our "high-skilled" and "low-skilled" groups in the post-period. They run descriptive analyses and calculate logistic and ordinary least squares (OLS) regression models for participation in the SIB group vs. the PFS group in the post-period. They find no statistically significant differences for the employment rate of the two groups. But they do find a statistically significant difference for incomes, with monthly incomes being 673 CHF higher on average for participants in the SIB group.

Hevenstone et al. 2023b conducted a mixed-methods study to measure the "SIB effect", i.e., the effect of the SIB financing mechanism on social assistance and labor market outcomes for program groups net of the program effects associated with an ALMP program itself. To do so they study a Dutch and a Swiss ALMP financed through a SIB and program data for non-SIB clients linked to data from administrative datasets. Alongside the quantitative analysis, they conduct qualitative interviews with key stakeholders for the programs and SIB contracts. For the Swiss case, they use the same linked dataset as this article for the SIB clients and the PFS clients in the pre-period. Since PFS clients in the pre-period are balanced to match the SIB clients in terms of characteristics and labor market and social assistance history, these coincide with our "high-skilled" groups in the post- and pre-period. In addition, they use information on a group of refugees derived from the population register data that did not participate in the studied ALMPs. This group is balanced to the SIB group to isolate the "SIB effect" using difference-in-differences estimation.

They find that the "SIB effect" decreased social benefit use and increased the employment rate and earnings, which is consistent with our results of the event-study analysis of the "high-skilled" groups for the second semester following program entry, although our difference-in-differences results are not statistically significant for the "high-skilled" groups.

3.6 Conclusion

Rapid labor market integration for refugees is a challenge for refugees as well as their host country. Relative to native job seekers refugees may face additional barriers to labor market integration which range from lacking proficiency in a local language and difficulties to get foreign degrees accredited to disadvantages due to temporary residence permits. As such, it is interesting to know which strategies work best for a rapid labor market integration for refugees.

In this study we look at two Swiss active labor market programs (ALMP) targeted at refugees. Both programs are offered by the same ALMP provider. While the first program targets all client skill levels, the second program targets only "mid- to high-skilled" clients. This introduces a skill-split between the two programs, whereas in the period preceding the second program's introduction (i.e., the pre-period) all client skill levels were served in the first program.

The first program is characterized by a lower caseload per job coach relative to the pre-period, while the second program is characterized by richer funding and more flexibility regarding the use of program funds relative to the pre-period. To assess the impact of the two different program strategies we link program data to administrative data on employment and earnings. We use balancing to replicate "high-skilled" and "low-skilled" client groups in the pre-period. We then use event-study analysis and difference-in-differences estimation to study how clients in the two programs performed in terms of employment rate and income relative to their skill-level counterparts in the pre-period.

In our event-study analysis, we find that the additional resources helped improve labor market outcomes on both ALMPs. However, we find larger effects for the lowered mean caseload for the job coaches working with the "lower-skilled" refugees than for the richer funding and more flexible use of funds on the program working with the "higher-skilled" refugees. Effects also take hold sooner following program entry for the "lower-skilled" group. We find a statistically significant difference-in-differences estimate only for the employment rate for the "lower-skilled" group which increased by 9.4 percentage points in the short-run.

The biggest limitation of our study is that we do not directly compare the two program strategies. We only assess how the "low-skilled" group was affected by the lower caseload of job coaches and how the "high-skilled" group was affected by the richer funding and more flexible use of program funds. However, it is reasonable to assume an interaction between the program strategy and skill-level. E.g., richer funding and more flexible use of program funds could possibly yield larger effects for the "lower-skilled" group than the ones found for the lowered mean caseload per job coach and vice-versa. To disentangle this possible interaction and be able to directly compare the effects of the two program strategies, the analysis would have to be re-run for "mid-skilled" groups of participants in both programs in the post-period and participants in the pre-period. This approach would also improve the balancing of the studied groups.

Appendix

Table 3.6: Client characteristics in the SIB and PFS program in the post-period.

		SIB		PFS		
		Mean / %-Share	**Sd**	**Mean / %-Share**	**Sd**	**p-value**
Age at programe entry (years)		34	8.2	33	8.6	0.07
Duration since arrival (years)		4	1.6	3	1.2	< 0.05
Male (%)		81.9		73.8		< 0.05
Education (%)	Comp. edu. n.c.	11.7		28.1		< 0.05
	Comp. edu.	52.4		45.5		0.13
	Higher edu.	35.9		26.5		< 0.05
German level (%)	A1	13.4		39.8		< 0.05
	A2	35.1		34.9		0.98
	B1+	51.5		25.3		< 0.05
N		232		442		

T-tests for differences in group averages or shares significant at 5%-level for: Years since arrival in Switzerland, Male, Compulsory education not concluded, Higher education, A1, B1+.

Table 3.7: Characteristics of the client pool in the pre- and post-period.

		pre-period (2010 - July 2015)		post-period (August 2015 - 2019)		
		Mean / %-Share	Sd	Mean / %-Share	Sd	p-value
Age at program entry (years)		33	8.1	33	8.5	0.21
Duration since arrival (years)		3	1.6	3	1.5	0.36
Male (%)		71.4		76.6		0.05
Education (%)	C. educ n. conc.	31.4		20.2		0.03
	C. educ. conc.	45.1		48.8		0.5
	H. education	23.5		31		0.12
German level (%)	A1	18.9		25.2		0.15
	A2	43.2		35		0.12
	B1+	37.8		39.8		0.71
N		503		674		

T-tests for differences in group averages or shares significant at 5%-level for: Male, Compulsory education not concluded.

Table 3.8: Assignment to types of assistance in the SIB and PFS program in the post-period.

	SIB		PFS		
	Mean / %-Share	Sd	Mean / %-Share	Sd	p-value
Number of conversations	4	3.6	7	4.6	< 0.05
Computer / Job search course	0.9		18.9		< 0.05
German course	22.4		23.2		0.81
N	232		442		

T-tests for differences in group averages or shares significant at 5%-level for: Number of conversations, Computer or Job search course.

Table 3.9: Covariate balance check for the “low-skilled” groups.

	unweighted			weighted		
	PFS	Pre-period w. t. PFS	t-test p-values	PFS	Pre-period w. t. PFS	t-test p-values
Age at program entry (years)	33.7	33.1	< 0.001	33.7	33.2	< 0.001
Duration since arrival in CH (years)	3.6	3.5	< 0.001	3.6	3.6	0.01
Male (%)	70.5	72.9	< 0.001	70.5	74.7	< 0.001
Proportion without concluded compulsory education (%)	28.6	21.9	< 0.001	28.6	21.4	< 0.001
Proportion with concluded compulsory education (%)	49.8	62.8	< 0.001	49.8	60.4	< 0.001
Proportion with higher education (%)	21.6	15.3	< 0.001	21.6	18.2	< 0.001
Proportion with German level A1 (%)	34.2	13.6	< 0.001	34.2	11.6	< 0.001
Proportion with German level A2 (%)	38.9	42.9	< 0.001	38.9	41.4	< 0.001
Proportion with German level B1 or higher (%)	26.9	43.5	< 0.001	26.9	47	< 0.001
N:	263	267		263	267	

Table 3.10: Covariate balance check for the "high-skilled" groups.

	unweighted			weighted		
	SIB	Pre-period w. t. SIB	t-test p-values	SIB	Pre-period w. t. SIB	t-test p-values
Age at program entry (years)	33.8	33	< 0.001	33.8	32.8	< 0.001
Duration since arrival in CH (years)	3.8	3.5	< 0.001	3.8	3.9	0.18
Male (%)	81.3	71	< 0.001	81.3	79.1	< 0.001
Proportion without concluded compulsory education (%)	10.5	22.7	< 0.001	10.5	13.7	< 0.001
Proportion with concluded compulsory education (%)	50.9	63.2	< 0.001	50.9	55.8	< 0.001
Proportion with higher education (%)	38.6	14.1	< 0.001	38.6	30.5	< 0.001
Proportion with German level A1 (%)	8.1	13.5	< 0.001	8.1	7.4	0.05
Proportion with German level A2 (%)	36.8	45.6	< 0.001	36.8	39.8	< 0.001
Proportion with German level B1 or higher (%)	55.1	40.9	< 0.001	55.1	52.8	< 0.001
N:	161	271		161	271	

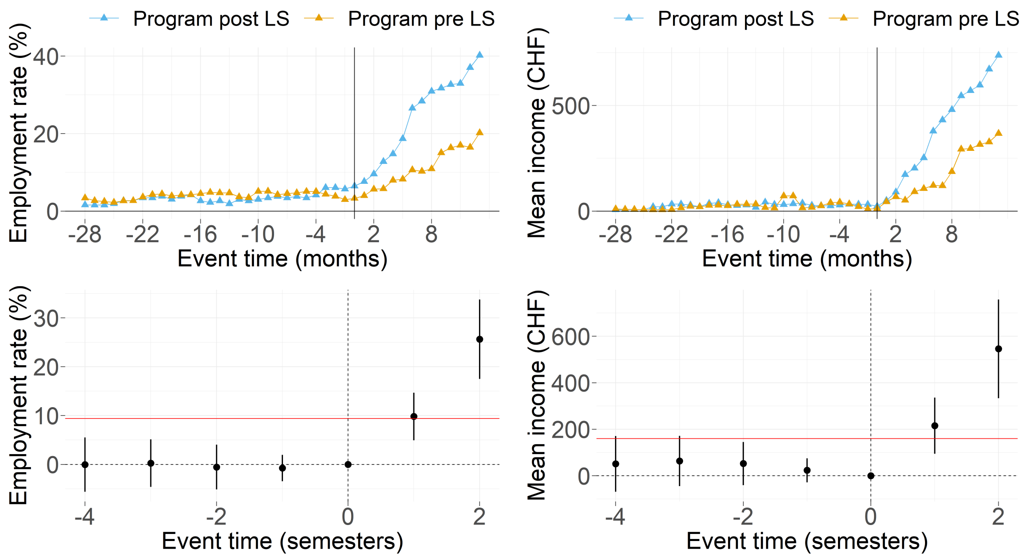

Figure 3.11: Weighted means, event-study analysis and difference-in-differences estimates for the “low-skilled” groups.
Note: The red line corresponds to the DiD estimate.

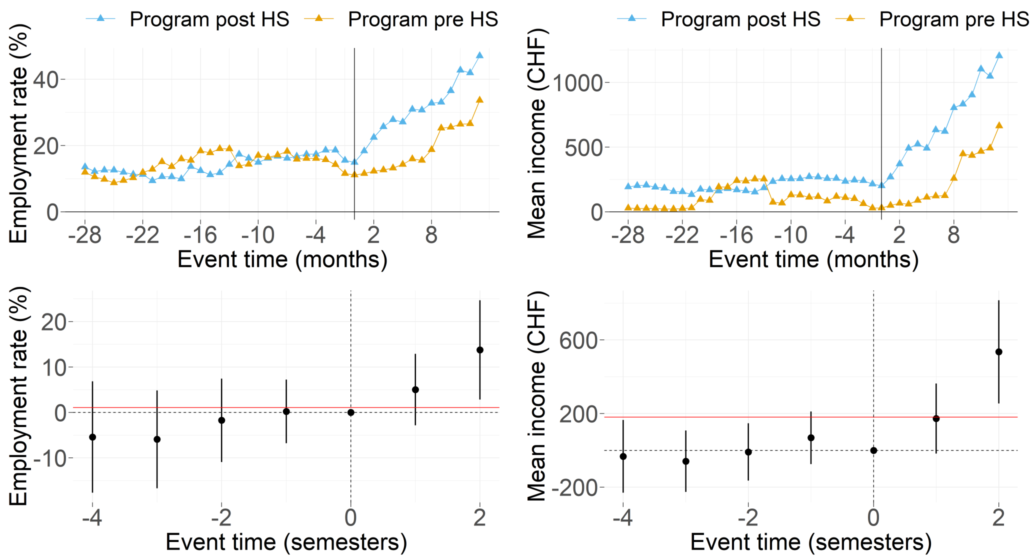

Figure 3.12: Weighted means, event-study analysis and difference-in-differences estimates for the “high-skilled” groups.
Note: The red line corresponds to the DiD estimate.

Bibliography

[1] Alberto Abadie. “Semiparametric Difference-in-Differences Estimators”. en. In: *The Review of Economic Studies* 72.1 (Jan. 2005), pp. 1–19.

[2] Samira Ali et al. “”Feeling Less Than a Second Class Citizen”: Examining the Emotional Consequences of Poverty in New York City”. en. In: *Journal of Family Issues* 39.10 (July 2018), pp. 2781–2805.

[3] S. Alkire and M. Apablaza. “Multidimensional poverty in Europe 2006–2012: illustrating a methodology”. en. In: *Oxford Poverty and Human Development Initiative Working Papers* (2016). ISSN: 2040-8188. URL: `https://ora.ox.ac.uk/objects/uuid:e28d3bc0-a74a-4034-a333-f3fc09fe8c2f` (visited on 05/24/2021).

[4] Facundo Alvaredo. “A note on the relationship between top income shares and the Gini coefficient”. en. In: *Economics Letters* 110.3 (Mar. 2011), pp. 274–277.

[5] Facundo Alvaredo et al. “The Top 1 Percent in International and Historical Perspective”. en. In: *Journal of Economic Perspectives* 27.3 (Aug. 2013), pp. 3–20.

[6] Alberta Andreotti, Enzo Mingione, and Emanuele Polizzi. “Local Welfare Systems: A Challenge for Social Cohesion”. en. In: *Urban Studies* 49.9 (July 2012), pp. 1925–1940.

[7] Eirini Andriopoulou and Panogiotis Tsakloglou. “Once Poor, Always Poor? Do Initial Conditions Matter? Evidence from the ECHP”. en. In: *SSRN Electronic Journal* (2011). ISSN: 1556-5068. DOI: `10.2139/`

ssrn.1933328. URL: https://www.ssrn.com/abstract=1933328 (visited on 08/25/2023).

[8] Eirini Andriopoulou and Panogiotis Tsakloglou. "The Determinants of Poverty Transitions in Europe and the Role of Duration Dependence". en. In: *SSRN Electronic Journal* (2011). ISSN: 1556-5068. DOI: 10.2139/ssrn.1842089. URL: https://www.ssrn.com/abstract=1842089 (visited on 01/05/2023).

[9] Jacob Nielsen Arendt. "Labor market effects of a work-first policy for refugees". en. In: *Journal of Population Economics* 35.1 (Jan. 2022), pp. 169–196.

[10] Klaus Armingeon. "Institutionalising the Swiss welfare state". en. In: *West European Politics* 24.2 (Apr. 2001), pp. 145–168.

[11] Klaus Armingeon, Fabio Bertozzi, and Giuliano Bonoli. "Swiss worlds of welfare". en. In: *West European Politics* 27.1 (Jan. 2004), pp. 20–44.

[12] Susan Athey. "21. The Impact of Machine Learning on Economics". In: *The Economics of Artificial Intelligence: An Agenda*. University of Chicago Press, 2019, pp. 507–552.

[13] Susan Athey and Guido W. Imbens. "The State of Applied Econometrics: Causality and Policy Evaluation". en. In: *Journal of Economic Perspectives* 31.2 (May 2017), pp. 3–32.

[14] Anthony B. Atkinson. *Measuring Poverty around the World*. en. Princeton: Princeton University Press, June 2019. ISBN: 9780691191898. DOI: 10.1515/9780691191898. URL: https://doi.org/10.1515/9780691191898 (visited on 08/25/2023).

[15] Anthony B. Atkinson, Eric Marlier, and Brian Nolan. "Indicators and Targets for Social Inclusion in the European Union". en. In: *JCMS: Journal of Common Market Studies* 42.1 (2004), pp. 47–75.

[16] Rob Atkinson and Simin Da Voudi. "The Concept of Social Exclusion in the European Union: Context, Development and Possibilities". en. In: *JCMS: Journal of Common Market Studies* 38.3 (2000), pp. 427–448.

[17] Daniel Auer. “Language roulette – the effect of random placement on refugees’ labour market integration”. en. In: *Journal of Ethnic and Migration Studies* 44.3 (Feb. 2018), pp. 341–362.

[18] Regina S. Baker. “Why is the American South Poorer?” In: *Social Forces* 99.1 (Aug. 2020), pp. 126–154.

[19] Mary Jo Bane and David T. Ellwood. “Slipping into and out of Poverty: The Dynamics of Spells”. en. In: *The Journal of Human Resources* 21.1 (Winter 1986), pp. 1–23.

[20] World Bank. “Monitoring Global Poverty”. In: *Poverty and Shared Prosperity 2020: Reversals of Fortune*. Oct. 2020, pp. 27–80. DOI: 10.1596/978-1-4648-1602-4_ch1. URL: https://elibrary.worldbank.org/doi/abs/10.1596/978-1-4648-1602-4_ch1 (visited on 08/27/2023).

[21] Michele Battisti, Yvonne Giesing, and Nadzeya Laurentsyeva. “Can job search assistance improve the labour market integration of refugees? Evidence from a field experiment”. en. In: *Labour Economics* 61 (Dec. 2019), p. 101745.

[22] Stefanie Behncke, Markus Frölich, and Michael Lechner. “Aktive Arbeitsmarktpolitik in Deutschland und der Schweiz – Eine Gegenüberstellung”. de. In: *Vierteljahrshefte zur Wirtschaftsforschung* 75.3 (July 2006), pp. 118–154.

[23] Stefanie Behncke, Markus Frölich, and Michael Lechner. “Unemployed and their caseworkers: should they be friends or foes?” en. In: *Journal of the Royal Statistical Society: Series A (Statistics in Society)* 173.1 (2010), pp. 67–92.

[24] Katy Bennett, Huw Beynon, and Ray Hudson. *Coalfields regeneration: Dealing with the consequences of industrial decline*. Policy Press, 2000.

[25] Gill Bentley and Lee Pugalis. “Shifting paradigms: People-centred models, active regional development, space-blind policies and place-based approaches”. en. In: *Local Economy* 29.4-5 (June 2014), pp. 283–294.

[26] Jessica L. Berrett and Bradley S. Holliday. "The Effect of Revenue Diversification on Output Creation in Nonprofit Organizations: A Resource Dependence Perspective". en. In: *VOLUNTAS: International Journal of Voluntary and Nonprofit Organizations* 29.6 (Dec. 2018), pp. 1190–1201.

[27] Paola Bertolini, Marco Montanari, and Vito Peragine. *Poverty and social exclusion in rural areas. Final study report.* European Commission DG Employment and Social Affairs, 2008.

[28] Anne-Laure Bertrand. "Refugees' trajectories in Switzerland: Impact of residence permits on labour market integration". en. In: *Quetelet Journal* 7.1 (Apr. 2019), pp. 71–99.

[29] Martin Biewen. "Measuring state dependence in individual poverty histories when there is feedback to employment status and household composition". en. In: *Journal of Applied Econometrics* 24.7 (Nov. 2009), pp. 1095–1116.

[30] BKSE. *Handbuch Sozialhilfe – Stichwort Grundbedarf für den Lebensunterhalt (GBL).* 2020. URL: `http://handbuch.bernerkonferenz.ch/stichwoerter/stichwort/detail/grundbedarf-fuer-den-lebensunterhalt-gbl/` (visited on 05/24/2022).

[31] Rebecca M. Blank. "Poverty, Policy, and Place: How Poverty and Policies to Alleviate Poverty Are Shaped by Local Characteristics". en. In: *International Regional Science Review* 28.4 (Oct. 2005), pp. 441–464.

[32] Stephen R Bond. "Dynamic panel data models: a guide to micro data methods and practice". en. In: *Portuguese Economic Journal* 1.2 (Aug. 2002), pp. 141–162.

[33] Giuliano Bonoli. "Time Matters: Postindustrialization, New Social Risks, and Welfare State Adaptation in Advanced Industrial Democracies". en. In: *Comparative Political Studies* 40.5 (May 2007), pp. 495–520.

[34] J. Bound et al. "Poverty Dynamics in Widowhood". en. In: *Journal of Gerontology* 46.3 (May 1991), S115–S124.

[35] Andrea Brandolini, Silvia Magri, and Timothy M. Smeeding. "Asset-based measurement of poverty". en. In: *Journal of Policy Analysis and Management* 29.2 (2010), pp. 267–284.

[36] Courtney Brell, Christian Dustmann, and Ian Preston. "The Labor Market Integration of Refugee Migrants in High-Income Countries". en. In: *Journal of Economic Perspectives* 34.1 (Feb. 2020), pp. 94–121.

[37] Monica Budowski, Robin Tillmann, and Manfred Max Bergman. "Poverty, Stratification and Gender in Switzerland". In: *Swiss Journal of Sociology* 28.2 (2002), pp. 297–317.

[38] Sebastian Butschek and Thomas Walter. "What active labour market programmes work for immigrants in Europe? A meta-analysis of the evaluation literature". en. In: *IZA Journal of Migration* 3.48 (Dec. 2014), pp. 1–18.

[39] David Card, Jochen Kluve, and Andrea Weber. "Active Labour Market Policy Evaluations: A Meta-Analysis". en. In: *The Economic Journal* 120.548 (Nov. 2010), F452–F477.

[40] David Card, Jochen Kluve, and Andrea Weber. "What Works? A Meta Analysis of Recent Active Labor Market Program Evaluations". en. In: *Journal of the European Economic Association* 16.3 (June 2018), pp. 894–931.

[41] Strobl Carolin and Zeileis Achim. *Why and how to use random forest variable importance measures (and how you shouldn't).* The R User Conference, Dortmund, 2008.

[42] Bennett-AbuAyyash Caroline et al. *The Evaluation of Immigrants' Credentials: The Roles of Accreditation, Immigrant Race, and Evaluator Biases*. CLSSRN working papers. Vancouver School of Economics, Mar. 2009. URL: `https://ideas.repec.org/p/ubc/clssrn/clsrn_admin-2009-27.html` (visited on 08/26/2023).

[43] Orsetta Causa and Mikkel Hermansen. "Income Redistribution through Taxes and Transfers across OECD Countries". In: *Inequality, Redistribution and Mobility*. Ed. by Juan Gabriel Rodríguez and John A. Bishop. Vol. 28. Research on Economic Inequality. Emerald Publishing Limited, Jan. 2020, pp. 29–74.

[44] Sin Yi Cheung and Jenny Phillimore. "Refugees, Social Capital, and Labour Market Integration in the UK". en. In: *Sociology* 48.3 (June 2014), pp. 518–536.

[45] European Commission. *Investing in Europe's future - Fifth report on economic, social and territorial cohesion*. en. LU: Publications Office, 2010. DOI: doi/10.2776/29620. URL: https://data.europa.eu/doi/10.2776/29620 (visited on 05/24/2021).

[46] Swiss Confederation. *Switzerland implements the 2030 Agenda for Sustainbale Development. Swizterland's Country Report 2018*. Tech. rep. Bern: Federal Department of Foreign Affairs FDFA, 2018.

[47] Andrew Copus et al. "Regional poverty mapping in Europe – Challenges, advances, benefits and limitations". en. In: *Local Economy* 30.7 (Nov. 2015), pp. 742–764.

[48] Mindy S. Crandall and Bruce A. Weber. "Local Social and Economic Conditions, Spatial Concentrations of Poverty, and Poverty Dynamics". en. In: *American Journal of Agricultural Economics* 86.5 (Dec. 2004), pp. 1276–1281.

[49] Eric Crettaz. "A state-of-the-art review of working poverty in advanced economies: theoretical models, measurement issues and risk groups". en. In: *Journal of European Social Policy* 23.4 (Oct. 2013), pp. 347–362.

[50] Yves Croissant and Giovanni Millo. "Panel Data Econometrics in R : The plm Package". en. In: *Journal of Statistical Software* 27.2 (July 2008), pp. 1–43.

[51] Francesco Devicienti. "Estimating poverty persistence in Britain". en. In: *Empirical Economics* 40.3 (May 2011), pp. 657–686.

[52] Francesco Devicienti, Valentina Gualtieri, and Mariacristina Rossi. "THE PERSISTENCE OF INCOME POVERTY AND LIFESTYLE DEPRIVATION: EVIDENCE FROM ITALY". en. In: *Bulletin of Economic Research* 66.3 (July 2014), pp. 246–278.

[53] Philipp Dubach et al. *Armutsbericht Basel-Stadt: Ursachen, Dynamiken, Handlungsempfehlungen*. de. 1. Aufl. Basel: Christoph Merian Verlag, 2010. ISBN: 978-3-85616-500-0.

[54] Bernhard Ebbinghaus. *Comparing Welfare State Regimes: Are Typologies an Ideal or Realistic Strategy?* en. Draft Paper presented at European Social Policy Analysis Network, Edinburgh, Sept. 2012.

[55] Fabian Eckert, Sharat Ganapati, and Conor Walsh. *Skilled Scalable Services: The New Urban Bias in Economic Growth*. en. preprint. Institute Working Paper, Sept. 2019. DOI: 10.21034/iwp.25. URL: https://www.minneapolisfed.org/institute/institute-working-papers/skilled-scalable-services-the-new-urban-bias-in-economic-growth (visited on 06/07/2021).

[56] Gosta Esping-Andersen. *Social foundation of post-industrial societies*. en. Oxford University Press, 1999.

[57] Gosta Esping-Andersen. *The Three Worlds of Welfare Capitalism*. en. Polity Press, 1990.

[58] Eurofound. *Access to Social Benefits: Reducing Non-Take-Up*. en. Publications Office of the European Commission, 2015.

[59] Ross Finnie and Arthur Sweetman. "Poverty dynamics: empirical evidence for Canada". en. In: *Canadian Journal of Economics/Revue Canadienne d'Economique* 36.2 (May 2003), pp. 291–325.

[60] Robert Fluder et al. *Ein Armutsmonitoring für die Schweiz: Modellvorhaben am Beispiel des Kantons Bern*. deu. Tech. rep. Bern: Berner Fachhochschule BFH, Soziale Arbeit, 2020. URL: https://arbor.bfh.ch/id/eprint/12959 (visited on 06/29/2022).

[61] Chiara Natalie Focacci. “”You reap what you sow”: Do active labour market policies always increase job security? Evidence from the Youth Guarantee”. en. In: *European Journal of Law and Economics* 49.3 (June 2020), pp. 373–429.

[62] Didier Fouarge and Richard Layte. “Welfare Regimes and Poverty Dynamics: The Duration and Recurrence of Poverty Spells in Europe”. en. In: *Journal of Social Policy* 34.3 (July 2005), pp. 407–426.

[63] Matt Foulkes and Kai A. Schafft. “The Impact of Migration on Poverty Concentrations in the United States, 1995-2000: Migration on Poverty Concentrations”. en. In: *Rural Sociology* 75.1 (Jan. 2010), pp. 90–110.

[64] Alec Fraser et al. *Evaluation of the Social Impact Bond Trailblazers in Health and Social Care Final report*. en. Policy Innovation Research Unit (PIRU), 2018.

[65] FSO. *Armut in der Schweiz: Konzepte, Resultate und Methoden Ergebnisse auf der Basis von SILC 2008 bis 2010*. Bundesamt für Statistik (BFS), 2012. ISBN: 978-3-303-20028-5.

[66] FSO. *Poverty*. de. Nov. 2020. URL: `https://www.bfs.admin.ch/bfs/de/home/statistiken/wirtschaftliche-soziale-situation-bevoelkerung/wohlbefinden-armut/armut-und-materielle-entbehrungen/armut.html` (visited on 06/04/2021).

[67] FSO. *Regionalporträts 2015: Gemeinden*. Bundesamt für Statistik (BFS), 2015.

[68] Rainer Gabriel et al. “The persistence of social stratification? A life course perspective on poverty in old-age in Switzerland”. en. In: *Swiss journal of Sociology* 41.3 (2015), pp. 465–487.

[69] Michael Gerfin and Michael Lechner. “A Microeconometric Evaluation of the Active Labour Market Policy in Switzerland”. en. In: *The Economic Journal* 112.482 (Oct. 2002), pp. 854–893.

[70] Michael Gerfin, Michael Lechner, and Heidi Steiger. "Does subsidised temporary employment get the unemployed back to work? An econometric analysis of two different schemes". en. In: *Labour Economics* 12.6 (Dec. 2005), pp. 807–835.

[71] Daniel Goller et al. "Active Labour Market Policies for the Long-Term Unemployed: New Evidence from Causal Machine Learning". en. In: *SSRN Electronic Journal* (2021). ISSN: 1556-5068. DOI: 10.2139/ssrn.3874358. URL: https://www.ssrn.com/abstract=3874358 (visited on 12/20/2022).

[72] David H Greenberg, Charles Michalopoulos, and Philip K Robins. "A Meta-Analysis of Government-Sponsored Training Programs". en. In: *Industrial and Labor Relations Review* 57.1 (Oct. 2003), pp. 31–53.

[73] Jürg Guggisberg et al. *"Evaluation Social Impact Bond 2015-2020"*. de. BÜRO FÜR ARBEITS- UND SOZIALPOLITISCHE STUDIEN BASS AG, May 2021.

[74] Elisabeth Gutjahr and Jean-Luc Heeb. "Social assistance trajectories in Switzerland: do they follow discernible patterns?" en. In: *European Journal of Social Work* 19.3-4 (July 2016), pp. 570–585.

[75] Sabine Häder, Michael Häder, and Mike Kühne. *Telephone Surveys in Europe*. en. Berlin, Heidelberg: Springer, 2012.

[76] Jens Hainmueller. "Entropy Balancing for Causal Effects: A Multivariate Reweighting Method to Produce Balanced Samples in Observational Studies". en. In: *Political Analysis* 20.1 (2012), pp. 25–46.

[77] Jens Hainmueller, Dominik Hangartner, and Duncan Lawrence. "When lives are put on hold: Lengthy asylum processes decrease employment among refugees". en. In: *Science Advances* 2.8 (Aug. 2016), e1600432.

[78] Jens Hainmueller et al. "Do Lower Caseloads Improve the Performance of Public Employment Services? New Evidence from German Employment Offices". en. In: *The Scandinavian Journal of Economics* 118.4 (Oct. 2016), pp. 941–974.

[79] Jane L. Harrison, Claire A. Montgomery, and P. Wilner Jeanty. “A spatial, simultaneous model of social capital and poverty”. en. In: *Journal of Behavioral and Experimental Economics* 78 (Feb. 2019), pp. 183–192.

[80] Virginia Hernanz, Franck Malherbet, and Michele Pellizzari. *Take-Up of Welfare Benefits in OECD Countries: A Review of the Evidence*. OECD Social, Employment and Migration Working Papers 17. OECD Publishing., 2004. URL: `http://dx.doi.org/10.1787/525815265414` (visited on 08/20/2015).

[81] Debra Hevenstone et al. “The impact of social impact bond financing”. en. In: *Public Administration Review* 83.4 (May 2023), pp. 930–946.

[82] Debra Hevenstone et al. “Why is impact measurement abandoned in practice? Evidence use in evaluation and contracting for five European Social Impact Bonds”. en. In: *Evaluation* 29.1 (Jan. 2023), pp. 91–109.

[83] V. Joseph Hotz et al. *Administrative Data for Policy-Relevant Research. Assessment of Current Utility and Recommendations for Development*. en. Northwestern University/University of Chicago Joint Center for Poverty Research, 1998.

[84] Martin Huber, Michael Lechner, and Giovanni Mellace. “Why Do Tougher Caseworkers Increase Employment? The Role of Program Assignment as a Causal Mechanism”. en. In: *Review of Economics and Statistics* 99.1 (Mar. 2017), pp. 180–183.

[85] Oliver Hümbelin. “Non-Take-Up of Social Assistance: Regional Differences and the Role of Social Norms”. en. In: *Swiss Journal of Sociology* 45.1 (Mar. 2019), pp. 7–33.

[86] Oliver Hümbelin and Rudolf Farys. “The suitability of tax data to study trends in inequality — A theoretical and empirical review with tax data from Switzerland”. en. In: *Research in Social Stratification and Mobility* 44 (June 2016), pp. 136–150.

[87] Oliver Hümbelin and Tobias Fritschi. "Pathways into and out of the Labor Market After Receiving Social Benefits: Cumulative Disadvantage or Life Course Risk?" In: *The Sociological Quarterly* 59.4 (Oct. 2018), pp. 627–654.

[88] Oliver Hümbelin, Lukas Hobi, and Robert Fluder. "Rich cities, poor countryside? Social structure of the poor and poverty risks in urban and rural places in an affluent country". en. In: *Local Economy* 37.3 (May 2022), pp. 169–193.

[89] Sarah Jarvis and Stephen P. Jenkins. "Low Income Dynamics in 1990s Britain". en. In: *Fiscal Studies* 18.2 (May 1997), pp. 123–142.

[90] Stephen P Jenkins. "Modelling household income dynamics". en. In: *Journal of Population Economics* 13.4 (Dec. 2000), pp. 529–567.

[91] Pernilla Andersson Joona and Lena Nekby. "Intensive Coaching of New Immigrants: An Evaluation Based on Random Program Assignment". en. In: *The Scandinavian Journal of Economics* 114.2 (June 2012), pp. 575–600.

[92] Preetha Kalambaden and Isabel Z. Martınez. *Intergenerational Mobility Along Multiple Dimensions Evidence from Switzerland*. en. Preliminary and incomplete version for conference submission, Aug. 2021.

[93] Lawrence F. Katz and David H. Autor. "Chapter 26 - Changes in the Wage Structure and Earnings Inequality". en. In: *Handbook of Labor Economics*. Ed. by Orley C. Ashenfelter and David Card. Vol. 3. Elsevier, Jan. 1999, pp. 1463–1555.

[94] Lawrence F. Katz and Robert A. Margo. *Technical Change and the Relative Demand for Skilled Labor: The United States in Historical Perspective*. en. Tech. rep. National Bureau of Economic Research, Oct. 2014. DOI: 10.7208/chicago/9780226163925.003.0002. URL: https://www.nber.org/books-and-chapters/human-capital-history-american-record/technical-change-and-

relative-demand-skilled-labor-united-states-historical-perspective (visited on 05/24/2021).

[95] Jochen Kluve. "The effectiveness of European active labor market programs". en. In: *Labour Economics* 17.6 (Dec. 2010), pp. 904–918.

[96] Anton Korinek, Johan A. Mistiaen, and Martin Ravallion. "Survey nonresponse and the distribution of income". en. In: *The Journal of Economic Inequality* 4.1 (Apr. 2006), pp. 33–55.

[97] Rafael Lalive, Michael Morlok, and Josef Zweimüller. *Applying for Jobs: Does ALMP participation help?* en. Working paper series / Department of Economics No. 19, University of Zurich, May 2011.

[98] Rafael Lalive, Jan C. van Ours, and Josef Zweimüller. "The Effect of Benefit Sanctions on the Duration of Unemployment". en. In: *Journal of the European Economic Association* 3.6 (Dec. 2005), pp. 1386–1417.

[99] Richard Layte and Christopher Whelan. "Moving in and out of poverty". en. In: *European Societies* 5.2 (Jan. 2003), pp. 167–191.

[100] Richard Layte and Christopher T. Whelan. "Cumulative Disadvantage Or Individualisation? A Comparative Analysis Of Poverty Risk And Incidence". en. In: *European Societies* 4.2 (Jan. 2002), pp. 209–233.

[101] Michael Lechner and Jeffrey Smith. "What is the value added by caseworkers?" en. In: *Labour Economics* 14.2 (Apr. 2007), pp. 135–151.

[102] Robert E. Leu, Stefan Burri, and Tom Priester. *Lebensqualität und Armut in der Schweiz*. de. Bern: Haupt, 1997. ISBN: 978-3-258-05570-1.

[103] Wolf Linder, Regula Zürcher, and Christian Bolliger. *Gespaltene Schweiz–geeinte Schweiz: gesellschaftliche Spaltungen und Konkordanz bei den Volksabstimmungen seit 1874*. Baden: Hier + Jetzt, Verlag für Kultur und Geschichte, 2008.

[104] Mengxiao Liu et al. “Using multiple linear regression and random forests to identify spatial poverty determinants in rural China”. en. In: *Spatial Statistics* 42 (Apr. 2021), p. 100461.

[105] Alexia Lochmann, Hillel Rapoport, and Biagio Speciale. “The effect of language training on immigrants’ economic integration: Empirical evidence from France”. en. In: *European Economic Review* 113 (Apr. 2019), pp. 265–296.

[106] Barbara Lucas, Jean-Michel Bonvin, and Oliver Hümbelin. “The Non-Take-Up of Health and Social Benefits: What Implications for Social Citizenship?” en. In: *Swiss Journal of Sociology* 47.2 (July 2021), pp. 161–180.

[107] Ali Madanipour. “Social exclusion and space”. In: *The city reader*. 2015, pp. 237–245.

[108] Ali Madanipour, Mark Shucksmith, and Hilary Talbot. “Concepts of poverty and social exclusion in Europe”. en. In: *Local Economy* 30.7 (Nov. 2015), pp. 721–741.

[109] Ali Madanipour and Sabine Weck. “Social exclusion and poverty in Europe: Territorial patterns”. en. In: *Local Economy* 30.7 (Nov. 2015), pp. 715–720.

[110] Linna Martén, Jens Hainmueller, and Dominik Hangartner. “Ethnic networks can foster the economic integration of refugees”. en. In: *Proceedings of the National Academy of Sciences* 116.33 (Aug. 2019), pp. 16280–16285.

[111] Anton Michálek and Ján Výbošťok. “Economic Growth, Inequality and Poverty in the EU”. en. In: *Social Indicators Research* 141.2 (Jan. 2019), pp. 611–630.

[112] Sarah Miller, Norman Johnson, and Laura R Wherry. “Medicaid and Mortality: New Evidence From Linked Survey and Administrative Data”. en. In: *The Quarterly Journal of Economics* 136.3 (June 2021), pp. 1783–1829.

[113] Robert Moffitt. “An Economic Model of Welfare Stigma”. en. In: *The American Economic Review* 73.5 (Dec. 1983), pp. 1023–1035.

[114] Mario Molina and Filiz Garip. “Machine Learning for Sociology”. en. In: *Annual Review of Sociology* 45.1 (May 2019), pp. 27–45.

[115] Carina Mood. “Logistic Regression: Why We Cannot Do What We Think We Can Do, and What We Can Do About It”. en. In: *European Sociological Review* 26.1 (Feb. 2010), pp. 67–82.

[116] Carina Mood. “The not-very-rich and the very poor: Poverty persistence and poverty concentration in Sweden”. en. In: *Journal of European Social Policy* 25.3 (July 2015), pp. 316–330.

[117] Carina Mood and Jan O. Jonsson. “The Social Consequences of Poverty: An Empirical Test on Longitudinal Data”. en. In: *Social Indicators Research* 127.2 (June 2016), pp. 633–652.

[118] Jakub Muck. *Dynamic panel data models. Nickell’s Bias. Anderson-Hsiao estimator. Arellano-Bond estimator. System GMM estimator.* en. SGH Warsaw School of Economics, 2022. URL: `https://web.sgh.waw.pl/~jmuck/AAE/AdvancedAppliedEconometrics12.pdf` (visited on 08/27/2023).

[119] Jakub Muck. *Panel data. Between and within variation. Random and fixed effects models. Between regression. Hausman-Taylor estimator.* en. SGH Warsaw School of Economics, 2022. URL: `https://web.sgh.waw.pl/~jmuck/AAE/AdvancedAppliedEconometrics9.pdf` (visited on 08/27/2023).

[120] Stephen Nickell. “Biases in Dynamic Models with Fixed Effects”. en. In: *Econometrica* 49.6 (Nov. 1981), pp. 1417–1426.

[121] Helena Skyt Nielsen, Torben Sørensen, and Christopher R. Taber. *Estimating the Effect of Student Aid on College Enrollment: Evidence from a Government Grant Policy Reform.* Working paper. Bonn, Germany: Institute for the Study of Labor (IZA), 2008.

[122] Saeed Nosratabadi et al. "Data Science in Economics: Comprehensive Review of Advanced Machine Learning and Deep Learning Methods". en. In: *Mathematics* 8.10 (Oct. 2020), p. 1799.

[123] Robert M. O'brien. "A Caution Regarding Rules of Thumb for Variance Inflation Factors". en. In: *Quality & Quantity* 41.5 (Sept. 2007), pp. 673–690.

[124] Michel Oris et al. "Long Lives and Old Age Poverty: Social Stratification and Life-Course Institutionalization in Switzerland". en. In: *Research in Human Development* 14.1 (Jan. 2017), pp. 68–87.

[125] Jan C. van Ours, Rafael Lalive, and Josef Zweimueller. "The Impact of Active Labor Market Programs and Benefit Entitlement Rules on the Duration of Unemployment". en. In: *SSRN Electronic Journal* (2000). ISSN: 1556-5068. DOI: `10.2139/ssrn.249007`. URL: `https://www.ssrn.com/abstract=249007` (visited on 12/29/2022).

[126] Howard Oxley, Thai Thanh Dang, and Pablo Antolín. *POVERTY DYNAMICS IN SIX OECD COUNTRIES*. en. OECD Economic Studies No. 30, 2000.

[127] Thomas Piketty. "Capital in the Twenty-First Century: a Multidimensional Approach to the History of Capital and Social Classes". en. In: *The British Journal of Sociology* 65.4 (Dec. 2014), pp. 736–747.

[128] Steven Pressman and Robert Scott. "Consumer Debt and the Measurement of Poverty and Inequality in the US". en. In: *Review of Social Economy* 67.2 (June 2009), pp. 127–148.

[129] Steven Pressman and Robert H. Scott. "Who are the Debt Poor?" en. In: *Journal of Economic Issues* 43.2 (June 2009), pp. 423–432.

[130] Sylvie Rochat, Jean-Paul Kauthen, and Philippe Eichenberger. *Strukturerhebung Aufstockungsmodelle für die Kantone*. de. Bundesamt für Statistik (BFS), Jan. 2009.

[131] Femke Roosma, Wim van Oorschot, and John Gelissen. “The Achilles’ heel of welfare state legitimacy: perceptions of overuse and underuse of social benefits in Europe”. In: *Journal of European Public Policy* 23.2 (Feb. 2016), pp. 177–196.

[132] Renate Salzgeber, Tobias Fritschi, and Thomas Graf. *Zeitliche Verläufe in der Sozialhilfe*. de. Berner Fachhochschule Soziale Arbeit, May 2010.

[133] Mark Shucksmith and Kai Schafft. *Rural Poverty and Social Exclusion in the United States and the United Kingdom*. en. Routledge, Feb. 2012, pp. 120–136. ISBN: 978-0-203-14427-5. DOI: 10.4324/9780203144275-15. URL: https://www.taylorfrancis.com/https://www.taylorfrancis.com/chapters/edit/10.4324/9780203144275-15/rural-poverty-social-exclusion-united-states-united-kingdom-mark-shucksmith-kai-schafft (visited on 05/24/2021).

[134] Mara S. Sidney. “Poverty, inequality and social exclusion”. In: *Theories of urban politics* (2009), pp. 171–187.

[135] Noel Smith, Sue Middleton, and Joseph Rowntree Foundation. *A review of poverty dynamics research in the UK*. en. York: Jospeh Rowntree Foundation, 2007. ISBN: 978-1-85935-577-0. URL: http://www.jrf.org.uk/bookshop/eBooks/2040-poverty-dynamics-review.pdf (visited on 07/05/2021).

[136] Schweizerische Konferenz für Sozialhilfe. *Armut und Armutsgrenze. Grundlagenpapier der SKOS*. Bern, Switzerland: SKOS, 2015.

[137] Ann Huff Stevens. “Climbing out of Poverty, Falling Back in: Measuring the Persistence of Poverty Over Multiple Spells”. en. In: *The Journal of Human Resources* 34.3 (Summer 1999), pp. 557–588.

[138] Ann Huff Stevens. “The dynamics of poverty spells: updating Bane and Ellwood”. In: *The American Economic Review* 84.2 (May 1994), pp. 34–37.

[139] Charles Tilly. *Durable inequality.* Berkley, Los Angeles, London: University of California Press, 1999.

[140] UN. *Guide on Poverty Measurement.* New York, Geneva: United Nations, 2017.

[141] Maria Vaalavuo. *Poverty dynamics in Europe – From what to why.* Working Paper 03: European Union, Nov. 2015. DOI: 10.2767/956213. (Visited on 08/27/2023).

[142] Maria Vaalavuo and Outi Sirniö. "Jobs against poverty: a fixed-effects analysis on the link between gaining employment and exiting poverty in Europe". en. In: *European Societies* 24.4 (Aug. 2022), pp. 431–462.

[143] Leen Vandecasteele. "Social Class, Life Events and Poverty Risks in Comparative European Perspective". en. In: *International Review of Social Research* 5.1 (June 2015), pp. 61–74.

[144] Philippe Wanner. *Vorbereitung einer Datenbank über die wirtschaftliche Situation der Menschen im Arbeits- und Rentenalter (WiSiER).* de. Forschungsbericht Nr. 4/19, Bundesamt für Sozialversicherungen (BSV), 2019.

[145] Marvin N. Wright and Andreas Ziegler. "ranger: A Fast Implementation of Random Forests for High Dimensional Data in C++ and R". en. In: *Journal of Statistical Software* 77.1 (Mar. 2017), pp. 1–17.

[146] Shihua Ye and Xiaochen Gong. "Funding the present and the future: Drivers of NPO's financial sustainability". en. In: *Nonprofit Management and Leadership* 32.2 (Dec. 2021), pp. 197–218.

[147] Yang Zhou and Yansui Liu. "The geography of poverty: Review and research prospects". en. In: *Journal of Rural Studies* 93 (July 2022), pp. 408–416.

[148] Eva Zschirnt and Didier Ruedin. "Ethnic discrimination in hiring decisions: a meta-analysis of correspondence tests 1990–2015". en. In: *Journal of Ethnic and Migration Studies* 42.7 (May 2016), pp. 1115–1134.

Methods appendix

This appendix contains additional information on the estimation methods and research designs used in Chapters 2 and 3 of this thesis.

Dynamic linear panel data models[1]

Bias of the OLS and Fixed-effects estimators

Let us consider a dynamic linear panel data model, which can be written as:

$$y_{it} = \gamma y_{i(t-1)} + x'_{it}\beta + u_{it},$$

where $u_{it} = \mu_i + \epsilon_{it}$ and $\epsilon_{it} \sim N(0, \sigma_\epsilon^2)$, γ is an autoregressive parameter, $y_{i(t-1)}$ is a lagged dependent variable and x_{it} is a vector of independent variables. We assume that y_{it} is a stable process (conditional on x_{it}). I.e., $|\gamma| < 1$. In other words, the effect of idiosyncratic shock (ϵ_{it}) dies out. The independent variables, x_{it}, are assumed to be strictly exogenous. μ_i is an individual-specific fixed-effect. Each observation can be written as:

$$y_{it} = \gamma^t y_{i0} + \sum_{j=0}^{t} \gamma^j \beta' x_{i(t-j)} + \frac{1-\gamma^t}{1-\gamma}\mu_i + \sum_{j=0}^{t-1} \gamma^j u_{i(t-j)},$$

where y_{i0} is the (non-stochastic) initial value. The demeaning transformation used to get the within estimator creates independent variables that are correlated with the error term. The mean of the lagged dependent variable, $\bar{y}_{i-1}$, is correlated with $\bar{\epsilon}_i$ even if the error term is not autocorrelated. The

[1]C.f. Muck 2022a.

average $\bar{\epsilon}_i$ contains the lagged error term $\epsilon_{i(t-1)}$ and, therefore, it is correlated with $y_{i(t-1)}$. As a result, the standard OLS estimator is inconsistent.

Taking the probability limit (plim) of the Fixed-effects estimator (as the number of observations approaches ∞):

$$\text{plim}\hat{\gamma}^{FE} = \gamma + \frac{\frac{1}{NT}(y_{i(t-1)} - \bar{y}_{i-1})(\epsilon_{it} - \bar{\epsilon}_i)}{\frac{1}{NT}(y_{i(t-1)} - \bar{y}_{i-1})^2}$$

it can be observed that the correlation between the lagged dependent variable, $\bar{y}_{i-1}$, and error term will lead to inconsistency of the Fixed-effects estimator. Writing the bias for the Fixed-effects estimator as the number of observations approaches ∞:

$$\text{plim}(\hat{\gamma}^{FE} - \gamma) = -\frac{(1+\gamma)}{T}\left(1 - \frac{1}{T}\frac{1-\gamma^T}{1-\gamma}\right)\left[1 - \frac{1}{T} - \frac{2\gamma}{(1-\gamma)T}\left(1 - \frac{1}{T}\frac{1-\gamma^T}{1-\gamma}\right)\right]^{-1}$$

It can be seen that the bias of the Fixed-effects estimator depends on T as well as γ. The bias will be larger for small T, as is the case with our dataset in Chapter 2.

Difference-in-Differences (DiD)[2]

For a $2*2$ DiD design we have a treated group k and an untreated group U. And we have a pre- and post-period for each group, pre(k), post(k), pre(U) and post(U). We calculate:

$$\hat{\delta}^{2x2}_{kU} = \left(\bar{y}_k^{post(k)} - \bar{y}_k^{pre(k)}\right) - \left(\bar{y}_U^{post(k)} - \bar{y}_U^{pre(k)}\right)$$

where $\hat{\delta}^{2x2}_{kU}$ is the estimated average treatment effect on the treated (ATT) for group k, and $\bar{y}$ is the sample mean for that particular group in a particular time period. The first parenthesis differences the treatment group, k, after minus before, the second parenthesis differences the untreated group, U, after minus before. And once these quantities are obtained, we difference the

[2]C.f. Mixtape - 9 Difference-in-Differences (scunning.com), last visited on 04.06.2023.

second term from the first. Let us rewrite the sample averages as conditional expectations:

$$\hat{\delta}_{kU}^{2x2} = \Big(E[Y_k \mid \text{Post}] - E[Y_k \mid \text{Pre}]\Big) - \Big(E[Y_U \mid \text{Post}] - E[Y_U \mid \text{Pre}]\Big)$$

Now let us use the switching equation, which transforms historical quantities of Y into potential outcomes. We also add zero to the right-hand side of the equation:

$$\begin{aligned}\hat{\delta}_{kU}^{2x2} = \Big(E[Y_k^1 \mid \text{Post}] - E[Y_k^0 \mid \text{Pre}]\Big) - \Big(E[Y_U^0 \mid \text{Post}] - E[Y_U^0 \mid \text{Pre}]\Big) \\ + E[Y_k^0 \mid \text{Post}] - E[Y_k^0 \mid \text{Post}]\end{aligned}$$

Now let us rearrange these terms to get the decomposition of the $2 * 2$ DiD in terms of conditional expected potential outcomes:

$$\begin{aligned}\hat{\delta}_{kU}^{2x2} = E[Y_k^1 \mid \text{Post}] - E[Y_k^0 \mid \text{Post}] \\ + \Big[E[Y_k^0 \mid \text{Post}] - E[Y_k^0 \mid \text{Pre}]\Big] - \Big[E[Y_U^0 \mid \text{Post}] - E[Y_U^0 \mid \text{Pre}]\Big]\end{aligned}$$

The $2 * 2$ DiD will isolate the ATT (the terms on the first line) if and only if the terms on the second line zero out. This is the case if the treated group, k, would have followed the same trend as the untreated group, U, in the absence of the treatment. This cannot be tested, since $E[Y_k^0 \mid \text{Post}]$ is counterfactual. There is no post-period where the treated group has not received the treatment. For this reason, the terms on the second line are often called the parallel trends assumption.

Even if we cannot test the assumption, we can examine the trends of the treated and untreated groups in the pre-period. If trends for the groups were similar in the pre-period, we would be somewhat assured that it is reasonable to assume parallel trends. We do this in Chapter 3 through plots of weighted means and event-study plots.

Event-study analysis

Event-study analyses essentially follow the same idea as the difference-in-differences estimator. Instead of differentiating only a pre- and post-period, we take a more fine-grained look at trends through event-times (e.g., semesters leading up to and following a certain event). To do so, we merely replace the dummy variable which measures the pre- and post-period by a set of indicator variables which measure event-times (c.f. Miller et al. 2021). One time period is omitted which serves as the reference period 0. In Chapter 3 we use the semester spanning from months -4 to +1 of program entry as the reference period for our event-study analysis.

Selbständigkeitserklärung

Ich erkläre hiermit, dass ich diese Arbeit selbständig verfasst und keine anderen als die angegebenen Hilfsmittel benutzt habe. Alle Stellen, die wörtlich oder sinngemäss aus Quellen entnommen wurden, habe ich als solche kenntlich gemacht. Mir ist bekannt, dass andernfalls der Senat, gemäss dem Gesetz über die Universität, zum Entzug des aufgrund dieser Arbeit verliehenen Titels berechtigt ist.

Bern, 4. Juni 2023

Lukas Hobi

Lukas Hobi