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The Fiscal Impact of Migration into Austria
Life-Cycle Accounting and Gelbach Decomposition Using Register Data

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# Contents

## List of Figures



## List of Tables

# 1 Introduction

Austria's foreign-born population has grown substantially over the past decade. Just over one in five residents was born abroad according to the 2021 register-based census (20.4%). By 1 January 2026 the share had climbed to 22.9% (Statistics Austria, 2026). These demographic shifts have coincided with public concern that immigration may strain the welfare state: in the October 2023 ÖIF *Integrationsbarometer*, 49% of Austrians named "exploitation of the welfare system" as a major integration challenge (Österreichischer Integrationsfonds, 2023).
Migration consistently ranks among the most salient political issues in Austrian elections at federal and regional levels (FORESIGHT & Institut für Strategieanalysen, 2024; ORF.at Redaktion, 2025). Against this backdrop, one question runs through much of the public debate on migration:

> *Do migrants impose a net fiscal cost on Austria's welfare state, and to what extent do observed differences between migrants and natives reflect compositional factors rather than differences in age-conditional fiscal behavior?*

Existing empirical evidence for Austria and other European countries is mixed and often sensitive to context, migrant characteristics, methodological choices and the design of the welfare system in question. Austria's administrative registers offer an opportunity to provide fine-grained fiscal evidence based on observed tax and transfer information.
In order to answer the overall research question I investigate multiple sub-questions, each addressed in a dedicated section:

1. How do natives, EU migrants and extra-EU migrants differ in age structure, gender, education and labor market attachment, and what do those differences *a priori* imply for expected fiscal contributions? (Section 5)

2. What is the unconditional aggregate fiscal position of each group, measured in their average net fiscal contribution? (Section 6.1)

3. How do the age-specific NFC profiles of natives, EU migrants, and extra-EU migrants differ by gender and by education across groups, and at which life stages do the profiles diverge? (Section 6.2)

4. How does the estimated migrant-native gap in NFC evolve once observable characteristics are controlled for, and do the same characteristics translate into similar fiscal outcomes across groups? (Sections 7.1 & 7.2)

5. Which blocks of observable characteristics account for the change in the migrant coefficient between baseline and full models according to a Gelbach decomposition? (Section 7.3)

These questions are addressed through two complementary methodological approaches. The first is descriptive life-cycle accounting. Most individuals are net recipients during childhood and old age, and net contributors during their working age. As a result, any aggregate comparison between groups obscures the distinction between age composition and differences in age-conditional fiscal behavior. Plotting mean net fiscal contributions (NFC) by age for each group separately, and decomposing them into tax and transfer components, makes the underlying mechanics of the fiscal life cycle traceable. It shows how and where groups' fiscal life cycles diverge with a focus on the transitions from education towards work and later to retirement. Methodologically, these profiles are based on a national-transfer-accounting framework close to Christl et al. (2022).

The second methodological approach is a regression framework paired with a Gelbach (2016) decomposition, quantifying how observable characteristics such as age, gender, education and labor-market attachment account for differences in group-specific fiscal contributions. The decomposition isolates the share of the gap between natives and migrants attributable to each channel of covariates, which matters because compositional gaps and gaps in behavior imply different policy responses. Questions 1 to 3 are descriptive and provide overview statistics, average group fiscal contributions and age-specific NFC profiles. Questions 4 and 5 rely on OLS regressions with alternative sets of controls and a Gelbach (2016) decomposition.

**Structure of the thesis.** Section 2 reviews existing evidence on the fiscal consequences of migration, first in Western countries, then with a focus on Austria. Section 3 describes the linked administrative register data, including coverage, inclusion rules, and credibility considerations. Section 4 outlines the methodological background, introducing the main accounting approaches including the national transfer accounting (NTA) framework used in this thesis. Section 5 provides descriptive statistics on the composition of migrant groups in Austria, covering origins, age and gender structure, education, and labour-market outcomes. Section 6 presents the main accounting results: average NFC by migration status and age group and the resulting life-cycle deficit measures, alongside a methodological discussion of these estimates. Section 7 reports the analytical results from the regression framework, including the empirical strategy, stepwise specifications, sample splits and the Gelbach decomposition. Section 8 discusses methodological weaknesses and limitations of the research . Section 9 discusses potential policy implications and outlines avenues for further research. Section 10 concludes.

# 2 Evidence on Migration and Public Finances

Debates about migration in Austria are closely intertwined with concerns about the fiscal sustainability and perceived fairness of the welfare state. In the 2024 national election in Austria, the right-wing party FPÖ achieved their best ever result and received 28.8% of votes. Their campaign was centered on negative consequences of migration with a strong focus on limiting access to the welfare state to migrants, especially asylum seekers (FORESIGHT & Institut für Strategieanalysen, 2024). One central argument by the party is the alleged financial burden of allowing migrants to access welfare without having contributed (Freiheitliche Partei Österreichs (FPÖ), 2024).
Boeri (2010) shows that negative attitudes towards migration in Europe are primarily driven by concerns of abuse of the welfare systems and the selection of welfare dependent migrants because of the generosity of welfare states. Dustmann and I. P. Preston (2007) further argue that since concerns about the fiscal burden of migration on the public budget dominate concerns about labor market competition and economic efficiency, much of the debate is not directly aimed at budgetary concerns, but rather perceived fairness of allocations within the welfare state. In the following section I will give an overview over the main literature investigating the fiscal impact of migration in many industrialized western countries. While some of the findings are target specific, many findings likely also apply to Austria. The second part will then focus on Austria in specific. Across this literature, methodology and data choice drive much of the variation in findings. This becomes central in the Austrian case, where the only research is either focused on refugees or based on EUROMOD microsimulations.

## 2.1 Fiscal Consequences of Migration in Western Countries

Empirical studies on the fiscal impact of migration however reach a broad array of conclusions. It is often difficult to directly compare findings because studies differ in the definition of fiscal contribution and migration, are based on different data sources with varying quality, cover different periods, cover different economies with regional differences in the labor market and different welfare regimes.

Much empirical work is based on accounting approaches, which compare generated tax revenue with public expenditure on welfare transfers.

Within this literature, several studies across many western nations report modest positive net contributions of migrants (Simon (1984) for the United States, Akbari (1989) for Canada, Straubhaar and Weber (1994) for Switzerland, Martinsen and Rotger (2017) for Denmark, Ruist (2014) for Sweden as well as Gieseck, Heilemann, and Loeffelholz (1994), Ulrich (1994) & Bonin, Raffelhüschen, and Walliser (2000) for Germany).

An exception to this is Weintraub (1984), who finds a negative fiscal effect, although limited to the subgroup of undocumented immigrants in the state of Texas. For Denmark Wadensjö (2000) & Wadensjö and Orrje (2002) find negative effects of non-Western immigration on the fiscal balance. A further disaggregation by administrative level shows that many of the fiscal burdens concentrate on the municipal level. Here, Wadensjö finds the main driver of the fiscal contribution to be the labor market participation and the unemployment rate, making time spent in the country and language skills good predictors of fiscal contribution (Wadensjö, 2007).

Ekberg (2011) finds a small positive effect on the welfare state for Sweden and projects an effect of $\pm 1\%$ of the GDP through 2050. He argues that in countries that exhibit more rapid aging such as Germany and Italy larger positive net contributions would be expected. Given the similarities between the population structure and welfare regime of Austria and Germany a similar difference can plausibly be expected for Austria.

Huber and Oberdabernig (2016) use an Oaxaca-Blinder decomposition to explore benefit receipt between migrants and natives as well as the selection into benefit take up. They find that after controlling for key characteristics like age, number of income generators, number of children, education etc. the differences in welfare dependence between migrants and natives largely diminish. Austria and Germany are the only two countries in the EU where after controlling for individual characteristics, migrants remain overrepresented in the group of benefit recipients. In contrast to much previous work they find a comparatively small effect of education attainment on welfare dependency and instead show that next to age, household size is a key driver of the net receipt of welfare which is a result of generous family benefits in many European countries (Huber and Oberdabernig, 2016, p.102)

Dustmann and Frattini (2014) analyze the fiscal contribution of migrants in the UK for the period 1995 until 2011 and find that EU migrants exhibit a positive fiscal contribution even the UK as a whole ran a budget deficit. Both non-EU migrants and natives showed a net fiscal burden on the public budget. Subpopulations that immigrated after 2000, especially from places that were integrated into the EU within the 2004 expansion, register the strongest fiscal contribution. They emphasize the methodological sensitivity of allocating the cost of children which can systematically distort estimates based on the number of children a subgroup has on average. They allocate the cost of migrants children to the migration subgroup, but their labor market earnings to the native subgroup resulting in an overestimation of migrants costs and especially migrant groups who tend to have many children (Dustmann and Frattini, 2014). The authors further argue that due to the cross-sectional nature of their research they cannot properly capture return migration which is a

common problem in the generalization of accounting approaches with yearly register data in the face or altering migration patterns. Many migrants tend to migrate back in later stages of lives which relieves much of the fiscal burden, however selection mechanisms as to whether economically successful migrants or those that live in poverty migrate back are largely unexplored. Further Dustmann and Frattini (2014, p.613) show that migrants careers tend to develop faster as they acquire host country labor market specific skills and thus exhibit annual wage growths 1.2% higher compared with the native population several years after immigration.
The fiscal relevance of labor market success is emphasized by Fiorio et al. (2023) who show that migrants contribute more to public finances in Germany, Spain and Italy when accounting for differences in characteristics which can be attributed to lower unemployment among migrants.
The report on *The economic and fiscal consequences of immigration* into the US by the National Academies of Sciences, Engineering, and Medicine (2017) argues, that for most economic scenarios low skilled immigrants pose a burden on public finances. The report analyzes direct fiscal contributions only and argues that indirect effects of low skilled immigration are "minor with respect to the overall economic activity". However Colas and Sachs (2024) find that low-skilled immigrants indirectly affect the local wages and labor supply and thus public finances stronger than previously assumed. In a general equilibrium model they estimate the indirect fiscal contribution per migrant in the US to be from $700 up to $2100 annually. Further they argue that this effect may offset the previously documented fiscal burden of low skilled immigrants (Colas and Sachs, 2024).
Two patterns appear throughout the literature: net contributions are sensitive to age structure across many studies and countries and methodological choices greatly influence aggregates.

## 2.2 Who Migrates? Who Stays?

A commonly raised concern in debates on the fiscal effects of migration is whether the generosity of the welfare state shapes who migrates and who remains in the host country.
The decision to migrate is socially and economically costly and must thus be determined by an expected increase in quality of life. Thus migrants are not composed of a random sample of the population of their country of origin but follow a selection logic.
Borjas (1987) argues that selection into migration is driven by differences in expected earnings. The model Borjas formulates links the decision to migrate to the difference in the relative return to skill in the origin and destination countries. Importantly, this implies that selection is also shaped by the economic and political characteristics of the origin country, since these determine the structure of earnings at home and thereby which individuals benefit most from emigration. As a result, differences in migrants' later outcomes partly reflect the pre-migration composition of migrant cohorts.
Following this logic, Borjas (1999) shifts his focus from the decision to migrate itself to the question of where migrants settle once they migrate. He argues that differences in welfare generosity influence the location choice of migrants across destinations and may therefore shape the composition of migrant inflows into certain welfare systems. Thus welfare institutions can act as a sorting mechanism: migrants with weaker expected labor market outcomes may have a stronger incentive to settle in more generous welfare systems. This sorting mechanism does not occur for people already living in the country, because the large costs for migration itself outweigh potential welfare gains. Welfare generosity thus enters as one possible determinant of destination choice, although not necessarily as the dominant driver of migration overall.
In a survey on the self selection of migrants into welfare systems, Giulietti and Wahba (2012) however conclude that although several studies link welfare institutions to immigrant selection,

welfare is only one factor among many. They conclude that "fears about immigrant abuse of the welfare system are somewhat unfounded or at least exaggerated"(Giulietti and Wahba, 2012).
There is, however, substantial heterogeneity in migration patterns and migrants net fiscal contributions across European states. For example, Giulietti, Guzi, et al. (2013) find that within the EU in Nordic countries migrants tend to show a negative fiscal contribution while in Austria, Germany and Spain migrants tend to have a positive net fiscal contribution which coincides with differences in the generosity of the welfare systems. At the same time they argue that while there are differences in economic incentives for migration between countries, the generosity of the welfare state is not central. In contrast Huber and Oberdabernig (2016) argue that heterogeneity within in welfare dependence of migrants among European countries are positively correlated with welfare generosity.
Bratsberg, Raaum, and Røed (2014) stress that migration is a continuous phenomenon and that there may be a selection into return migration based on welfare dependency. They first estimate life cycle profiles of migrants based on longitudinal data for Norway and find the difference between source and destination country to be a particularly good indicator of the labor market integration and performance in the long term. Migrants from high income countries tend to perform well in the labor market and often leave Norway after a while. However immigrants from low-income developing countries tend to settle more permanently and have a higher risk of unemployment and reliance on social insurance (Bratsberg, Raaum, and Røed, 2014, p.650). They further identify that the immigrant-native differential decreases in the first decade, indicating a form of assimilation of migrants in the host country labor market. However for migrants who stay for 10-15 years they find this gap to widen again. The process they call *dissimilation* is often triggered by economic downturn which affects the employment and earnings of migrants more strongly than that of natives (Bratsberg, Raaum, and Røed, 2014, p.668).

## 2.3 The Special Case of Refugees

In the case of refugees, migration is less economically self selected and often there is no explicit choice of destination. This, in addition to policy rules, expectantly lowers initial labor market attachment drastically.
Brell, Dustmann, and I. Preston (2020) argue that refugees have considerably more difficulties to integrate into the labor market upon arrival. This is reflected in substantially lower employment rates in the first decade after arrival. This difference diminishes substantially in the second decade. The remaining differences to other migrants can largely be attributed to educational attainment. Additional disadvantages that refugees face in contrast to other migrants include the mental and physical health problems associated with fleeing itself as well as the causes of the flight. Evidence from the Netherlands (Vroome and Tubergen (2010) & Bakker, Dagevos, and Engbersen (2017)), Switzerland (Hainmueller, Hangartner, and Lawrence (2016)), Denmark (Hvidtfeldt et al. (2018)) and Germany (Brücker et al. (2019)) shows that prolonged stays in asylum accommodations significantly lower likelihood and quality of further employment. Fasani, Frattini, and Minale (2018) find that refugee groups with higher rates of being granted permanent status exhibit better long-term labor-market outcomes.

## 2.4 The Austrian Case

Much of the recent literature investigating the fiscal impact of migration to Austria is limited to refugee migration (e.g. Jestl, Landesmann, et al. (2022); Jestl and Tverdostup (2023); Poledna et al. (2024) & Holler and Schuster (2020)).

Jestl, Landesmann, et al. (2022) compare the probability of employment of refugee migrants with other non-European migrants as well as with Austrian natives. They find that even after controlling for individual characteristics, a gap in employment probability of 30 percentage points remains after the first seven years. The gap then declines with time. This resembles the gap in employment probability of other migrants. When controlling for a set of explanatory variables including age, gender, education, number of children, age of the youngest child and household type the gap reduces to 10 percentage points.
The labor market integration is a key driver of the fiscal impact of an individual. Jestl and Tverdostup (2023) analyze the labor market entry and subsequent job stability for both refugees and non-humanitarian migrants from 2014-2016. They find that the labor market integration is driven by similar attributes for both groups. Older age, being female, having a higher level of education and having young children are strongly associated with a slower labor market integration. However, while non-refugees integrate into the labor market directly the refugees' integration is delayed by three years due to legal restrictions during the asylum application process. The second key difference between the two migrant groups is that, while for non-humanitarian migrants, high education is a good predictor of high job stability, no such effect can be observed for refugees.
Using a quantile regression approach Joxhe, Scaramozzino, and Zanaj (2024) demonstrate that migrants in Austria are net contributors to the welfare state. Not only can they not identify a difference in welfare dependence between natives and migrants for any income quantile. They also find a slight positive, although statistically insignificant, difference in net fiscal contribution for both migrant groups compared to the native population.
Poledna et al. (2024) estimate refugee migration to have a positive effect on aggregate consumption and on the GDP while showing a reduction in GDP per capita for the Austrian economy. In their simulations the scenario with large-scale migration yields a one percentage point increase in public debt over the investigated five-year period. The increase is largely driven by high short term costs in the first years after immigration which are then mitigated by demand-side multiplier effects from added consumption (Poledna et al., 2024, p.15).
These results are confirmed by Holler and Schuster (2020) who estimate the impact of the 2015 refugee migration on the Austrian economy and also find positive effects on aggregate consumption and GDP accompanied by a reduction of GDP per capita.
Evidence for Austria is either restricted to refugee migration or based on simulated welfare eligibility based on EURO SILC data in combination with EUROMOD microsimulations. Joxhe, Scaramozzino, and Zanaj (2024) and Christl et al. (2022) provide the closest comparable research programs but do not decompose where group-level differences originate which is possible due to my usage of register data and the Gelbach decomposition.

# 3 Data

This chapter documents the administrative micro-data used to observe individuals' *fiscal inflows* to the public sector (taxes and social-insurance contributions) and *fiscal outflows* (cash and in-kind public benefits). A central strength of this project is that fiscal impacts are computed from *administrative registers* rather than EUROMOD simulations, unlike much prior work ( e.g. (Christl et al., 2022; Fiorio et al., 2023)). Register data records realized tax payments and welfare take-up directly, whereas microsimulations impute them from eligibility rules and tax rates applied to survey income. The near-universal coverage also preserves heterogeneity that survey-based

approaches may smooth over especially for smaller groups.
This however requires explicit information about (i) who enters each register, (ii) how linkage works, and (iii) remaining selection and measurement issues. Note also that, by definition, migrants appear in the registers only *after* arrival. Cohort composition and entry timing therefore matter for interpretation.

## 3.1 Sources and Coverage

The analysis uses two datasets from *Statistik Austria* covering the year 2021: the *Coordinated Employment Statistics* (AEST; *Abgestimmte Erwerbsstatistik*) and the *Integrated Wage and Income-Tax Statistics* (LUE; *Integrierte Lohn- und Einkommensteuerstatistik*). Both datasets are joined using a pseudonymous unique identifier that is provided by Statistik Austria.

**AEST (population and characteristics)** AEST assembles person-level demographics, education, labor-market status and household variables by integrating several administrative sources. The backbone is the Central Register of Residents (ZMR; *Zentrales Melderegister*), which records all persons with a registered main or secondary residence in Austria. The portion of the dataset relevant for my analysis is complemented by inputs from the Central Civil Status Register (ZPR) and the Central Citizenship Register (ZSR), records of the Social Insurance Umbrella Association (DV; including the employer account ID, HV-ID), the tax authority's database (STR), Public Employment Service records (AMS) and the education registers (BSR; school and higher-education statistics). (Statistik Austria, 2021; Statistik Austria, 2010b) Coherence checks are performed against comparison registers; AEST follows CES recommendations and EU regulations for comparability (Statistik Austria, 2010a). As Huber, Fink, and Horvath (2020) emphasize, AEST data is highly useful for integration research but cannot by itself identify migrants motivation, distinguish circular migration, or date migration events more accurately than to the calendar year of arrival.

**LUE (earnings, taxes, transfers)** LUE contains wage, pension and other taxable income, income taxes, social-insurance contributions, selected cash transfers as well as some general information about individuals such as age, gender and social standing. The LUE dataset covers all persons for whom employers report payroll data and/or for whom an income tax assessment is issued in the reference year. Primary sources are the wage and income tax database (BMF) and transfer-payment databases (BMF; Austrian Health Insurance Fund(ÖGK)). (Statistik Austria, 2023b) AEST and LUE are linked via a project-specific pseudonymous person identifier (`p_id`) that is *stable across years and across sources*, yielding a person-year dataset for 2021 that includes information on individual characteristics and on the individuals' interaction with the welfare state.

## 3.2 Inclusion Rules and Selection

The AEST data contains Austria‘s residential population including all legally registered residents (irrespective of labour-market status or citizenship). This also includes minors and retirees. It excludes undocumented residents and individuals that stay short enough to evade registration. Registration and deregistration obligations imply that some short-term movers and circular migrants may be mis-timed.

**Coverage and Timing** AEST is anchored in Austria's residence–registration regime (*Meldegesetz 1991*): new residents must register a dwelling and de-register when moving out. Both actions are time-bound.(Federal Ministry for European and International Affairs (BMEIA), 2025; Republic of Austria - Federal Chancellery (BKA), 2025; Republic of Austria - Federal Chancellery (BKA), 2023). Statutory exceptions explain residual under-coverage: very short stays in private dwellings (up to three days), free accommodation up to two months, and short hotel stays are exempt from immediate registration. As a result, *very short stays, some circular moves, and irregularly staying persons* may be missing or *mis-timed* in AEST. Triangulated research indicates that the *irregular stock* in Europe is small in share terms: MIrreM's comparative estimates for 12 countries put the 2016–2023 range at $\approx$ 2.6–3.2 million (< 1% of the combined population), with Austria ranging among countries where levels are higher than in 2008 but still small in share (Kierans and Vargas-Silva, 2024; Rössl, Schütze, and Kraler, 2024).

**Why this matters little for *fiscal* outcomes.** Persons who are *not registered* are generally outside mainstream social-assistance and social-insurance schemes and, by construction, outside LUE's payroll and tax records. Asylum seekers receive separate, temporary *Grundversorgung* rather than Sozialhilfe. Recognized refugees gain access to Sozialhilfe only after status recognition. Third-country nationals even face additional residence conditions (Bundesministerium für Soziales, Gesundheit, Pflege und Konsumentenschutz, 2025). In Vienna, even *Grundversorgung* applications require proof of residence (Meldebestätigung/Meldezettel), illustrating the practical role of registration as eligibility proof (Fonds Soziales Wien, 2025).
Family-related benefits generally require lawful residence and a center of life in Austria which is typically acknowledged by registration documents Bundeskanzleramt (2024). Therefore, individuals not represented in AEST/ZMR are typically outside mainstream transfer systems and thus absent from LUE on the benefit side. At the same time, LUE includes *non-resident* taxpayers who are subject to limited tax liability on Austrian-source employment income (Bundeskanzleramt - Rechtsinformationssystem (RIS), 2025a; Bundeskanzleramt - Rechtsinformationssystem (RIS), 2025b). Under EU social-security coordination (Reg. 883/2004), a narrow set of benefits (mainly family benefits and healthcare entitlements) may be coordinated across borders (European Union, 2004; Republic of Austria - Federal Chancellery (BKA), 2024). To keep the estimates clear, I define NFC for *registered residents* and omit LUE-only non-residents.

**Implications for linked dataset.** The linked dataset inherits *complementary selection*: AEST covers the resident base, while LUE comprises fiscal flows for participants. Consequently, some AEST person-years will have no LUE record. In the later analysis, these individuals will be treated as having no interaction with the welfare state. In total, 93.87% of individuals in the LUE could be matched to the AEST, while about 80% of AEST records could be linked to the LUE. This asymmetry reflects the broader coverage of the AEST, which includes individuals without recent labor market activity. Overall, the linkage is high leaving no concerns about selective matching and supports the data‘s representativeness.

## 3.3 Data Quality

Both sources are administrative by-products collected under legal reporting obligations and embedded in institutional audit trails. The administrative register data used in this thesis are produced and maintained by Statistik Austria and are subject to comprehensive quality assurance procedures. These procedures follow the quality framework of the European Statistical System (ESS) and include systematic checks throughout the statistical production process, such as input validation, internal consistency checks, and coherence assessments across registers as well as regular random sampling checks.

The applied standards and quality controls are documented in the official *Standarddokumentation and Methodenhandbuch of Statistik Austria* (Statistik Austria, 2021). This institutional quality framework provides a reliable foundation for the use of administrative register data in the subsequent analysis. As the registers are based on administrative records of granted transfers and received taxes, the data captures realized fiscal flows with a high degree of precision and without reliance on self-reported information.

# 4 Methodological Overview

Building on the demographic and fiscal backdrop outlined in Chapter 2, this section discusses the life-cycle approach to measuring migrants' net fiscal contribution (NFC).[1] Since received transfers and paid taxes systematically vary with age, fiscal effects of migration relative to natives are strongly affected by differing concentrations of groups along their respective life cycles.

The methodological foundation of this thesis is the construction of individual-level net fiscal contributions (NFC) from administrative register data, attributing realized taxes, social-security contributions, and cash and in-kind transfers to individuals according to a national-transfer-accounting logic. The individual NFC is the common input to all subsequent analysis.

Subquestions 2 and 3 are addressed by aggregating it: averaging over groups yields the unconditional ANFC (question 2), averaging over (group, age) cells yields the life-cycle profiles that characterize how fiscal contributions evolve across the life course (question 3). Subquestions 4 and 5 are addressed by using the same NFC variable as the dependent variable in an OLS regression paired with a Gelbach (2016) decomposition, which quantifies how the migrant–native gap evolves as observable compositional differences are absorbed into the specification (question 4) and which blocks of covariates account for that change (question 5). Subquestion 1, which characterizes the demographic and labor-market composition of the groups themselves, is descriptive and is addressed in Chapter 5.

The questions I ask in this thesis are quantification and accounting questions, not treatment-effect questions. What I estimate in each case is a feature of the realized 2021 cross-section under current Austrian institutions: a group mean, an age-conditional profile, or a decomposition of an observed gap. The accounting framing is the right one for this thesis because, as the analysis will show, a large share of the migrant–native gap is compositional: migrants and natives differ systematically in age, education, and labor-market attachment. The causal effects of each channel are well documented and largely known mechanisms due to the construction of the Austrian welfare state. The question of whether migrants draw more from the welfare state than they contribute, which is what the public debate and the literature actually ask, is best answered with a simple accounting framework.

Subsection 4.1 introduces the calculation of the NFC, illustrates the ANFC calculation and discusses the construction of fiscal lifecycle profiles.

Section 4.2 gives an overview over common design and methodological debates in the fiscal accounting literature and situates my research within those.

Section 4.3 outlines the regression and decomposition strategy used to address questions 4 and 5.

[1] I use *net fiscal contribution* (NFC) to mean the difference between total taxes paid and transfers received by an individual (or group) over a given time period.

## 4.1 The Fiscal Life Cycle

A fiscal life cycle describes how an individual's net interaction with the public sector evolves with age. Young and old individuals typically require more support in the form of public services and transfers than they contribute in taxes, producing a negative NFC. Working-age adults, whose labor income generates tax revenue that exceeds the transfers they receive, tend to show a positive NFC (United Nations, 2013). In welfare states like Austria, the government is the primary institution managing this intergenerational redistribution, so changes in the age composition of the population translate directly into changes in the fiscal balance. This makes an age-disaggregated accounting framework well suited for evaluating the fiscal impact of migration, where the age structure of migrant populations differs from that of natives.

### 4.1.1 Net Fiscal Contribution: Definition and Calculation

Methodologically I follow Christl et al. (2022) by basing my analysis on calculated net-fiscal-contributions (NFC) on the individual level. The NFC is constructed as the difference between transfer payments (TR) by the state and fiscal contributions (FC).

$$NFC_i = FC_i - TR_i \tag{1}$$

The fiscal contributions an individual makes to the welfare system are indirect (TIN) and direct (TDI) taxes as well as social security contributions (SSC). SSCs include health insurance, long-term care insurance, accident insurance, pension insurance and unemployment insurance. The direct taxes include - among others - taxes on income through labor, rental income, capital gains. Indirect taxes are often related to consumption of specific goods like mineral oil, tobacco, alcohol but also groceries and durable consumption goods.

The transfer side includes pensions (PEN), care allowance (Bundespflegegeld (BPG)), unemployment benefits (UB), child benefits (CB), family allowance (FA) as well as other types of social aid (OA).

$$NFC_i = (SSC_i + TIN_i + TDI_i) - (PEN_i + BPG_i + UB_i + CB_i + FA_i + OA_i) \tag{2}$$

Several difficulties need to be addressed in this stage: The main challenge is that there is no data for some of the observations. On the contribution side, there is accurate data on the SSC and the direct taxes (TDI) but not on the indirect taxation (TIN) which is largely made up of the value added tax (VAT). The indirect taxation is imputed based on insights from EUROSTAT which estimates the share of income that is used for consumption by income quintile (Eurostat, 2025). Together with income quintile specific VAT rates the VAT of an individual can be approximated based on their income quintile and specific income.

On the transfer side there are more complications. The main lacking variable here are in-kind benefits such as housing benefits received by individuals and education. They constitute a large share of transfers payed out by the state and thus require special attention. Dustmann and Frattini (2014) address this problem in their analysis of the impact of migration on the welfare system in the UK by introducing large margins of conservatism and testing the results for a set of potential assumptions and modeling decisions. I am unable to factor in housing benefits that preserve any meaningful heterogeneity. However, based on data from Statistik Austria (2023a) I reconstruct average costs for each education level, which are allocated towards current students in calculating their NFC. Due to missing data and bigger potential heterogeneity, preschool expenses cannot be

meaningfully included.
While methodologically similar to the microsimulation approach by Christl et al. (2022), my research differs in three respects. First, the dataset is larger, improving overall accuracy and making it possible to create group averages by migration group, age, gender and education that still provide systematic evidence. Second, the use of administrative register data eliminates potential data simulation errors. Third, the use of such data also is not limited to capturing simulated eligibility but also allows to observe actual take-up of welfare, thereby preserving potential differences in claiming behavior between migrant groups and natives.

### 4.1.2 Average Net Fiscal Contribution by Migration Status

The average net fiscal contribution (ANFC) by migration status compares natives, EU migrants, extra-EU migrants and refugees for their specific age-groups. I further include the average net fiscal contribution by education and gender. It is defined as:

$$ANFC^j = \frac{\sum_{i=1}^{N} NFC_i^j}{n} \tag{3}$$

and describes the average fiscal contribution of all individuals $i$ with migration status, education or gender $j$.
The ANFC gives an insight into the current impact of different groups on the welfare state. Since it does not account for group specific age profiles or migration patterns, it does not provide conclusive insights on the contributions of individuals belonging to different population subgroups (Hinte and Zimmermann, 2014).
As with most fiscal metrics, these numbers are incomplete - for example due to missing social-housing and therefore warrant comparative interpretation only.

### 4.1.3 From NFC to Life Cycle Profiles

With the age structure being increasingly important due to rapid changes within the recent decades increased attention has been directed towards so called *average life cycle contribution* profiles in the literature (eg. (Christl et al., 2022; Spielauer et al., 2022)). Like the ANFC above, the following graphs depict the cross section of Austria's population in the year 2021. For each age $a$ and group $g$,

$$\overline{\text{NFC}}_{a,g} = \frac{1}{N_{a,g}} \sum_{i \in (a,g)} \text{NFC}_i \tag{4}$$

the average NFC is calculated and arranged by age to produce a life-cycle shape. Values are cross-sectional means (€/person/year). They describe current age patterns, not cohort life-cycles.

## 4.2 Design Choices in Fiscal Accounting Studies

This section gives a brief overview of methods typically used in age and group-disaggregated fiscal accounting and situates. It further positions my research in commonly held methodological debates and design choices.

### 4.2.1 National Transfer Accounting

The central idea of analyzing the economy in a way that is sensitive to the age structure of the given population stems from the insight that summary statistics and most economic models cannot adequately capture age specific differences in the dependence on and the interaction with others in society and through the welfare state (United Nations, 2013, p.1). This is especially interesting for countries undergoing rapid changes in their demographic structure such as developing countries where education levels sharply increase in the young populations or most western countries where the average population age increases due too low birth rates (ibid).

NTA defines three main channels of reallocation within a society: public transfers, private transfers and asset-based transfers. The unit of analysis can be an individual's life cycle deficit. It can also focus on the reallocation among age groups, which is how it was originally intended.

Like all accounting frameworks, NTAs are purely descriptive. They document how resources flow between age groups under current institutions. They do not, however, allow for any causal interpretation. NTAs are cross-sectional as they describe the current economic flows between age-groups for a given year. NTAs from multiple years can be used to construct a pseudo panel which can then be interpreted as synthetic cohorts.

As governments are substantially involved in inter-generational redistribution and the inverse of the LCD can be interpreted as the fiscal sustainability of the welfare state, many studies have applied the NTA methodology exclusively to the public dimension.[2] Three applications illustrate the range of this public-dimension approach and are methodologically similar to my research. Miller, C. Mason, and Holz (2011) estimate the fiscal effect of demographic changes in 10 Latin American countries based on the public dimension of national transfers.

Sambt and Prskawetz (2011) analyze Austria in 2010 and find am average fiscal life-cycle dominated by low education, population aging and early exits from the labor market paired with a generous public transfer system especially for pensioners.

Christl et al. (2022) estimate the effect of migration on the fiscal balance of the welfare state and contrast the effects of particular migrant subgroups.

These public sector analysis share the NTA logic while differing in their data sources, as well as their definitions of benefits and time horizons. I discuss possible approaches and situate my research design choices in the following section.

### 4.2.2 Accounting Approaches – Key Dimensions

Studies that compute migrants' NFC all subtract public-transfer receipts from taxes and social-insurance payments, yet they often diverge along the following methodological axes:

- *Data source.* In terms of the data source, studies either use survey-based data (e.g. Dustmann and Frattini (2014)), data based on microsimulation (e.g. Christl et al. (2022) and Fiorio et al. (2023)), or data from administrative registers. In this thesis, I use the latter.

- *Benefit scope.* Benefit scope can be measured either through observed take-up of transfers or through simulated entitlement based on eligibility rules. The distinction is relevant if claiming behavior differs systematically between groups. While Bruckmeier and Wiemers (2017) find no significant difference in terms of welfare take-up conditional on eligibility in Germany, register data has the advantage of not requiring any assumption about take-up behavior.

[2] Terminology: Following popular contributions to the literature on the public dimension of NTA, such as Christl et al. (2022) or Miller, C. Mason, and Holz (2011), I use the term *life-cycle deficit (LCD)* to denote the **public-dimension** of the life-cycle fiscal balance by age.

- *Time horizon.* Regarding the time horizon, studies either employ a single cross-section approach (Dustmann and Frattini (2014)) - which is also what I do in this thesis - or use forward-looking projections ( e.g. Christl et al. (2022)).

- *Unit of analysis.* In existing studies, the unit of analysis is either the individual-level allocation of taxes and transfers or household-level pooling. The choice affects how jointly received benefits such as child allowances or housing support are attributed across household members. In this thesis I focus on the individual level.

- *Treatment of indirect taxes.* Indirect taxes are either included directly via EUROMOD microsimulation, imputed from income or consumption data (as in this thesis, using EUROSTAT consumption shares by income decile), or omitted entirely. The inclusion of indirect taxes raises every individual's NFC mechanically.

- *Public goods and indivisible expenditure.*The literature typically handles non-rival public spending (defence, infrastructure, debt service) in three ways: equal per-capita allocation, marginal-cost treatment, or exclusion. This thesis restricts attention to individually attributable flows and thus implicitly employs an equal per capita allocation. The implications of this choice are discussed below.

- *Migrant classification.* Studies on migrants' NFC classify migrants either based on the country of birth, on citizenship, or on self-reported background. This thesis classifies migration status by country of birth. This approach captures first-generation migrants regardless of naturalization status. It does not identify second or third generation immigrants as migrants. Again, I contextualize the consequences of this methodological choice below.

I classify individuals as EU migrants if the country they were born in or its legal successor, is an EU country in 2021. Individuals born in Austria are classified as natives. Individuals born neither in Austria nor a today EU member state are classified as extra-EU migrants.
Classifying individuals into migrant groups by country of birth has the mechanical consequence that children of migrants are allocated to the native population. This substantially shifts the share of education expenses towards the native population. As a consequence of this, the ANFC for natives is elevated, while it is lowered for migrants. This should be taken into account when comparing the ANFC among migrant groups. The alternative of extending the migrant population to the second and third generation would require parental birthplace data, which I do not have access to in my data.
This methodological choice does not influence the life cycle profiles, because some children migrate at early ages with their parents and the age-conditional averages used in the life cycles are insensitive to bucket-size. Since education costs are imputed identically for all groups, smaller cell size does not affect accuracy in this case.
The second methodological choice requiring further justification is the exclusion of public spending that is not directly welfare relevant in the construction of the NFC. Government expenditures on defense, infrastructure, debt service and administration cannot be traced to individual beneficiaries. There are two common ways of addressing this issue (National Academies of Sciences, Engineering, and Medicine, 2017, ch.8): One option is to assign an equal per-capita share to each resident, thereby lowering all NFCs by a uniform amount. Since this shift is identical across subgroups it does not influence migrant group differences, which are the objects of interest in this thesis. The other option for addressing this, is to treat migrants as marginal users of public non-rival goods. This approach greatly improves the fiscal balance of migrants.

I choose to only depict the direct, individual transfers or in-kind benefits individuals receive. This is warranted because with migration rates reaching above 20% it is plausible to assume that public good provision has responded meaningfully. By excluding indivisible expenditure, I avoid assumptions about what marginal cost an additional migrant adds. Instead, I treat all individuals equally in fiscal terms and only analyze clearly attributable fiscal flows. This, however, leads to NFCs that do not reflect the budgetary position of the state.

All accounting approaches share the inability to include administrative costs of welfare provision, which are not recorded at the individual level.

Finally, all accounting approaches are unable to capture secondary effects of migration e.g. changes in firm-level tax revenues due to productivity increases.

## 4.3 Regression Framework and Decomposition

The average net fiscal contributions and life-cycle profiles as described in the sections above can identify differences in the fiscal contribution of groups but cannot cleanly quantify them and differentiate between compositional and systematic fiscal differences. In this section, I introduce the regression and decomposition approaches that I use to investigate the nature of the fiscal differences among migrant groups and natives.

### 4.3.1 Baseline Specification

To quantify conditional differences in annual net fiscal contributions between migrants and natives, I estimate the following baseline model using an ordinary least squares (OLS) regression framework:

$$\text{NFC}_i = \beta\, \text{Migrant}_i + \varepsilon_i, \tag{5}$$

where $\text{NFC}_i$ denotes the net fiscal contribution of individual $i$, and $\text{migrant}_i$ is an indicator for foreign-born status.

Equation (5) captures unconditional mean differences. To analyze whether these differences stem from compositional factors (e.g. education, age, marital status), I estimate a series of expanded models:

$$\text{NFC}_i = \beta\, \text{Migrant}_i + X_i'\gamma + \varepsilon_i, \tag{6}$$

where $X_i$ contains observable demographic and socioeconomic characteristics.

### 4.3.2 Stepwise addition of Covariates

Firstly, I sequentially add covariates to the base regression of the dummy variable on the fiscal net contribution. I start by including a set of control variables targeting differences in demographic characteristics of migrant groups. Next, I add age dummies to remove differences in age structure. I then account for differences in education, in gender composition and in the number of children. Finally, I sequentially add labor market relevant variables such as employment and student or pension status.

This stepwise expansion of the regression model shows how the migration coefficient evolves as observable differences between groups are absorbed in the control variables. Changes in the migrant coefficient can either imply the absorption of compositional advantages or disadvantages into the set of control variables depending on the average influence of the control variable on the fiscal net contribution. The concrete interpretation of changes in the migrant dummy is discussed with the results.

#### 4.3.3 Sample Split Regression

The second regression approach estimates the same fully specified model separately for natives, EU migrants, and extra-EU migrants, as well as for the 15 largest origin-country groups.
The sample-split results thus describe how the same observable characteristics translate into fiscal contributions differently across groups. The return of education or the penalty of being a pensioner may, for example, be substantially different for German and Syrian migrants.

#### 4.3.4 Gelbach Decomposition

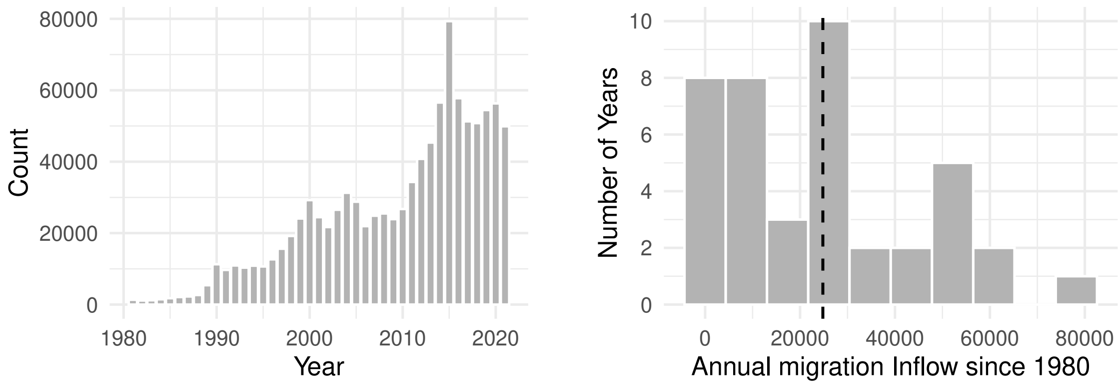
After using standard OLS regressions to partially explain the differences in NFC between the population subgroups, I use a Gelbach (2016) decomposition to estimate how each factor contributes to the overall differences in NFC.
This decomposition approach essentially treats every factor as an omitted variable in the relationship between the migration dummy and the NFC and measures the resulting bias if the factors were excluded. The Gelbach decomposition has the advantage over sequentially adding covariates that the order of the addition is irrelevant. This is of particular importance if it is suspected that some explanatory variables are correlated. (Gelbach, 2016)
I first estimate a baseline model with the migrant dummy variable as the only regressor. Subsequently, a second model with full specification is estimated. In a third step via the omitted variable bias formula, the effect of the additional covariates of the second, full specification on the migrant dummy are estimated. This analyzes, how much change in the migrant dummy estimate between the two model specification can be attributed to which additional regressor.
The Gelbach (2016) methodology is frequently used when estimating labor market differences between men and women or groups with different ethnicity.

# 5 Descriptive Analysis

This section analyzes three key descriptive attributes of population subgroups that will make up key covariates used in later regression models: demographic structure, educational attainment, and labor market attachment. From the descriptive graphics alone, two counteracting mechanisms on the migrant groups' fiscal impacts can be inferred: Migrants are concentrated in working-age groups but partially show lower education and labor market attachment.
Throughout this thesis, I classify individuals as either *natives*, *EU migrants* or *extra-EU migrants*. As I do not have access to information on the location of residency prior to the migration to Austria, I rely on the country of birth in order to infer where an individual migrated from. This classification is best suited for the analysis as many migrants, and especially refugees, often migrate through and briefly live in several countries before arriving at their destination. I do not rely on citizenship in order to avoid missclassifying non-migrants or second-generation migrants with foreign citizenship as migrants, which would diminish accuracy. Second and third generation immigrants are classified as natives. The data does not include the birthplace of an individual's parents, making it impossible to depict further heterogeneity in the native population. All figures are based on the year 2021.

## 5.1 Compositions of Origin in Austria

Figure 1a depicts the annual immigration into Austria from 1980 until 2021 and is based on the 2021 AEST data described above. The y-axis shows the number of people immigrating per year who were neither born in Austria, nor have an Austrian citizenship. The x-axis indicates the calendar years. The figure only includes individuals moving to Austria that were not born in Austria, so that Austrians who have lived abroad and moved back are not included.




(a) Migration to Austria per year since 1980 (b) Histogram of annual migration to Austria

**Figure 1.** Migration inflows to Austria, 1980–2021

*Notes:* Panel (a) plots the number of foreign-born non-citizens immigrating to Austria per calendar year. Panel (b) shows the histogram of the same annual series; the dashed line marks the mean annual inflow of approximately 25,000 persons.
*Source:* AEST 2021; author's calculations.

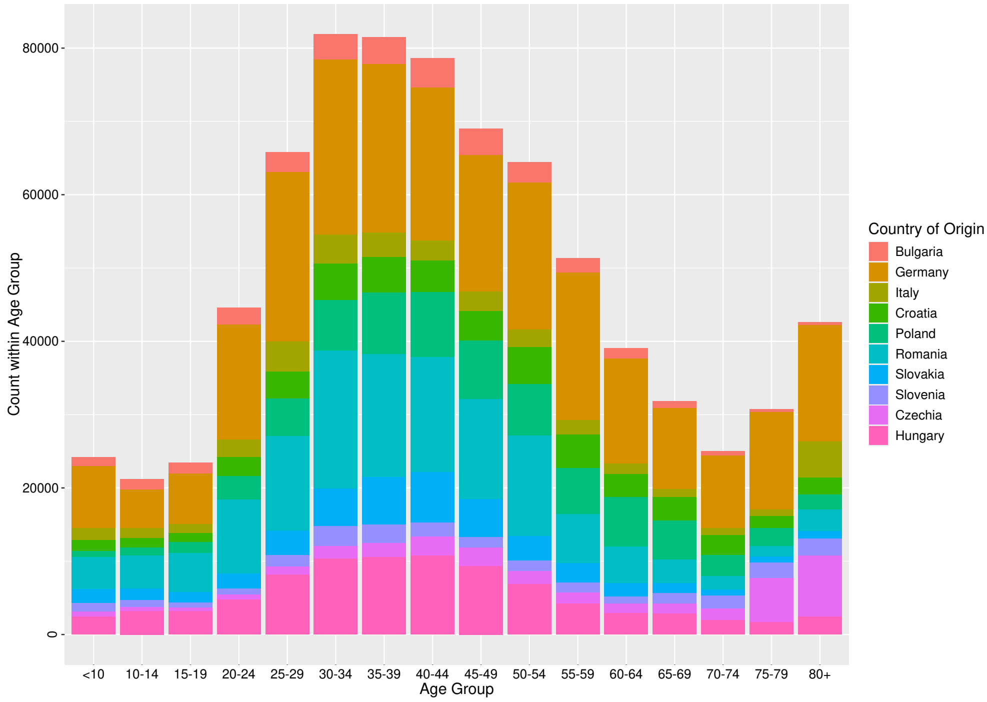
During the 1980s, immigration into Austria was stable at a low level of under 3,000 migrants per year. The sudden increase around 1990 can be attributed to the fall of the Iron Curtain and the collapse of the Soviet Union. Migration further rose until it reached a local maximum in 2000. Between 2002 and 2011 immigration remained on a steady level below 25,000 people per year. The rise towards the global maximum in 2015 coincides with the civil war in Syria, which sparked a large escape movement towards Europe. After 2015, migration settled at under 50,000 persons per year through 2021. Overall, this graph illustrates Austria's shift towards becoming an immigration country. This shift motivates the analysis of the fiscal impact of the demographic change in the later chapters. Figure 1b shows the distribution of annual inflows over the same time period. The distribution is right-skewed with a mean annual inflow of 25,000 persons (dashed line). This indicates that migration is a strongly fluctuating pattern with 2015 being the large outlier to the right. However, the skewness also reflects the long time horizon with low migration numbers in the 1980s and migration in the past ten years consistently exceeding the mean.

Figures 2a and 2b show the origin composition of migrants by birthplace and age. In contrast to many official statistics, I do not classify individuals by citizenship but by birthplace. While citizenship reflects the legal status, my aim is to identify individuals who were not born in Austria and thus actually migrated.

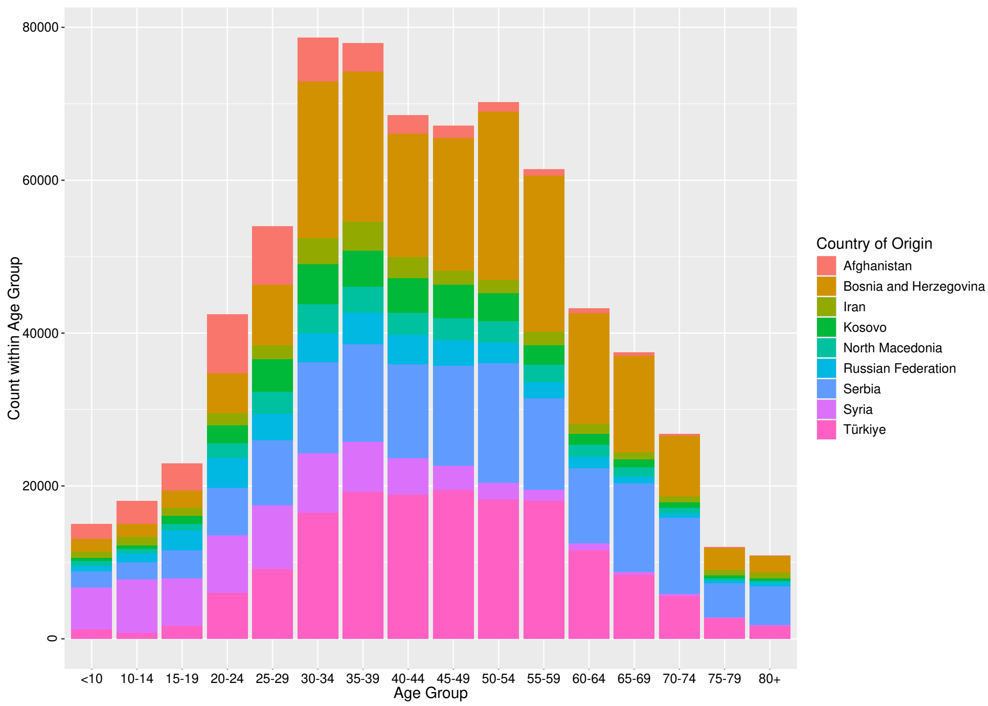
The graphic is separated into EU (top) and extra-EU (bottom) migrants and gives the absolute numbers and the relative share of migrants' birthplaces for each age group. To ensure readability, I depict the top 10 countries from each pool.

In total, the biggest group of foreign nationals comes from Germany. The second largest group was born in Romania, while the third-largest group was born in Bosnia-Herzegovina. Note that in most official statistics that use citizenship as a classifier, the third largest group is from Turkey. Among EU migrants, the biggest group across all age groups was born in Germany, followed by Romania and Hungary. The relative depiction in the within EU migrant group shows, that Germans are represented in all age groups, although they make up a larger percentage in the older age groups.[3] Romanians are concentrated below 50. Extra-EU migrants show greater heterogeneity. Bosnia-

[3]Relative figures could not be included in the final version due to bucket size in construction.




(a) EU migrants




(b) Extra-EU migrants

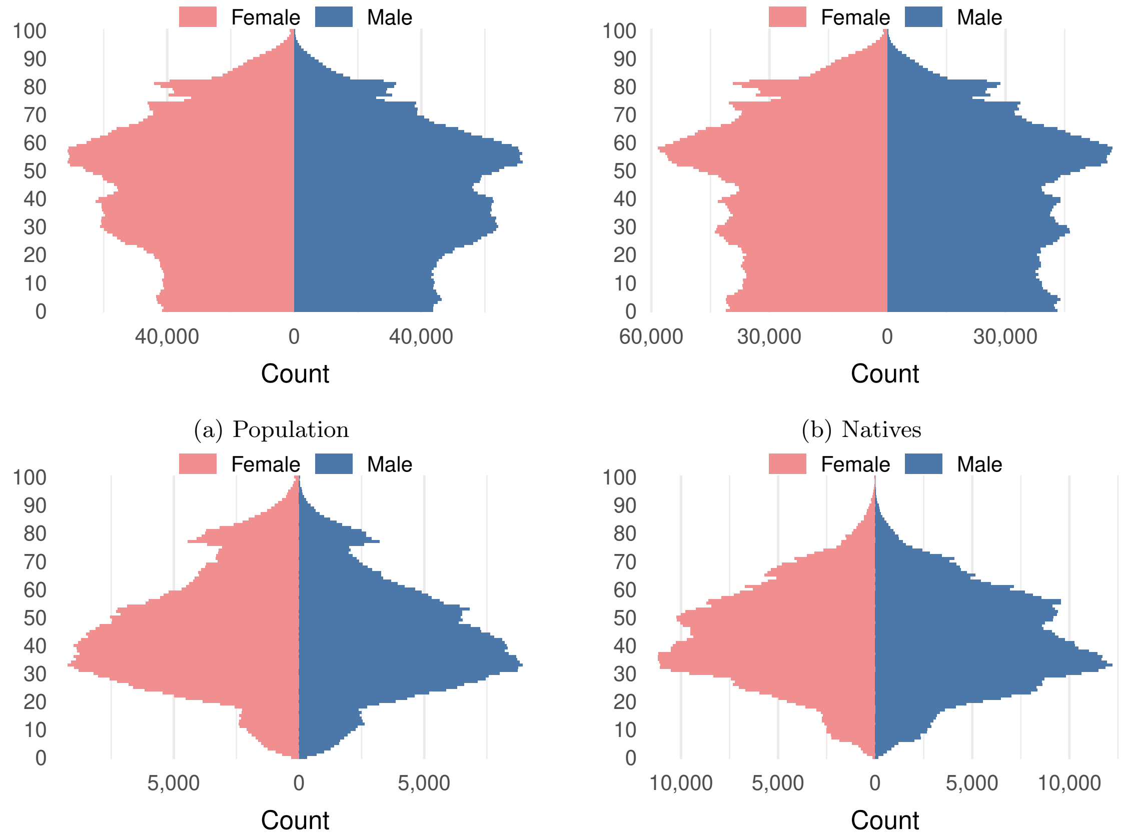
**Figure 2.** Origin country composition by age group

*Notes:* The figure shows the origin countries of foreign-born residents in Austria in 2021 broken down by age group for the 10 biggest foreign born subpopulations in Austria. Panel (a) covers EU-born migrants; panel (b) covers extra-EU-born migrants.
*Source:* AEST 2021; author's calculations.

Herzegovina constitutes the largest group, followed by Turkey and Serbia. The relative depiction of extra-EU migrants across age groups tells a different stories of migration for different countries of origin. People from Bosnia-Herzegovina and Kosovo are largely concentrated around working ages from 25 to 65. Individuals from Afghanistan and Syria are much younger, which coincides with more recent displacement due to civil wars. Moreover, Serbs tend to be older than other extra-EU migrant. However, not only the age structure among migrant origin groups differs. The aggregate migrant groups also show substantial differences when compared to the native population. These differences are central to the overall fiscal sustainability of the welfare state.

## 5.2 Age and Gender Distribution

In order to present a more detailed overview over the gender specific age structure, I construct classic *age pyramids* for each migration subgroup in the following section.




(a) Population

(b) Natives

(c) EU Migrants

(d) Extra-EU Migrants

**Figure 3.** Age Profiles by Migrant Background.

*Notes:* Population pyramids for Austria in 2021 by age and gender. Panel (a) covers the full resident population; panels (b)–(d) restrict to the indicated subgroup(natives, EU migrants, Extra-EU migrants). Bars to the right of the axis represent men, bars to the left represent women; the horizontal axis shows the number of individuals. Note that the horizontal scale differs across panels.
*Source:* AEST 2021; author's calculations.

In the register data, the average age of Austria's total population is 42.7, compared to a higher average of 43.2 years for the foreign-born population and a slightly lower average age of 42.6 for the native population. This overall comparison masks substantial heterogeneity among different migrant subgroups. The EU migrant subgroup shows a substantially higher average age of 44.1 years, reflecting earlier migration waves and a larger share of settled families.[4] By contrast, the

[4]The average ages reported here differ from official statistics (Statistik Austria reports 43.2 years for 2021). This is likely due to selection effects (e.g., young children in the native population) and to the fact that the averages here were calculated based on the reported year of birth. This leads to a downward bias compared with monthly reported ages.

average age of the extra-EU migrant subgroup is 42.5 years. A large share of the difference at younger ages between natives and the foreign-born population stems from the nature of migration itself, as very young children rarely migrate independently. Further, the children of immigrants who were born in Austria are treated as natives. This decreases the share of children among migrants and increases the share of children in the native population. Beyond this, however, the pyramids clearly show that migrants are disproportionately concentrated in the core working ages, giving them a structurally more favorable age profile despite higher average ages.
The pension and retirement system is particularly sensitive to changes in the age structure of the population. This is because it alters the ratio of workers to retirees, which in turn increases the dependency ratio with the aging of the population.

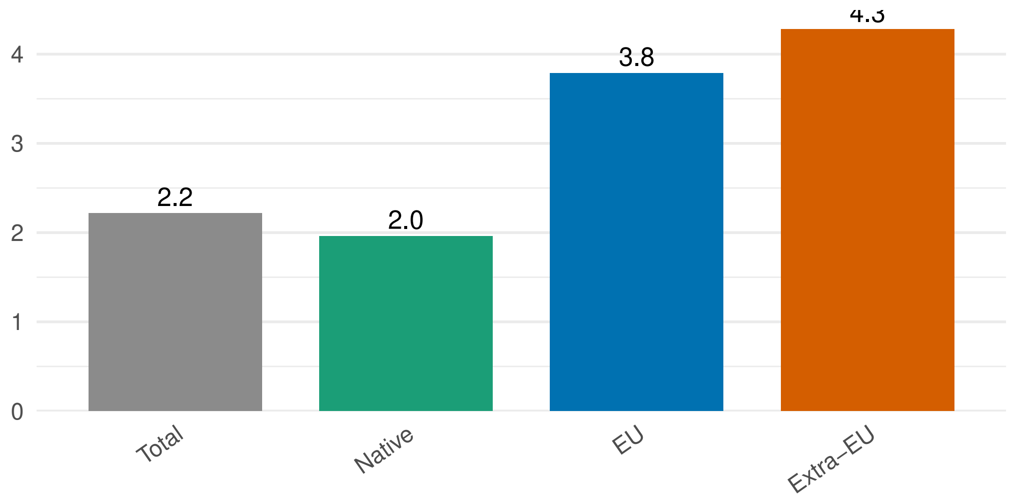



**Figure 4.** Workers per pensioner by migration background.

*Notes:* The figure shows the ratio of employed individuals to pension recipients in 2021, separately for natives, EU migrants, and extra-EU migrants. Higher values indicate a larger contributing base relative to pension recipients within the group. The cut-off number for extra-EU migrants is 4.3.
*Source:* AEST 2021, LUE 2021; author's calculations.

The lowest worker to retiree ratio, with only 2.0 active workers per retiree, is observed for the native population. In contrast, all migrant subgroups show higher worker to pensioners ratios with especially favorable ratios for extra-EU migrants, who show 4.3 workers per retiree.
Unlike the conventional dependency ratio, which compares cohort sizes and thus gives information about the age structure of the population, I depict the actual support ratio. Comparing people who actively contribute to the pension system with people who actually receive pensions, gives a more accurate insight into the realized fiscal flows of each group than comparing the size of particulatr age groups. This approach leads to a much lower actual support ratio when compared to cohort-size-based estimates of the dependency ratio. This is mostly because not all working-age persons contribute (e.g., schooling, early retirement, unemployment). In addition, the share of early retirements has increased, lowering the actual average retirement age below 64, which is the threshold used by the Austrian BMF (Federal Ministry of Finance (BMF), 2025).
The support ratio is of high importance in pay-as-you-go pension systems like the one in Austria. In these pension systems, the current working population finances the pensions of those already retired. A lower ratio of the working to the retired population increases the per capita financial burden of the working population, resulting in higher pension insurance contributions. The *Ageing Working Group* of the *Economic Policy Committee* projects that the dependency ratio, measured by the size of age groups, could increase from 32.2% in 2022 to over 57% in 2070. This would

increase public pension spending by 8.7 pp of Austria's GDP (Economic Policy Committee – Ageing Working Group, 2023, p.17). The OECD's estimates show that a sustained annual migration of 2% of the population would stabilize the dependency ratio on average in OECD countries. This is much higher than the current 0.3% per year average and presupposes perfect labor market integration (Koutsogeorgopoulou, 2025, p.44). Current migrant populations, with their more favorable age structure, could ease the financial pressure by contributing more workers relative to retirees if they are otherwise identical to the native population.

An important caveat to the interpretation of the support ratio is that it implicitly treats all workers and pensioners as equally fiscally relevant. Lee and A. Mason (2010) show that the increase in productivity in many Western countries has partially offset the declining support ratio. However, with increasing productivity, pensions also rise, rendering the fiscal effect of changes in productivity ambiguous.

Since differences in productivity are closely linked to education, the next section addresses the potential ambiguity in the support ratio by comparing subgroup-specific education compositions.

## 5.3 Education Distribution

Educational attainment shapes both workers' productivity and employment prospects. This makes it a strong predictor of an individual's or a groups' fiscal situation.

The AEST education variable distinguishes eight categories, ordered by ISCED level. These are: Pflichtschule (compulsory schooling, ISCED 2), Lehrabschluss (apprenticeship, ISCED 3), Berufsbildende mittlere Schule (BMS, vocational secondary without Matura, ISCED 3), Allgemein bildende höhere Schule (AHS, academic secondary with Matura, ISCED 3-4), Berufsbildende höhere Schule (BHS, vocational upper secondary with Matura, ISCED 3-4), Kolleg (post-secondary non-tertiary, ISCED 4-5), Akademie/Hochschulverwandte Lehranstalt (tertiary-equivalent academy, ISCED 5-6), and Hochschule (university degree, ISCED 6-8). Following Austrian convention, I have categorized the acquired education into four levels: compulsory schooling (Pflichtschule), apprenticeships and intermediate VET (BMS), academic secondary and higher VET (Matura) as well as tertiary education (Hochschule).

The figure compares the educational attainment among all individuals who are currently not in school and have at least completed compulsory schooling. I exclude currently enrolled individuals to focus the comparison on the working and retired population. Further, I exclude individuals with missing education because I suspect data quality issues. Unlike *Statistik Austria*, which usually selects the population between 25 and 64, I do not exclude individuals above or below a certain age threshold. This decreases the share of higher educational attainments, as education has risen steadily in Austria over the past 100 years.

Of the total population, 17% hold compulsory schooling as their highest completed education. The largest group in Austria has completed apprenticeships or intermediate VET (47%). *Matura* makes up 18%, and 17% have acquired a university degree.

The Austrian born population shows a largely similar pattern with slightly more people concentrated in the second level of education (53%) and less compulsory schooling (11%).

For EU migrants, the share of university degrees is 5 percentage points higher, making up 22% of the subgroup. The EU migrants are also much less represented at the secondary AHS / high VET level and show a higher share in compulsory schooling (20%).

The extra-EU migrant group shows substantially higher concentrations at the compulsory schooling level, which makes up 45% of the subgroup. Both Matura and tertiary attainment are at 14%, which is the lowest of any subgroup.

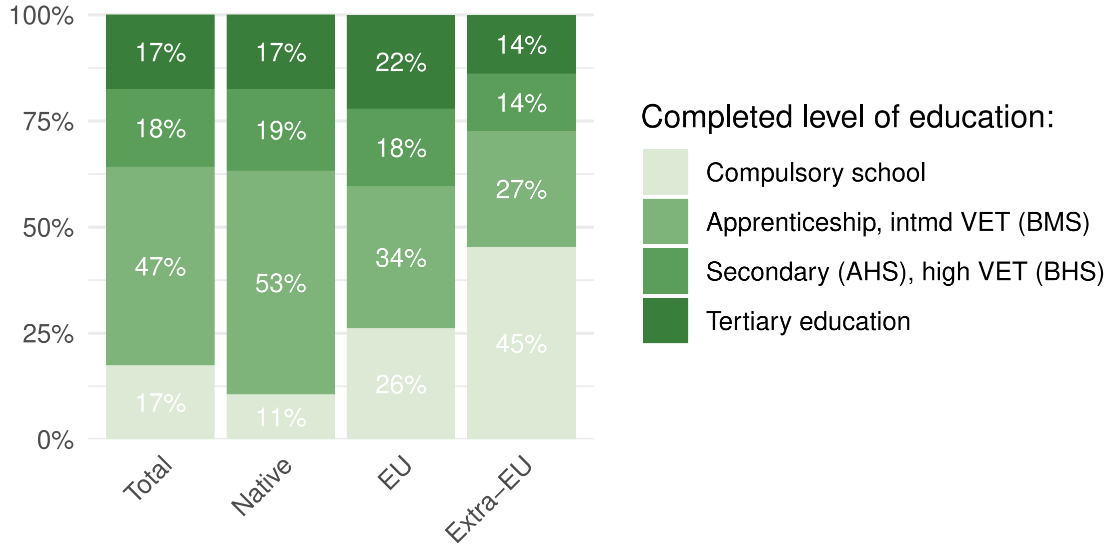


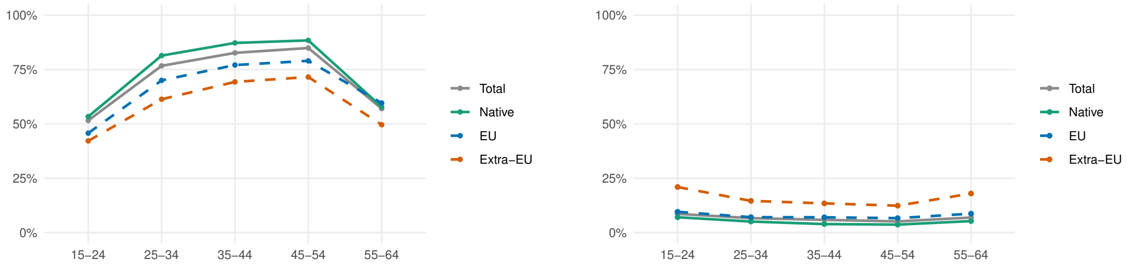

**Figure 5.** Educational attainment composition by background

*Notes:* The figure shows the share of each migration groups' (natives, EU migrants, extra-EU migrants) highest completed level of education in 2021. Bars sum to 100% within each group. Due to issues with data quality NA entries are removed.
*Source:* AEST 2021; author's calculations.

Whether or not the potential associated with the level of education is realized on the labor market, is what finally determines individuals' fiscal outcomes. Especially for migrants, there can be notable differences in how education translates into labor market attachment due to limited recognition or legal restrictions.

## 5.4 Employment and Unemployment Rates

Figure 6a illustrates the share of the working-age population that is employed. The count of working individuals includes part-time workers. The employment rates denominator includes inactive people who may be caregivers, in early retirement or otherwise not able or not willing to work.
In contrast, Figure 6b gives the share of people who are registered as unemployed per age and migration subgroup. I give the shares for five age buckets to remove some of the age-composition effects on both measures in order to preserve comparability between subgroups. Both shares are correlated but complement each other in interpretation.
The employment rate figure shows the expected life cycle of schooling and retirement, lowering the share of employed individuals at both ends. For the ages between 15 and 34 the share is much lower than in the following age buckets due to education and the compulsory military or civil service not being counted towards the working population.
All three groups run largely parallel to each other, with natives showing the highest employment rate followed by EU migrants and extra-EU migrants. The difference between EU migrants and natives diminishes in the 55-64 age bucket, which together with unchanged unemployment rates, indicates earlier retirement by natives.
The unemployment figure shows consistently higher unemployment among extra-EU migrants. EU migrants show slightly higher levels of unemployment than natives. For extra-EU migrants, there are increases in unemployment for the youngest and oldest age buckets. The increased unemployment in the early age group likely reflects a high concentration of refugees in that bucket. Refugees face substantially higher unemployment rates due to legal restrictions and additional difficulties as described in Section 2.3.




(a) Employment rate by background (age 15-65) (b) Unemployment rate by background (age 15-65)

**Figure 6.** Labor market attachment by migration background

*Notes:* Panel (a) shows the employment rate, defined as the share of employed individuals among the population aged 15–65. Panel (b) shows the unemployment rate, defined as the share of unemployed individuals among the labor force (employed plus unemployed) aged 15–65. Both rates are reported separately for natives, EU migrants, and extra-EU migrants as well as the total resident population in 2021.
*Source:* AEST 2021, LUE 2021; author's calculations.

**Result 1:** Natives, EU migrants and extra-EU migrants differ along three dimensions with opposing fiscal implications. The descriptive figures establish the compositional landscape but cannot resolve which force dominates. For extra-EU migrants, the advantageous age structure, illustrated in the age pyramids and support ratio is associated with a positive net fiscal position. It may be offset or dominated by less advantageous educational attainment and lower labor market attachment.
EU migrants show a similar advantageous age structure, but more closely resemble natives in education. For both groups, it is not clear from observable characteristics alone how their average fiscal outcomes compare. Which force dominates depends on how education and labor market attachment are concentrated along the life cycle. These interactions are addressed through the construction of group-conditional life cycle profiles in the next chapter.

# 6 Life Cycle Contribution

There are two main counteracting compositional patterns established in 5: age structure and education/labor market attachment. However, which compositional difference dominates the fiscal outcomes cannot be read of the descriptive figures. Table 1 gives a first indication by providing the average net fiscal contribution (ANFC) by migration status, gender and education for the year 2021. With EU migrants being the subgroup with the larges ANFC, and extra-EU migrants being lower but close to natives, the age structure seems to dominate the fiscal outcomes. The life-cycle profiles developed in the second part of this chapter illustrate this mechanism. For all age groups and subgroup selections, natives consistently show higher fiscal contributions. This implies that the favorable fiscal outcomes of migrant subgroups are largely a result of compositional differences.

## 6.1 Average Net Fiscal Contribution

As reported in Table 1, EU migrants exhibit the highest ANFC, followed by natives, with extra-EU migrants lower on average. Within the extra-EU migrants, refugees contribute substantially less than non-refugees. The largest differences can be observed for different education attainments where the ANFC rises sharply from compulsory schooling to higher secondary education. The large difference in educational attainment likely is not only caused by earning differences, but also represents a trend towards higher education over the past decades, concentrating pensioners

**Table 1.** Average Net Fiscal Contribution (ANFC) by subgroup, 2021

| **Subgroup** | **ANFC (EUR)** |
|---|---|
| *Overall* | 4 350 |
| *By migration status* | |
| Natives | 4 316 |
| EU migrants | 5 466 |
| Extra–EU migrants | 3 669 |
| Extra–EU (non-refugee) | 3 864 |
| Refugees | 1 751 |
| *By gender* | |
| Female | 1 295 |
| Male | 7 491 |
| *By education* | |
| Compulsory schooling only | 645 |
| Higher secondary | 15 784 |

*Notes:* The table reports the average net fiscal contribution (ANFC) per individual in EUR for the Austrian resident population in 2021, broken down by migration status, gender, and select education. Education figures exclude individuals currently enrolled. Values are rounded to the nearest euro.
*Source:* AEST 2021, LUE 2021; author's calculations.

in lower education buckets. Individuals currently enrolled in education are excluded from the education breakdown.

The average contribution of the entire population in the year 2021 is 4350,12 EUR. When conditioning on population subgroups the highest average contribution of 5465,54 EUR comes from migrants within the European Union. The second highest contribution of 4315,86 EUR is provided by native Austrians, while extra-EU migrants trail behind with an average net fiscal contribution of 3668,54 EUR. Further granularity within the extra-EU migrant population by refugee status shows an ANFC for refugees of 1751,08 and the non-refugees of 3863,73 EUR. The ANFC by educational attainment shows the largest differences ranging from 645,03 EUR for individuals with compulsory schooling only to 15783,84 EUR for individuals with a higher secondary education. Note that all individuals taking part in schooling are excluded from both sets here.

One central limitation to the interpretation of the calculated NFC numbers is that all direct and indirect taxes are used in full, although a part of them is not used in the welfare state, but rather for general government expenditure such as defense, infra structure or administration. As discussed in chapter 4.2, I assume an average cost allocation of public spending to all individuals. Thus, the additional taxes that do not go towards the welfare state shift the NFC uniformly.

**Result 2:** EU migrants exhibit the highest average net fiscal contribution followed by natives and extra-EU migrants. This resolves the ambiguity of the descriptive overview of the observable characteristics in section 5. The ANFC further varies greatly by gender and educational attainment. The ANFC captures the per-capita contribution for each group to the welfare state. Since most of the welfare state is funded through a pay-as-you-go system, these metrics reflect how much the groups actually contribute per capita to the welfare state in 2021. On this measure the gaps between migrants and natives are small when compared to within-group differences in education or gender.

To explore how such differences in ANFC arise, I will analyze how fiscal behavior varies along the life-cycle within each group in the following section; chapter 7 then quantifies compositional differences between the groups.

## 6.2 Life-Cycle Deficit Figures

The figures used throughout this section represent the average annual per-capita fiscal flows in the year 2021. The lines compared in panel d are equivalent to the net lines in panels a–c, where the disaggregation by component is illustrated. In this form of presentation, positive net lines indicate net positive contributions while negatives indicate net recipient age groups. All groups are net recipients in their childhood and in old age. Moreover, all groups show a positive plateau during working ages. In panel d the years from 0 to 10 are depicted. These, however, do not warrant conclusive evaluation. This is because the costs of kindergarten and other types of early childcare were not imputed. Further, much of the care work during the ages 0 to 3 is performed by family members and thus not monetized.

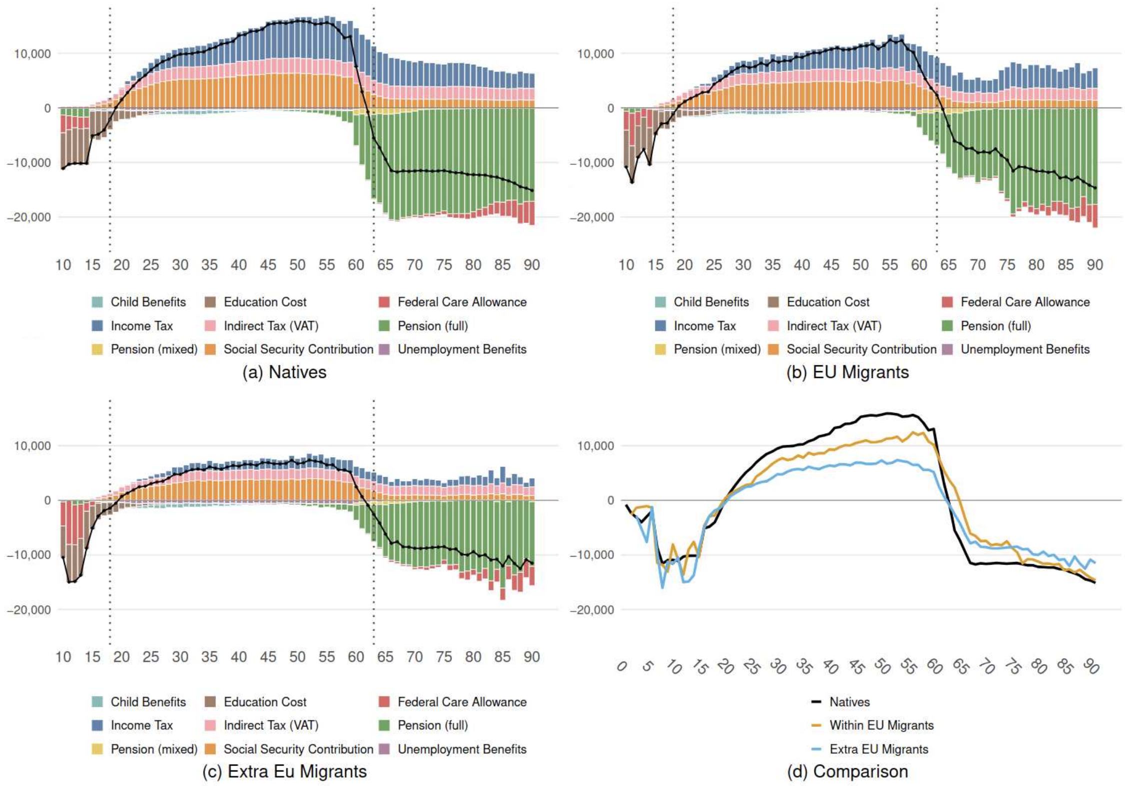



**Figure 7.** Net fiscal contribution life-cycle profiles by origin group

*Notes:* Cross-sectional mean net fiscal contribution by year of age, in EUR, in 2021. Panels (a)–(c) decompose the NFC into its tax and transfer components for natives, EU migrants, and extra-EU migrants, respectively; the line in each panel marks the net balance. Panel (d) overlays the net balances from panels (a)–(c) to allow direct comparison across groups.
*Source:* AEST 2021, LUE 2021; author's calculations.

In the years 6 to 15, all children are assigned the average cost of schooling while for the years 16 to 25 the education specific averages are utilized. The main differences to younger children lie in the reception of the federal care allowance. This is highest among EU migrants but shows large heterogeneity in both migration subgroups due to small populations. Even though all education costs are based on education specific average costs, the transfer side figure 8 shows modestly higher transfers towards natives between the ages 16 and 25. This reflects that a larger share of natives remains in full time education after the age of 15. The first transition to a net positive fiscal contribution, however, takes place at 20 years of age in all groups.

In the prime working time, between 20 and 60 life-cycle profiles begin to substantially diverge. From 20 to 45 all three profiles increase largely parallel to each other with natives above EU migrants

who, in turn, produce a larger fiscal contribution. At age 45 both migrant groups remain on a similar trajectory while the natives show a stronger increase in fiscal contribution. Notably extra-EU migrant's fiscal contribution levels off a lot earlier and only shows limited growth compared to the other two groups. Natives as well as EU migrants - though to a lesser extent - show a visible indentation around the ages 30 to 40. This can be attributed to a temporary reduction in labor market participation due too children and the receipt of child benefits. Over the entire life-cycle, unemployment benefits remain largely invisible, indicating that the differences in unemployment rate identified in chapter 5 may not be fiscally salient. Increased volatility in the EU migrant and extra EU migrant subgroups can be attributed to the rather small samples for specific migration patterns in specific age groups particularly in very young and very old ages.
The second extensive shift in the life-cycle profile is the entry into retirement. Here, the native population differs substantially from both migrant groups. The pensions, represented in green, reach their maximum much earlier and decrease steeper after the age of 60. Notably the pensions received by natives are almost double compared to those received by extra-EU migrants. The transitionary role of mixed pensions is comparatively small. With pensions being proportional to wages, the ordering of fiscal contributions unexpectedly reverses in retirement where natives exhibit the highest fiscal net-negative, followed by EU and extra-EU migrants. A second mechanism contributing to lower pensions towards both migrant groups, is that a large share does not contribute as long as the native population. This further lowers received pensions. In old age, federal care allowances start to become fiscally relevant - although minor across all groups.
The fact that pensions visibly decrease in old age is a result of the construction of life cycles on cross sectional data. Wages and pensions have generally increased over time. Therefore, people who have entered retirement more recently receive higher pensions. This, however, does not imply that pensions on average decrease in old age. Rather, one would expect pensions to rise in old age due to higher income being a predictor of longer lifespans.

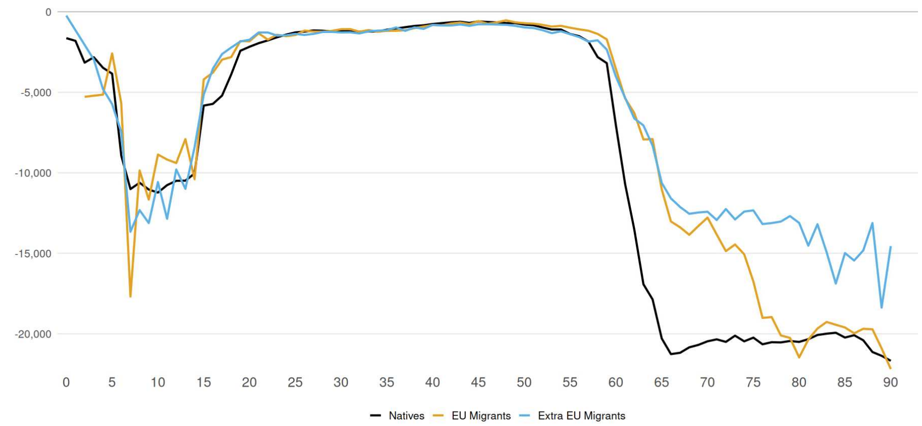



**Figure 8.** Average transfers received by age and origin group

*Notes:* The figure plots the cross-sectional mean of total transfers received per individual by year of age, in EUR, in 2021, separately for natives (black), EU migrants (yellow), and extra-EU migrants (blue). Transfers include pensions, unemployment benefits, child benefits, federal care allowance, and imputed education costs. Values are shown with a negative sign, reflecting that transfers reduce the individual net fiscal contribution.
*Source:* AEST 2021, LUE 2021; author's calculations.

Figure 8 depicts the transfers individuals receive on average and thus only reflects the cost side of the individuals participation in the welfare state from the governments perspective. For all three subgroups, the total-lines move nearly identically until pensions start to be relevant. As pensions are proportional to previous income, the higher salaries and longer contribution periods of the natives start to show here. The graph illustrates that differences in the net contribution lines in figure 7 do not stem from higher transfers or larger take-up of welfare programs. Instead, they mainly reflect lower contributions due to lower salaries.[5]

The largest differences in fiscal contribution, however, do not run between migration groups but through them. Gender and education produce substantially larger gaps in ANFC than migration status alone. At the same time, these demographic attributes have a different effect on the life-cycle shape of the fiscal contributions in all groups. Especially the earning of trajectories and the transition into retirement differ for natives, EU migrants and extra-EU migrants.

### 6.2.1 Gender and LCD

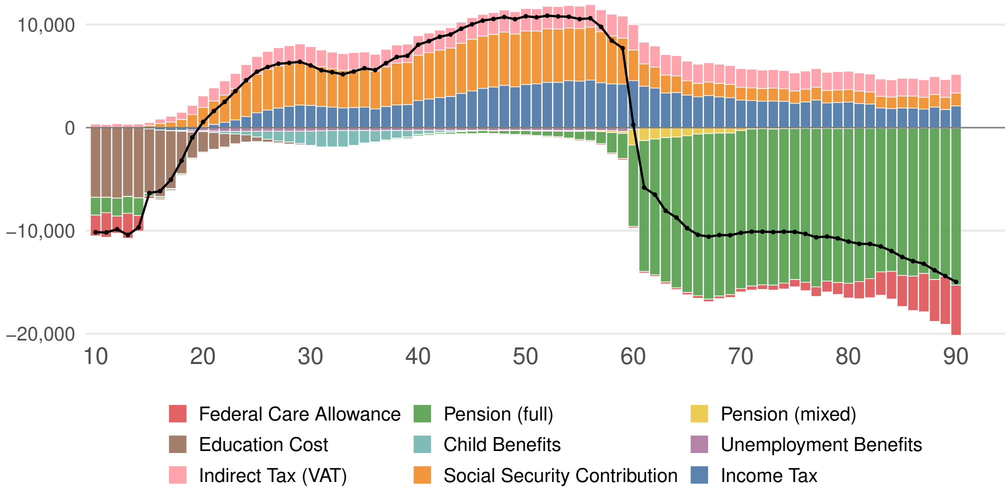
The persistent concentration of childcare responsibilities on women, combined with the gender pay gap and differences in employment intensity, produces systematically lower fiscal contributions for women across all three groups throughout the working years. At their respective earning peaks men contribute about double the women's contribution. The largest absolute contribution of over 20.000€ comes from native men with EU migrant men second followed by native women. The lowest fiscal contributions come from extra-EU women.

**Child Penalty:** While the male net-contribution lines show a steady increase in contributions over the working ages, the women's growth stalls or declines between 30 and 40. This effect is strongest in the native group. Figure 9a illustrates the source of the reduction in net contribution. Firstly income and thus all forms of taxes and SSC decline. Secondly child benefits, colored light blue start to be fiscally relevant and increase received transfers. Only 4.1% of child benefits (Kindebetreuungsgeld) is payed out to fathers (2022) (Rechnungshof Österreich, 2024). Neither effects are present in figure 9b where earnings uniformly rise and no child benefits are visible. Across both migration groups a similar pattern arises. In figure 10 around the age of 29 for EU migrants and around 26 for extra-EU migrants the women's net contributions stalls or declines. However in contrast to the native population the increase after 40 is much less steep for both groups.

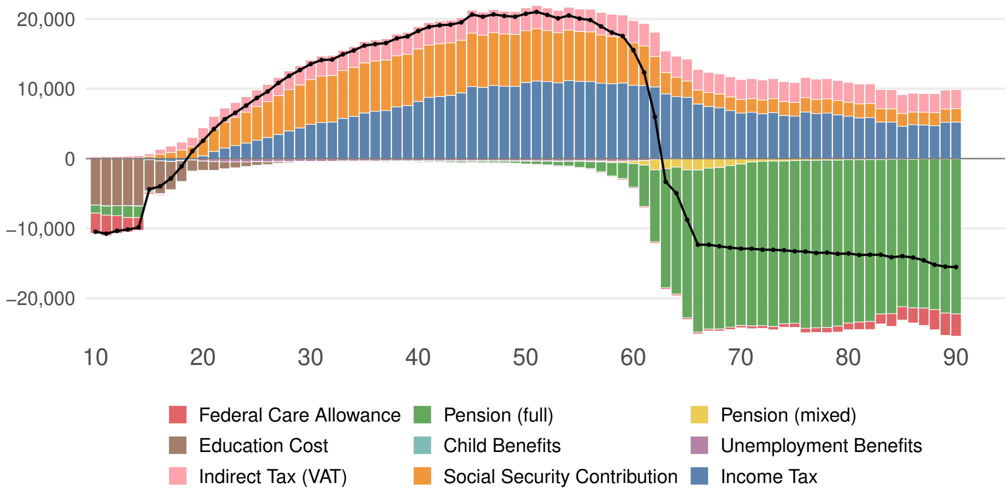
**Education Differences:** For natives the first notable differences arise in the school age. Boys are overrepresented in occupation-specific upper-secondary tracks (apprenticeships): 61.6% of participants are male. By contrast, 50.7% of women attain the *Matura* versus 36.0% of men (Statistik Austria, 2022). At the tertiary level, 22.8% of women hold a degree compared with 18.1% of men. In the fiscal contribution profiles, these differences show up as smaller net negatives for men after finishing compulsory education with 15 because apprenticeship participants enter paid employment earlier and pay taxes/SSCs while peers remain in full-time education. In addition to a smaller share of men continuing towards secondary and tertiary education, different levels of entry pay and the self selection into higher paying jobs further explain the gap (Glaser and Geisberger, 2025). The differences in school ages are less pronounced but also present for both migrant subgroups.

**Earnings Trajectory:** Compared to later differences, both plots move roughly parallel to each other until the age of 25. After that men continue on a steep upward trajectory. Natives peak around 52-54 at just over 21.000 EUR. Eu migrants peak later around 15.000 EUR. Extra-EU migrants reach a stall in earning trajectory much earlier but also exhibit a peak around 53 at 10.000 EUR. For women, the rise slows from about age 25 and comes to a halt near 27 reaching

[5] Note that this graph is sometimes depicted inversely. I choose to keep this orientation to ensure readability in comparison to the other figures.




(a) Female Native




(b) Male Native

**Figure 9.** Gender and LCD Natives

*Notes:* Cross-sectional mean net fiscal contribution by year of age, in EUR, in 2021, restricted to native-born residents. Stacked bars decompose the NFC into its tax and transfer components; the line marks the net balance. Panel (a) covers women, panel (b) covers men.
*Source:* AEST 2021, LUE 2021; author's calculations.

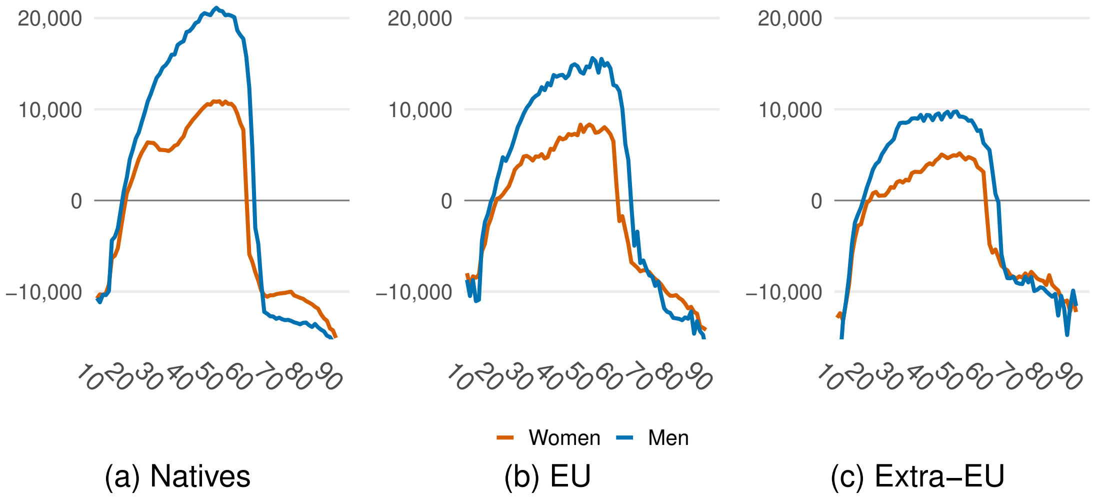



**Figure 10.** Gender Comparison All Groups

*Notes:* The figure plots the cross-sectional mean net fiscal contribution by year of age, in EUR, in 2021, separately for women and men. The three panels cover natives (left), EU migrants (center), and extra-EU migrants (right). The detailed figures are included in the Appendix.
*Source:* AEST 2021, LUE 2021; author's calculations.

a local maximum of roughly 6.000 EUR. From 27 to about 33 there is a downward trend that reaches it minimum at 5.000 EUR before starting to increase again although on a smaller gradient as the male counterparts. The native women's fiscal contribution then reaches a plateau at a peak contributions between ages 48 and 56 at around 11.000 EUR. EU migrant peak above 8.000 EUR and extra-EU migrant women just above 5.000 EUR.

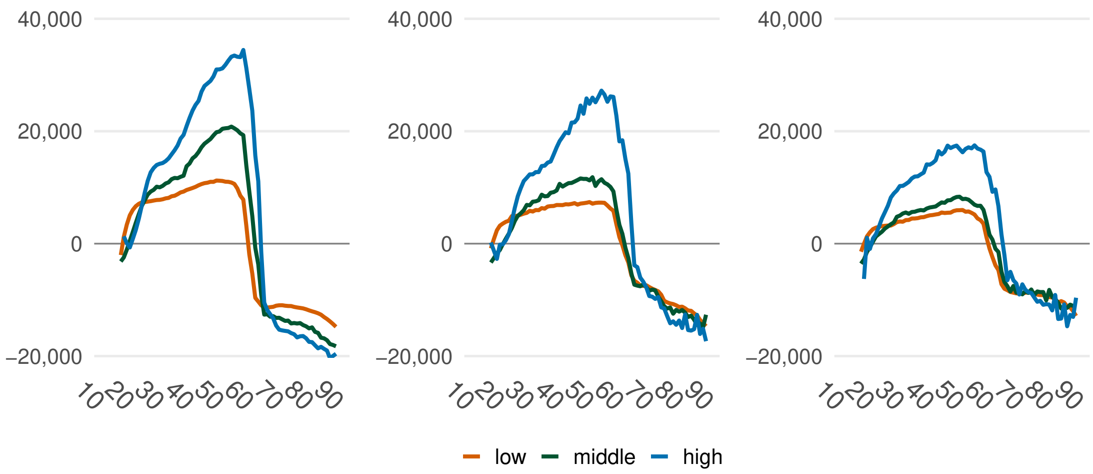
**Pensions** After their respective peaks all three groups first show a moderate, then a sharp decline in their fiscal contribution between the ages 56 and 65. Women cross the zero line into a negative net contribution around age 60, men around 64, consistent with statutory retirement ages. Natives' contributions stabilize, for women around -10.000 EUR, for men around -12.000 EUR until roughly at age 80. After 80 the decline in net contribution continues due to long-term care allowances rising. EU and extra-EU migrants' transition towards retirement compared to natives is less abrupt. The immediate drop after the age of 60 is less steep but fiscal contribution continues to gradually decline until death. This is likely an effect of natives retiring more completely and simultaneously when the pension age is reached while EU and extra-EU migrants in aggregate shift more gradually due to lower contribution times and lower wages. A final gender difference can be observed in care allowance. Here women's higher life expectancy increases received care in old age.

### 6.2.2 LCD and Education

Education is among the strongest predictors of fiscal contributions. The education levels I use for this disaggregation are constructed as follows: Low education describes individuals with compulsory schooling only; medium education is *matura* or an equivalent as a maximum educational attainment; high is a university degree or equivalent.[6] During the working years the within-group ordering, where high education is associated with high NFC, remains stable. In all groups low education produces the lowest NFC and middle education lies between both lines. There are however

[6] All graphs are cut of at 20 years of age where bucket sizes were partially not sufficiently high to preserve data privacy.

striking differences in NFC level between migration groups of the same education.
The spread is biggest for the native population, indicating a particularly high return on the educational investment. Returns to educations are smallest for extra-EU migrants, with EU migrants ranging in the middle. For both migrant groups the return of middle education is only marginally greater than that of low education. High education in all cases more than doubles the peak contribution of low education. This also is, where the largest between group difference can be observed: peak NFC for high education extra-EU migrants lies below that of the middle education natives (20,000 EUR).
An important caveat to returns to education distributions that is especially salient for extra-EU migrants is that high educational attainments may not translate as directly into labor market outcomes as for EU migrants and natives. Especially in medicine, law and education there may be legal restrictions, for other fields there may be differences in education curricula or institutional recognition.
The low education groups, where formal credentials matter less, are the most similar across the three groups
The compressed returns to education for migrants are consistent with Hofer et al. (2017), who document that there is a stronger discrimination of migrants in the upper part of the wage distribution in the Austrian labor market. They further find that discrimination is strongest for non European migrants, especially from Africa and Asia. (Hofer et al., 2017, p.119)
This compressed return to education for extra-EU migrants mirrors a broader pattern documented in OECD (2025). Relying on a Gelbach (2016) decomposition, the authors show that migrants at labor market entry earn substantially less than the native-born even after accounting for differences in educational attainment.



(a) Natives (b) EU (c) Extra−EU

**Figure 11.** Net fiscal contribution by education and origin group

*Notes:* The figure plots the cross-sectional average net fiscal contribution by year of age in EUR in 2021, separately by highest completed level of education. The three panels cover natives (left), EU migrants (center), and extra-EU migrants (right). Education levels are grouped as low (compulsory schooling), middle (Matura / upper secondary), and high (tertiary degree). The detailed figures are included in the Appendix.
*Source:* AEST 2021, LUE 2021; author's calculations.

Across migration status, high education groups show a later entry into the labor market consistent with more time spent in education. Low education individuals start contributing first and remain above both higher education groups until 30, where they are surpassed by middle and high education individuals simultaneously. Unlike the top contribution levels, there is little variation in the timing of entry into the labor market between the migration groups. Similarly, the lowest child penalty can be observed in the low education category across all migrant groups.

When transitioning towards pensions the reverse of the labor market entry order can be observed. Low education individuals leave the labor market first, middle education next and high education last. This likely reflects longer contributions due to earlier labor market entry and more physically demanding work in low qualification occupations. Across the three groups high education individuals transition last but most abruptly where middle and low education fall more steadily. For both migrant groups the spread between education levels largely disappears in the retirement age. For natives however it persists such that high education is associated with high pensions and thus lower NFC.

**Result 3:** The fiscal life-cycle profiles reveal similar shapes across all migration groups as well as gender and education subpopulations. All groups start off fiscally dependent, contribute during their working years and rely on pensions in old age. What is striking however is, that there are large level differences which are almost entirely driven by contribution differences during the working years. In retirement the ordering reverses and natives impose the larges fiscal burden followed by EU migrants and extra-EU migrants. There is a strong child penalty in the native population which is present in all groups, but less pronounced across the migrant groups. The education comparison reveals the expected ordering within migration groups, but middle education natives show higher peak fiscal contributions than high education extra-EU migrants. In the next sections, I will quantify how much these differences and other observable characteristics determine fiscal outcomes for each group.

# 7 Analytical Results: Regression Analysis and Gelbach Decomposition

Building on the descriptive life-cycle fiscal contribution profiles developed in Section 5, the objective of this chapter is to quantify how much of the fiscal differences between migrants and natives can be explained by observable characteristics such as education, age structure, employment, and certain household composition characteristics.

The chapter proceeds in three steps. First, I estimate a sequence of regression models that incrementally introduce covariates, thereby showing how conditional fiscal differences evolve as differences in selection between the groups are accounted for. Second, I estimate sample-split regressions to assess group-specific heterogeneity in the impact of demographic characteristics on fiscal contributions. Third, I apply a Gelbach decomposition to attribute the change of the migration coefficient across multiple specifications to specific selections of covariates, thereby analyzing how much of the change in the NFC of a given migration group is affected by which covariate.

**Method:** As described in Section 4.2, I estimate versions of the following OLS regression framework for both the stepwise and the sample-split models.

$$\mathrm{NFC}_i = \alpha + \beta\,\mathrm{Migrant}_i + X_i'\gamma + \varepsilon_i, \tag{7}$$

The vector $X_i$ includes single-year age dummies (baseline: age 40), education in eight categories (baseline: compulsory schooling), gender (baseline: male), number of children (baseline: zero), pension status, unemployment, student status, and urban residence, with baselines chosen such

that the reference individual is in the fiscally most favorable state in each case. Depending on the specification, covariates are added sequentially in the stepwise models or included jointly in the sample-split regressions.
These estimates indicate *conditional mean differences*, not causal effects. The stepwise design traces how the migration coefficient shifts as compositional differences are successively removed, while the sample-split regressions show how the same covariates operate differently within each group.

## 7.1 Stepwise Regression Models

This section presents the evolution of the migration coefficient as covariates are added sequentially. Firstly I will estimate the base model that only includes the migrant dummy variables. Secondly I add age in the form of a set of one-year-age-bucket dummy variables. The third model includes education, gender and the number of children. Finally I add labor market relevant variables such as pension status.

**Model 1: Unconditional Differences.** This model includes only the migration indicator. It measures the raw fiscal gap between the two migration status dummy variables *EU* and *extra EU* and the baseline defined as the native subpopulation.
The intercept, which reflects the average native fiscal contribution, is 4,800.4 EUR/year. The estimates show that EU migrants exhibit a fiscal contribution that is 1,288.9 EUR/year higher than that of natives, while extra-EU migrants on average contribute 175.5 EUR/year less.

**Model 2: Adding Age Structure.** Age is the single most important demographic predictor of net fiscal contributions. Migrants are concentrated in working ages, which increases their overall average fiscal contribution.
The largest change in the migration group coefficients appears once a set of age dummies is added as a control. The intercept, now reflecting a 40-year-old native male, increases to 13,813.1 EUR/year. The EU coefficient reverses sign and now reduces the intercept by 1,654.9 EUR/year. The extra-EU coefficient reduces the intercept by 4,208.8 EUR/year. That both coefficients become substantially more negative once age is controlled for indicates that the favorable age composition of migrant populations substantially improves their unconditional fiscal position, an advantage that is removed once age structure is held constant. A precise attribution of how much of the change in the migration coefficient is due to specific covariates is provided by the Gelbach decomposition in Section 7.3.
The effects of the age coefficients themselves follow an upward slope during the working years, decline during pension ages and have increasingly large confidence intervals for higher ages. At this specification the age buckets serve as proxies for education cost, contribution plateau and pension status. The explanatory power of age is greatly reduced in the later specification. Overall, the age coefficients follow the life-cycle pattern documented in Chapter 6.2 and are not reported individually.

**Model 3: Adding Education.** In the third step I add gender, the number of children and education as dummy variables.
Fiscal contributions rise with education level: acquiring a university entrance qualification (Higher VET/BHS) increases the NFC by 5,453.3 EUR/year relative to the compulsory-schooling baseline, and holding a tertiary degree (University) by 12,674.7 EUR/year. The estimate for the female

**Table 2.** Stepwise OLS Regression of Net Fiscal Contributions with Migration Status

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Intercept | 4800.408*** | 13813.139*** | 12491.844*** | 15171.799*** |
| | (28.271) | (177.453) | (187.334) | (180.022) |
| EU Migrants | 1288.895*** | −1654.949*** | −1574.896*** | −2353.867*** |
| | (86.949) | (78.623) | (77.482) | (74.259) |
| Extra-EU Migrants | −175.518* | −4208.753*** | −3218.810*** | −3667.454*** |
| | (82.749) | (75.036) | (76.595) | (74.807) |
| Apprenticeship | | | 124.994+ | −654.247*** |
| | | | (66.921) | (63.672) |
| Intermediate VET (BMS) | | | 1775.517*** | 484.247*** |
| | | | (79.379) | (75.626) |
| Academic secondary (AHS) | | | 1299.380*** | 391.813*** |
| | | | (103.321) | (99.138) |
| Higher VET (BHS) | | | 5453.347*** | 3500.880*** |
| | | | (94.789) | (90.575) |
| Kolleg | | | 4100.466*** | 2017.191*** |
| | | | (270.096) | (256.918) |
| Tertiary academy | | | 4995.304*** | 1975.471*** |
| | | | (168.344) | (160.350) |
| University | | | 12674.736*** | 10059.870*** |
| | | | (81.561) | (78.930) |
| Female | | | −5698.830*** | −4783.716*** |
| | | | (45.110) | (43.104) |
| Number of Children 1 | | | −121.718* | −643.913*** |
| | | | (58.674) | (56.046) |
| Number of Children 2 | | | 366.454*** | −402.473*** |
| | | | (68.865) | (66.036) |
| Number of Children 3 | | | −529.730*** | −1232.659*** |
| | | | (112.754) | (107.507) |
| Number of Children 4 | | | −1230.005*** | −1915.311*** |
| | | | (230.804) | (219.457) |
| Number of Children 5 | | | −1721.448*** | −2552.320*** |
| | | | (483.917) | (459.920) |
| Number of Children 6 | | | −1595.945* | −2826.004*** |
| | | | (751.849) | (714.521) |
| Pension Status: worker+pension | | | | 1440.873*** |
| | | | | (183.221) |
| Pension Status: pension only | | | | −27624.899*** |
| | | | | (114.905) |
| Pension Status: pension+work | | | | −40395.191*** |
| | | | | (175.724) |
| Unemployed | | | | −8524.269*** |
| | | | | (82.304) |
| Active Student | | | | −14641.450*** |
| | | | | (174.473) |
| Urban Residence | | | | 354.681*** |
| | | | | (44.536) |
| Num. Obs. | 937488 | 937488 | 937488 | 937488 |
| $R^2$ | 0.000 | 0.194 | 0.235 | 0.309 |
| $R^2$ Adj. | 0.000 | 0.194 | 0.235 | 0.309 |
| $F$ | 117.056 | 2825.927 | 3069.929 | 4201.469 |
| Age Controls | No | Yes | Yes | Yes |

*Notes:* The table reports OLS estimates from a stepwise specification of individual net fiscal contributions (EUR/year, 2021) on migration status and successively added covariates. Column (1) is the unconditional specification; column (2) adds single-year-of-age dummies; column (3) adds education, gender, and number of children; column (4) adds pension status, unemployment, active student status, and urban residence. The reference category is a native, male, employed, non-pensioner, non-student with Pflichtschule education and zero children. Standard errors in parentheses. Significance: $^{+}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

*Source:* AEST 2021, LUE 2021; author's calculations.

dummy is −5,698.8 EUR/year, likely attributable to the gender gap in earnings and the concentration of child-care allowance receipt among women.
The effects on the migration coefficients differ between groups. The EU coefficient changes only modestly to −1,574.9 EUR/year, while the extra-EU coefficient improves to −3,218.8 EUR/year. This asymmetry suggests that differences in education and demographic composition account for a larger share of the extra-EU gap than of the EU gap.
The number-of-children coefficients are generally negative and increase in the number of children.

**Model 4: Adding labor market Controls.** In the final model I include employment status, student status, pension status, and urban residence. The estimates for the added controls are strongly negative for pensioners (−27,624.9 to −40,395.2 EUR/year depending on category), active students (−14,641.5 EUR/year), and unemployed individuals (−8,524.3 EUR/year). The effects on the migration status dummies again differ by subgroup. The EU gap widens to −2,353.9 EUR/year, while the extra-EU coefficient increases modestly to −3,667.5 EUR/year. The attribution of these shifts to specific covariate blocks is addressed in the Gelbach decomposition in Section 7.3.
Overall, the stepwise regression demonstrates the importance of the group-specific age structure as well as groups' education and their likelihood of being a student, unemployed or retired.

**The German and the Turkish Case.** In order to demonstrate the effect of differences in selection into migration and other differences I include the same stepwise OLS model for two subsamples that only include German, respective Turkish immigrants and the Austrian population.

**Table 3.** Migration coefficient across stepwise specifications: German and Turkish origin

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| German | 4129.758*** | 1665.752*** | 501.498** | −241.621 |
| | (192.278) | (178.117) | (175.909) | (170.350) |
| Turkish | −1350.953*** | −6564.607*** | −4741.619*** | −4594.378*** |
| | (305.820) | (293.360) | (300.487) | (295.600) |
| Age Controls | No | Yes | Yes | Yes |
| Education, Gender, Children | No | No | Yes | Yes |
| Labor Market Controls | No | No | No | Yes |

*Notes:* The table reports the migration coefficient from origin-specific OLS regressions of individual net fiscal contributions (EUR/year, 2021), estimated separately for individuals born in Germany and in Turkey, each paired with the native baseline. The four columns mirror the stepwise specification of Table 2: column (1) is unconditional, column (2) adds age dummies, column (3) adds education, gender, and number of children, and column (4) adds pension status, unemployment, and active student status. Standard errors in parentheses. Significance: $^{+}\,p < 0.1$, $^{*}\,p < 0.05$, $^{**}\,p < 0.01$, $^{***}\,p < 0.001$.
*Source:* AEST 2021, LUE 2021; author's calculations.

The hypothesis of this procedure was that Germans and Austrians are similar with respect to labor market specific skills that cannot be observed because they share the same language and are culturally close. Therefore, the majority of the difference in fiscal contribution should be reducible to changes in selection. For the subset including only Turkish immigrants and the Austrian population there also is the self selection within the Turkish migrants, but other job market relevant attributes like language and understanding of institutions may vary.
While both cases already differ in their unconditional effect, where the German dummy shows a strong positive effect and the Turkish model shows a less pronounced but still significant negative effect on the fiscal contribution, the progression of the effects notably also diverges as covariates are added. The effect of the German dummy variable becomes smaller and finally statistically non-significant. The effect of the Turkish dummy decreases and remains statistically significant. In

both cases there is a negative impact on the migration group dummy when age is added, indicating a favorable age structure within the migrant groups. Then, once education, gender, the number of children as well as employment and pension status are added to the model, the effect for German migrants entirely disappears, while for the Turkish migrants there remains a negative coefficient of $-4,594.6$EUR/year.

As noted in Section 6.2.2, labor market discrimination against migrants is an additional mechanism that has been documented in Austria and could explain part of the residual negative coefficient for Turkish migrants. Hofer et al. (2017) estimate a 15-percentage-point immigrant wage penalty that persists after controlling for human capital and job position. Weichselbaumer (2017) documents hiring discrimination against migrant job applicants in Austria using a correspondence test. My research design cannot distinguish differences in characteristics that are observable in principle but not present in my data from not observable labor market discrimination which requires a separate identification strategy. It is, however, likely that several mechanisms contribute to the negative residual Turkish coefficient.

## 7.2 Sample-Split Regressions

While the previous section estimates how the migrant coefficient evolves as covariates are added, it constrains all covariate effects to be identical across groups. In this section I will estimate the fully specified model separately on natives, EU migrants and extra-EU migrants, allowing coefficients to vary between the groups.

I proceed in two steps: First I estimate three models on the broad subgroups mentioned above. Second I perform country level sample splits for the largest 15 migrant populations in Austria.

The intercept across the three sub-models defined in the note to Table 4) is 17,185.2 EUR/year for natives, 10,768.3 EUR/year for EU migrants, and 5,956.1 EUR/year for extra-EU migrants. This difference of over 11,200 EUR/year between natives and extra-EU migrants persists after conditioning on all included observables, indicating that a substantial share of the fiscal gap cannot be attributed to differences in age structure, education, labor market status, or household composition. Since the transfer side of the NFC is largely determined by the covariates already controlled for, the residual gap is predominantly driven by earnings differences.

The education coefficients differ substantially across groups. For natives, the returns to education levels below university entrance (Levels 2–4) are small or even negative relative to compulsory schooling, while for both migrant groups they are strongly positive, ranging from approximately 700 to 5,200 EUR/year.

However, given the large intercept differences, these higher marginal returns do not close the gap in levels. This is consistent with the compressed education gradient documented in Figure 11.

At the university education level, the estimates converge to 9,802, 10,951, and 9,014 EUR/year for natives, EU, and extra-EU respectively, suggesting that cross-group differences in the marginal return of education are concentrated in the middle of the education distribution.

The gender penalty exists for all groups but is largest for EU migrants ($-5,619$ EUR/year), followed by natives ($-5,084$ EUR/year), and smallest for extra-EU migrants ($-3,852$ EUR/year). The smaller absolute penalty for extra-EU migrants may partly reflect the lower baseline earnings level.

The number-of-children coefficients are negative and broadly increasing in magnitude across all groups, though the estimates for extra-EU migrants are somewhat larger at higher child counts. One interesting outlier for natives and EU migrants is two children. Here for natives the fiscal impact is smaller than for one child, for EU migrants the effect is even positive, but statistically insignificant. This may reflect selection, as the cumulative financial conditions required for having two children filter out individuals with lower fiscal capacity. Beyond two children, the mechanical fiscal cost of additional dependents likely dominates any remaining selection effect.

The pension coefficients exhibit a clear ordering: pension-only status reduces the NFC by 24,379 EUR/year for natives, 17,407 EUR/year for EU migrants, and 13,259 EUR/year for extra-EU migrants. This ordering reflects differences in pension entitlements accrued within the Austrian system where longer and higher contribution histories produce higher pension payments and thus larger fiscal costs.

The same gradient appears for unemployment, where the penalty is 9,115 EUR/year for natives, 7,711 EUR/year for EU migrants, and 6,405 EUR/year for extra-EU migrants, likely reflecting pre-unemployment earnings differences that determine the level of unemployment benefits received. The active student coefficient is strongly negative across all groups, with the largest estimate for EU migrants (−15,960 EUR/year) likely reflecting a higher concentration of EU students in costlier tertiary programs. Both migrant submodels include years since immigration, which shows a positive and significant association with NFC for both groups: 80.9 EUR/year for EU migrants and 103.6 EUR/year for extra-EU migrants.

This suggests a substantial fiscal assimilation effect likely driven by the acquisition of host-country-specific skills such as language and professional networks. The urban residence dummy is positive for natives (332.8 EUR/year) and EU migrants (364.8 EUR/year) but negative for extra-EU migrants (−236.5 EUR/year). While statistically significant for all groups, the magnitudes are small relative to the other covariates.

**Country Splits.** To further investigate how covariate effects vary across origin groups, I estimate the same specification separately for the fifteen largest origin-country populations, each paired with the native baseline.

While the direction of the effects is broadly consistent across groups, their magnitudes differ substantially. The following figures report selected coefficients from these country-level regressions.

Figure 12 illustrates the unemployment effect on NFC. The effect is strongly negative for all groups, but more pronounced for Italy, Germany, and to a lesser extent the Czech Republic and Austria. The unemployment penalty is smallest for Syrian migrants. These differences likely represent pre-unemployment earnings differences as unemployment benefits are initially proportional to prior income.

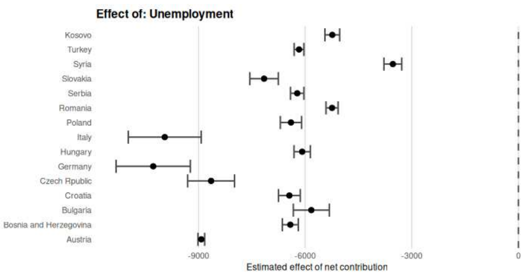



**Figure 12.** Country Level Sample-Split: Unemployment

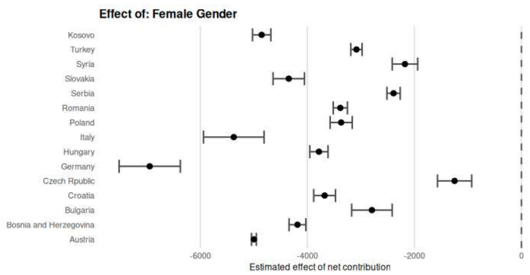



**Figure 13.** Country Level Sample-Split: Female

*Notes:* Figures 12 and 13 report point estimates and 95% confidence intervals from origin-specific OLS regressions of individual net fiscal contributions (EUR/year, 2021). The specification extends the sample-split approach of Table 4 to a finer origin classification, estimating the same model separately for the fifteen largest origin-country populations, each paired with the native baseline. The displayed coefficients are on the unemployment indicator (left) and the female indicator (right).
*Source:* AEST 2021; author's calculations.

**Table 4.** Sample-Split OLS Regression of Net Fiscal Contributions by Origin Group

| | Native | EU | Extra-EU |
|---|---|---|---|
| Intercept | $17185.231^{***}$ | $10768.340^{***}$ | $5956.145^{***}$ |
| | (211.671) | (653.249) | (393.622) |
| Apprenticeship | $-1464.897^{***}$ | $1077.706^{***}$ | $1342.100^{***}$ |
| | (75.401) | (203.789) | (115.684) |
| Intermediate VET (BMS) | $-155.974^{+}$ | $3090.054^{***}$ | $2583.271^{***}$ |
| | (85.845) | (279.973) | (178.748) |
| Academic secondary (AHS) | 75.791 | $2203.257^{***}$ | $720.336^{***}$ |
| | (119.629) | (266.104) | (166.188) |
| Higher VET (BHS) | $3091.436^{***}$ | $5214.816^{***}$ | $3817.401^{***}$ |
| | (102.010) | (327.964) | (230.667) |
| Kolleg | $1245.960^{***}$ | $5217.769^{***}$ | $4937.747^{***}$ |
| | (276.628) | (913.701) | (701.538) |
| Tertiary academy | $1149.289^{***}$ | $7938.370^{***}$ | $4377.128^{***}$ |
| | (171.377) | (674.533) | (556.406) |
| University | $9802.126^{***}$ | $10950.881^{***}$ | $9014.441^{***}$ |
| | (94.741) | (218.627) | (142.589) |
| Female | $-5084.157^{***}$ | $-5618.899^{***}$ | $-3851.573^{***}$ |
| | (48.153) | (146.706) | (89.329) |
| Pension Status: worker only | $5288.881^{***}$ | $3716.457^{***}$ | $4005.023^{***}$ |
| | (114.029) | (298.234) | (205.343) |
| Pension Status: worker+pension | $5926.402^{***}$ | $3558.525^{***}$ | $5132.596^{***}$ |
| | (223.194) | (743.630) | (464.412) |
| Pension Status: pension only | $-24379.291^{***}$ | $-17406.873^{***}$ | $-13258.642^{***}$ |
| | (161.052) | (499.550) | (297.203) |
| Pension Status: pension+work | $-37304.056^{***}$ | $-28834.199^{***}$ | $-21959.510^{***}$ |
| | (215.291) | (785.796) | (459.717) |
| Unemployed | $-9114.811^{***}$ | $-7710.633^{***}$ | $-6405.185^{***}$ |
| | (101.182) | (215.740) | (123.810) |
| Number of Children 1 | $-699.294^{***}$ | $-507.142^{**}$ | $-480.490^{***}$ |
| | (62.694) | (187.458) | (117.376) |
| Number of Children 2 | $-517.678^{***}$ | $552.465^{*}$ | $-587.895^{***}$ |
| | (74.929) | (216.062) | (124.410) |
| Number of Children 3 | $-1101.742^{***}$ | $-512.223$ | $-2021.041^{***}$ |
| | (126.995) | (371.164) | (164.541) |
| Number of Children 4 | $-1953.557^{***}$ | $-1487.985^{*}$ | $-3044.558^{***}$ |
| | (274.734) | (756.045) | (270.528) |
| Number of Children 5 | $-1740.579^{**}$ | 1494.459 | $-4093.303^{***}$ |
| | (637.670) | (1360.280) | (530.685) |
| Number of Children 6 | 975.125 | $-4851.256^{**}$ | $-3955.502^{***}$ |
| | (1029.991) | (1716.645) | (846.202) |
| Active Student | $-14443.812^{***}$ | $-15960.294^{***}$ | $-13965.674^{***}$ |
| | (185.346) | (680.518) | (469.982) |
| Urban Residence | $332.817^{***}$ | $364.827^{*}$ | $-236.508^{*}$ |
| | (48.551) | (156.680) | (113.251) |
| Years since Immigration | | $80.934^{***}$ | $103.600^{***}$ |
| | | (8.892) | (5.628) |
| Num. Obs. | 750826 | 81032 | 94926 |
| $R^2$ | 0.339 | 0.184 | 0.258 |
| $R^2$ Adj. | 0.339 | 0.183 | 0.257 |
| $F$ | 3888.808 | 182.710 | 329.687 |
| Age Controls | Yes | Yes | Yes |

*Notes:* The table reports OLS estimates from origin-specific regressions of individual net fiscal contributions (EUR/year, 2021), estimated separately on the native, EU-migrant, and extra-EU-migrant samples. All specifications include single-year-of-age dummies. The reference category is a male, non-pensioner, non-worker, non-student with Pflichtschule education and zero children. Years since immigration is omitted from the native specification by construction. Standard errors in parentheses. Significance: $^{+}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.
*Source:* AEST 2021, LUE 2021; author's calculations.

The effect of the female gender depicted in Figure 13 follows a similar pattern. Across all origin groups, the coefficient on the female dummy is negative, indicating that women exhibit lower net fiscal contributions than men, given all other controls. Again, Germans, Italians and Austrians exhibit the highest female-penalty. For Syrian, Turkish, and Czech migrants the effect is smaller. These differences likely reflect cross-group heterogeneity in labor market attachment, working hours, earnings trajectories, as well as differences in fertility patterns and transfer receipt and take-up.

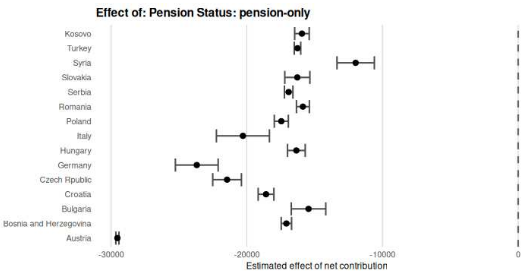



**Figure 14.** Country Level Sample-Split: Pension

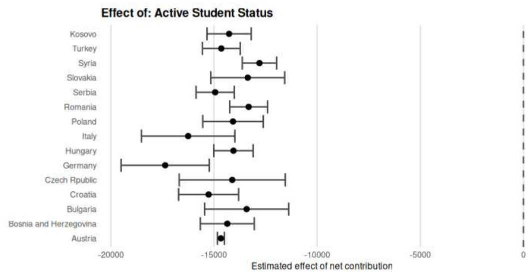



**Figure 15.** Country Level Sample-Split: Active Student

*Notes:* Figures 14 and 15 report point estimates and 95% confidence intervals from origin-specific OLS regressions of individual net fiscal contributions (EUR/year, 2021). The specification extends the sample-split approach of Table 4 to a finer origin classification, estimating the same model separately for the fifteen largest origin-country populations, each paired with the native baseline. The displayed coefficients are on the pension-only indicator (left) and the active student indicator (right).
*Source:* AEST 2021; author's calculations.

Figure 14 reports the estimated effect of pension status on individuals' net fiscal contribution by country of origin. Unsurprisingly, the effect is strongly negative for all groups, reflecting the combination of pension benefit receipt and the absence of labor market income and associated tax payments. While the sign of the effect is uniform, its magnitude varies considerably across origin countries. The fiscal impact of pension-only status is the largest for Austria. Within the migrant groups Germany, Italy and the Czech Republic have the strongest negative effect of the pension status. Several migrant origin groups exhibit a considerably smaller pension penalty, with Syria at the lower end. These differences likely reflect heterogeneity in pension entitlements accumulated within the Austrian system, driven by differences in prior level and duration of income.

The effect of the active student coefficient in Figure 15 is strongly negative due to the cost of education and the lack of contributions for most active students. It is homogeneous across subgroups, with Italy and Germany showing the largest negative estimates. This is likely a product of my proxy for education cost, where I assign the average cost of education by education level, which happens to be highest for university degrees. Since there is no heterogeneity with respect to migrant group, these differences reflect selection into higher education by Germans and Italians and the age structure of the respective migrant groups. If there are more young children, the slightly less costly lower education statuses are overrepresented, leading to a smaller negative impact for Syrian or Romanian migrants.

Taken together, the four figures illustrate that while labor market and lifecycle states systematically alter the NFC across all origin groups, the magnitude of these effects varies substantially, reflecting heterogeneity in earnings capacity, institutional entitlements, and lifecycle positioning.

**Result 4:** The stepwise and sample-split results jointly answer Question 4. In the stepwise framework, the baseline estimate for EU migrants is positive, while it is negative for extra-EU migrants. When covariates are added sequentially, both migrant estimates decline substantially.

A large shift for both subgroups arises when the age structure is controlled for. The sample-split regressions further reveal three central patterns. First, a substantial intercept gap remains even after conditioning on all observables. Second, covariate effects are consistent in direction but differ in magnitude across groups. Education returns are larger for migrants but do not close the intercept gap. Pension and unemployment penalties are largest for natives. Years-since-immigration estimates indicate fiscal assimilation. Third, the country-level splits confirm that this heterogeneity extends beyond the broad EU and extra-EU categories.
These regressions, however, cannot properly attribute documented differences to specific sets of covariates. In particular, comparing coefficients across separate regressions does not reveal whether cross-group differences are driven by labor market characteristics, demographic composition, other observable factors, or labor market discrimination. The following section addresses this limitation by applying a Gelbach decomposition, which quantifies the contributions of distinct covariate blocks to the observed differences in estimated fiscal outcomes.

## 7.3 Gelbach Decomposition

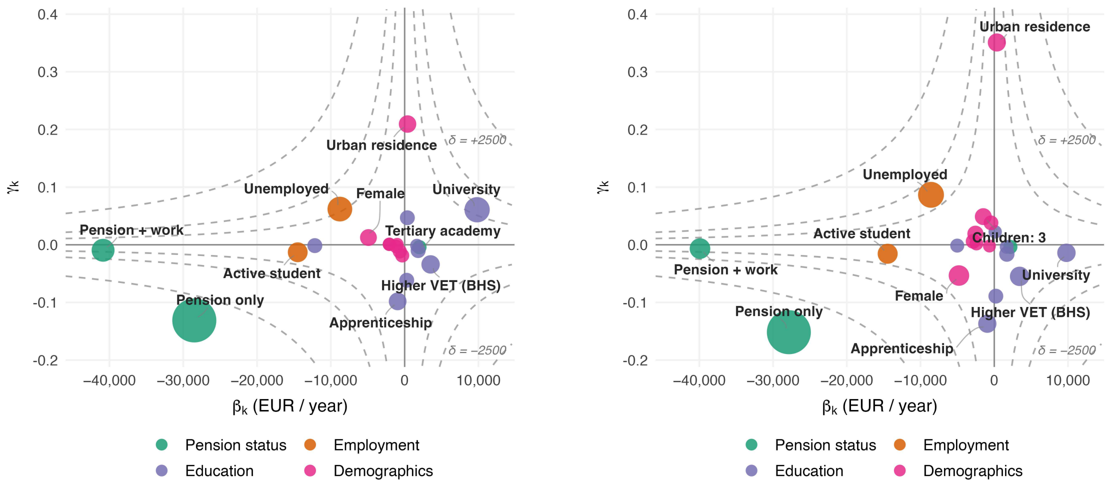
Many covariates included in the full specification, such as age, pension status, labor market participation, and education, imply an individual's position along the fiscal life cycle. As demonstrated in Section 6.2, the life cycle is characterized by systematic age-specific patterns in taxes paid and transfers received. The Gelbach decomposition quantifies how observable characteristics differ in frequency and what portion of the overall change in the migrant estimate can be attributed to each covariate.
As observed in the stepwise addition of covariates in Section 7.1 does not reduce the gap, but rather increases the estimated difference in NFC between both migrant subgroups and the native population. The inclusion of age, gender, labor market participation, education and other demographic characteristics shifts the estimated migrant coefficient from being positive to negative. Mechanisms behind this shift are due too frequency differences of characteristics in subgroups and their association with higher or lower NFCs. The four mechanisms that can underlie covariate changes when moving to a full model specification are illustrated in Table 5. The cell layout mirrors the quadrants of the scatter panels in Figure 16.

**Table 5.** Interpretation of covariate contributions by position in the $(\beta_k, \gamma_k)$ plane.

| | $\beta_k < 0$ (negative NFC) | $\beta_k > 0$ (positive NFC) |
|---|---|---|
| $\gamma_k > 0$ (over-rep.) | **Q2:** reinforced disadvantage<br>$\delta_k < 0$ — e.g. Unemployed | **Q1:** suppressed advantage<br>$\delta_k > 0$ — e.g. University |
| $\gamma_k < 0$ (under-rep.) | **Q3:** suppressed advantage<br>$\delta_k > 0$ — e.g. Pension only | **Q4:** reinforced disadvantage<br>$\delta_k < 0$ — some education groups |

The Y-orientation gives the concentration of the migrant group relative to the natives. The X-orientation indicates the fiscal contribution estimate. Thus an observation in quadrant 1, like having a university degree, reflects, that a migrant group is more likely to posses a characteristic which is associated with a positive NFC. An observation in Q2 indicates, that a migrant group is overrepresented in a given characteristic which is associated with ones NFC negatively. In other words, the Gelbach identity $\sum_k \delta_k = \beta_{\text{baseline}} - \beta_{\text{full}}$, says, that a positive $\delta_k$ indicates a suppressed compositional advantage (covariate $k$ accounts for a portion of the unconditional migrant coefficient that disappears under controls); a negative $\delta_k$ indicates a reinforced disadvantage.
Figures 16a and 16b show the Gelbach decompositions of the NFC gap relative to native Austrians

for EU and extra-EU migrants. Despite differences in the level of the residual NFC gap, the overall structure of the decomposition is similar across both groups.




(a) EU migrants vs. natives

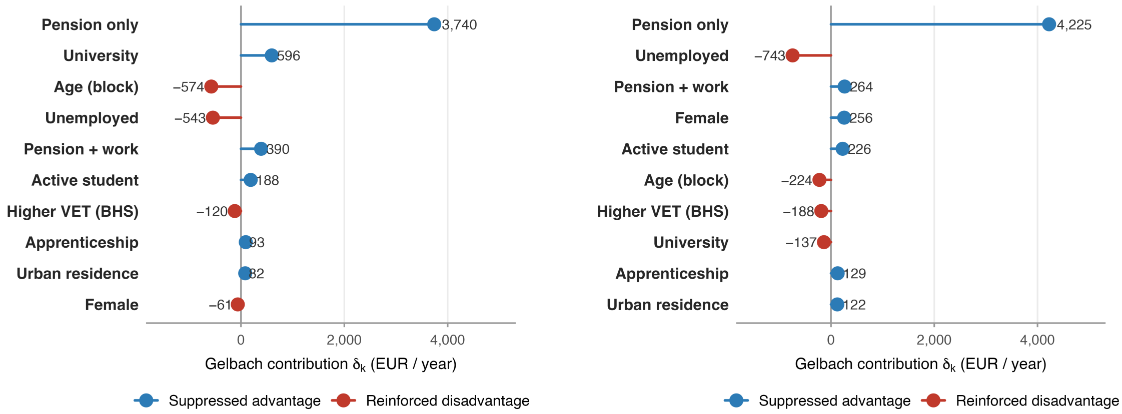
(b) Extra-EU migrants vs. natives

**Figure 16.** Gelbach decomposition of the NFC gap relative to natives - scatter plot

*Notes:* Auxiliary regression coefficient $\gamma_k$ against full-model coefficient $\beta_k$ for each covariate. Point area is proportional to $|\delta_k| = |\gamma_k \beta_k|$. Dashed grey curves are iso-contribution contours $\gamma_k \beta_k = c$ for $c \in \{\pm 500, \pm 1{,}000, \pm 2{,}500\}$ EUR; covariates lying on the same contour contribute equally to the gap. Top-10 covariates are labelled.
*Source:* AEST 2021, LUE 2021; author's calculations.

In the example of EU migrants, both *Pension Only* and *University* show a compositional advantage. They however arise through different channels. For the pension variables, that are situated in the third quadrant there is an underrepresentation of migrants relative to natives in a category that is associated with a negative NFC. In the first quadrant, where university education is situated, EU migrants are overrepresented in a sub-population that is associated with a positive NFC. In contrast as can be seen in the second quadrant both migrant groups are over-represented in the unemployed subpopulation which is associated with a negative NFC. The fourth quadrant is generally less populated, but shows an under-representation in a subgroup that is associated with a negative NFC.
In Figure 17 the products of frequency $\gamma_K$ and effect $\beta_K$ are depicted for the 10 largest absolute covariate changes in bar charts.[7] Together with Figures 16 they show, that in both migrant groups, the largest negative change in the migrant coefficient is due to the pension covariates.
Here, both migrant groups are substantially underrepresented in the group of pensioners which in turn is associated with a negative NFC. The pension status thus makes up the largest part of the positive compositional advantage of migrants. For EU migrants, pension status alone accounts for 51% of the total absolute change in the migrant coefficient between the baseline and full specifications. Together with *pension + work* the overall impact of the pensions is above 56%. For extra-EU migrants the pension status accounts for 50.6% of the total absolute change in the migrant coefficient and over 53% when including *pension + work*. As indicated in the figures above, the pension covariates are the most important estimates when explaining the fiscal impact of migrants when compared to natives. The pension + work variable is less substantial in the Gelbach decomposition due too the smaller difference in composition between both migrant groups and natives, even though the $\beta_K$ is much larger. The EU migrant coefficient further carries a sizable, although much smaller positive compositional advantage due to the higher likelihood of

[7] I report the exact numbers for these covariates at the end of this chapter.




(a) EU migrants vs. natives

(b) Extra-EU migrants vs. natives

**Figure 17.** Gelbach decomposition of the NFC gap relative to natives - bar chart

*Notes:* The figure decomposes the change in the migrant coefficient between the baseline (column 1) and full (column 4) specifications of Table 2 into contributions from each block of covariates, following Gelbach (2016). Each bar represents the contribution $\gamma_k \times \beta_k$, where $\gamma_k$ is the coefficient from auxiliary regressions of covariate $k$ on migrant status and $\beta_k$ is the coefficient on covariate $k$ in the full model. Positive bars indicate suppressed compositional advantages (covariates whose omission inflates the migrant coefficient); negative bars indicate reinforced disadvantages (covariates whose omission depresses it). Panel (a) shows the decomposition for EU migrants relative to natives; panel (b) for extra-EU migrants relative to natives.
*Source:* AEST 2021, LUE 2021; author's calculations.

EU migrants to hold a university degree. The share of EU migrants with a university degree exceeds that of natives by 6.1 percentage points. Since high education is positively correlated with a higher NFC the higher likelihood of a university degree makes up for 8% of the total change in the migrant coefficient. Extra EU migrants are 1 percentage point less likely to hold a university degree which makes up 1.5% of the total gap.
The negative effect of the inclusion of covariates on the migrant dummy variable is the unemployment covariate. This indicates that as illustrated in Figure 12, EU migrants have 6pp higher likelihood of being unemployed. Extra EU migrants have a 8.6% higher likelihood of being unemployed. Since being unemployed correlates strongly with a negative NFC, the compositional disadvantage makes up 7.4% (/EU migrants) and 8.9% (extra EU migrants) respectively.

**Result 5:** The Gelbach decomposition reveals that the fact, that migrants are significantly underrepresented in the group of pensioners greatly improves their fiscal position, making up 51% of the total absolute change in the migrant coefficient for EU and 50.6% for extra-EU migrants.
For EU migrants, the larger probability of holding a university degree is reflected in the migrant native gap, making up 8.1% of the total gap. Both migrant groups exhibit a larger probability of being unemployed than natives. Controlling for unemployment produces the largest positive effect on the migrant estimates, making up 7.4% and 9% of the total absolute gap, respectively.
Controlling for these life-cycle positions removes compositional advantages and disadvantages and reveals a more negative NFC gap relative to natives. In this sense, the Gelbach decomposition complements the age-profile analysis by quantifying how differences in life-cycle composition, rather than differences in age-conditional fiscal behavior, account for observed group differences in net fiscal contributions.
The Gelbach decomposition on the pension-status covariate quantifies that the favorable aggregate migrant coefficient depends to over 50% on the smaller relative share of migrants in the pensioner population. Due to the rapid increase in migration over the past 40 years and the tendency of

migrants to be younger than the native population, they are underrepresented in the pension ages. A second mechanism can be observed in Section 7.2: Those migrants who receive pensions and migrated as adults have a lower accumulated pension.

The underrepresentation of migrants among pensioners is a consequence of the current demographic situation which erodes as present working-age cohorts age into retirement under constant or declining migration flows. Only under sustained or increasing inflows of working-age migrants would the underrepresentation be maintained.

The second comparative advantage is structural and persists as long as adult migration remains a significant share of total flows.

As the first comparative advantage erodes, part of the fiscal advantage is mechanically preserved by the second. However the aggregate advantage is expected to shrink as the pension status is far more consequential in determining NFC than gradual changes in the amount paid out as pensions.

**Table 6.** Ten largest covariate contributions to the Gelbach decomposition

| Covariate | $\beta_k$ (EUR) | $\gamma_k$ | $\delta_k$ (EUR) | Share |
|---|---|---|---|---|
| *Panel A: EU migrants vs. natives* | | | | |
| Pension only | −28,504 | −0.1312 | 3,739.7 | 51.0% |
| University | 9,819 | 0.0607 | 596.4 | 8.1% |
| Age (block) | — | — | −574.0 | 7.8% |
| Unemployed | −8,779 | 0.0619 | −543.3 | 7.4% |
| Pension + work | −40,866 | −0.0095 | 389.6 | 5.3% |
| Active student | −14,489 | −0.0130 | 188.3 | 2.6% |
| Higher VET (BHS) | 3,515 | −0.0341 | −119.7 | 1.6% |
| Apprenticeship | −948 | −0.0982 | 93.0 | 1.3% |
| Urban residence | 394 | 0.2094 | 82.4 | 1.1% |
| Female | −4,907 | 0.0125 | −61.4 | 0.8% |
| *Top 10 share of total absolute change* | | | | 86.9% |
| *Panel B: Extra-EU migrants vs. natives* | | | | |
| Pension only | −27,860 | −0.1516 | 4,224.8 | 50.6% |
| Unemployed | −8,582 | 0.0866 | −743.4 | 8.9% |
| Pension + work | −39,916 | −0.0066 | 263.8 | 3.2% |
| Female | −4,792 | −0.0533 | 255.7 | 3.1% |
| Active student | −14,460 | −0.0156 | 225.6 | 2.7% |
| Age (block) | — | — | −223.9 | 2.7% |
| Higher VET (BHS) | 3,437 | −0.0548 | −188.3 | 2.3% |
| University | 9,788 | −0.0140 | −136.6 | 1.6% |
| Apprenticeship | −944 | −0.1369 | 129.3 | 1.5% |
| Urban residence | 349 | 0.3509 | 122.4 | 1.5% |
| *Top 10 share of total absolute change* | | | | 78.0% |

*Notes:* The table reports the ten covariates with the largest absolute Gelbach contributions $|\delta_k|$ for each migrant group, ranked in descending order. $\beta_k$ is the coefficient on covariate $k$ in the full OLS specification (see Table 2). $\gamma_k$ is the coefficient on the migrant indicator in the auxiliary regression of $k$ on migrant status. Age dummies are reported as a block sum because the two regressions use different reference age categories. The block sum is invariant to the choice of reference within a regression, the individual age-bin contributions are not. Shares are computed against $\sum_k |\delta_k|$ over all individual covariates. $N = 846{,}389$ (EU); $N = 856{,}123$ (extra-EU).
*Source:* AEST 2021, LUE 2021; author's calculations.

# 8 Limitations

There are several methodological limitations due to the nature of this analysis. They are clustered around the causal interpretation, the definition of NFC, the inclusion and salience of covariates as

well as temporal and dynamic limitations of cross-sectional register data.
The first is a lack of causality. The life cycle profiles and other overview statistics are descriptive. The regression and decomposition approaches show which observable characteristics are associated with positive or negative fiscal outcomes. They further give information about compositional differences in observable characteristics that in turn are associated with fiscal outcomes.
Many variables, however, allow for plausible speculation on mechanisms behind higher or lower NFCs. For some observables such as unemployment or pension status the direct effect on NFC is mechanistic and clear. For others, like the urban or rural residence or the time spent in the country, there could be a variety of causal explanations which cannot be distinguished based on these data. As a large part of the difference in fiscal contribution is attributed to compositional differences, the lack of causality does not render the results meaningless or not actionable.
A consequence of using education as an explanatory variable is the uncertainty about whether its salience in the labor market is heterogeneous. Especially for extra-EU migrants educational attainment may be reported in the statistics but not recognized in the labor market. Thus, the return to education may be compressed by only a share of degrees being labor market relevant. Figure 11 as well as the regression estimates thus give the lower bound of the return to education and would likely be less compressed if only recognized degrees were included.
There further persists a large remaining difference between migrants' and natives' fiscal contributions. Information like language, proxies for professional networks, credential recognition, legal status (short- or long-term planned residence) or health could absorb part of the residual gap but is not included in the register data.
As mentioned in section 4.2, the NFC framework includes the entire *income* side, meaning the full set of direct and indirect taxes. It, however, only includes welfare-relevant transfers. This makes it highly likely that on average all groups produce positive NFCs. Under the proposed per capita allocation of contribution to indivisible public goods, the inclusion of the entire tax revenue constitutes a uniform shift in level which does not affect comparison between the groups. It does, however, make it impossible to disentangle whether the smallest NFC, in my case provided by extra-EU migrants, constitutes a fiscal burden or a reduced contribution. Normalizing the NFC to a reference group such as natives does not add information and thus does not resolve the ambiguity.
A central limitation for the life cycle profiles is, that they are synthetic in the sense that they are built on the complete population in the year 2021 but ordered in a way that shows the fiscal position for each age group. This is important for interpretation. The life cycle profiles give an indication as to how a typical life cycle could look like, but different age groups have been brought up in different education regimes or were at different life cycle stages when certain economic shocks like the introduction of the Euro transformed the Austrian economy.
Methodologically, the cross-sectional data makes it impossible to make statements about circular migration patterns and whether return migration is selective on economic success. This problem is common when working on cross-sectional data and also discussed by Dustmann and Frattini (2014). Bratsberg, Raaum, and Røed (2014) find that in Norway, migrants from high-income countries tend to leave after some years, while migrants from low-income countries tend to stay permanently.
Further, the observation window presents a snapshot of an evolving pattern. Bratsberg, Raaum, and Røed (2014) show that migrants are disproportionately affected by macroeconomic downturns. This can cause what they call a *dissimilation* process which means the reversal of previous assimilation. In such situations, welfare take-up is expected to rise, while tax contributions shrink. This strongly reduces the migrants' NFC. 2020 is an atypical year, reaching the highest level of unemployment since the mid-1990s due to the COVID-19 pandemic (Wirtschaftskammer Österreich,

2026). While the unemployment numbers recovered in 2021, it is likely that the recovery took longer for migrants as they are usually affected more strongly by economic downturn (Bratsberg, Raaum, and Røed, 2014, p.668). They likely have still been disproportionately affected by the economic shock. Therefore 2021 may be a structurally unfavorable snapshot for migrants. 2021 estimates can thus be read as a lower bound on migrant NFC for the recent years.

A final limitation, that comes with using a single cross-section of register-data is that it is impossible to identify secondary effects through elevated demand or changes in labor supply. These effects are best addressed through equilibrium models such as the one proposed by Colas and Sachs (2020), who estimate the effect of low-skilled migration on native wages and labor supply.

# 9 Policy Implications

The finding that differences in NFC during working years are almost entirely made up by differences on the contribution side (see Figure 8) changes the focus of the policy debate away from restricting welfare access for migrant groups towards finding ways to close wage gaps between the groups.

Thus, the question that, according to my findings, should be discussed more is how to increase the wages of extra-EU migrants. Based on my findings, three policy angles will be discussed in the following: composition of and returns to educational attainments, labor market attachment, and labor market access for humanitarian migrants. Finally, I discuss the role of the large pension composition advantage of migrant groups in the context of pension system reforms.

The education distribution itself may be altered by migration programs targeting skilled workers. The compressed returns to education for extra-EU migrants (see Figure 11) may be improved through more efficient credential recognition or programs that close educational gaps for specific foreign diplomas.

A lever that is partially addressed by reforms in education is the remaining difference in the probability of being unemployed. A structural lack of professional networks, language and other unobservable labor market skills lies in the nature of migration and will likely only improve with time spent in the country. This is supported by the positive *Years since Immigration* estimate in Table 4.

Further it is a normative political discussion of whether humanitarian migrants' fiscal contributions are relevant metrics, as society accepts the cost in order to generate a positive moral externality in the form of humanitarian aid to displaced individuals. This cost, in my framework, is attributed to extra-EU migrants and lowers the group's NFC. While it is factually correct one can debate whether in-group heterogeneity on this level may be too large to derive concrete policy implications. However, while the inclusion of refugees in the extra-EU bucket does lower its ANFC (from 3864 EUR to 3669 EUR, see table 1) the difference is not large and the ordering, while showing a smaller gap to natives, is preserved.

For refugees, who show an ANFC of 1751 EUR (see Table 1), lifting restrictions on labor market access and reducing time spent in refugee camps could both reduce costs in the form of direct transfers of welfare and increase contributions in the long run through better labor market attachment and increased direct and indirect tax revenue (see Section 2.3).

Given the large compositional advantage (see Section 7.3) that will likely erode as current migrant cohorts age into retirement, in addition to the aging of the native population, the role of pensions is crucial to the fiscal sustainability of the Austrian welfare state in the future.

Currently, migrants do not retire as completely and abruptly as the native population (see Figure 11). It is to be expected that more established migrants assimilate to natives in their retirement patterns over time. However, migrants will structurally always have shorter contribution histories

and thus lower pensions. A substantial share of the current ANFC advantage of migrant groups should therefore be understood as transitory.
With the current comparatively advantageous composition within migrant and native subgroups, represented in the support ratio and Gelbach results (see Figure 4 and Section 7.3) likely deteriorating, pension system reforms are urgent and time sensitive. Pension reforms with transitional provisions, which are often necessary for political support, are more easily absorbed under the more favorable composition than when large cohorts move into retirement and the fiscal pressure grows. One such reform currently being implemented raises the statutory retirement age for women stepwise to 65, aligning it with the retirement age of men. Further, the corridor pension's (Korridorpension) earliest access age is being raised stepwise from 62 to 63 starting in 2026.
Both measures lengthen contribution periods and postpone the transition into the fiscally most costly lifecycle phase, which in turn becomes shorter. Whether the pace and scope of the reforms will be sufficient to reduce or stabilize the federal budget contribution to the pension system is an open question.

# 10 Conclusion

In this thesis I asked the question whether migrants pose a net fiscal burden on the Austrian welfare state and how much of these existing differences stem from differences in age-dependent fiscal behavior or differences in group composition.
To address these questions I have relied on two methodological pillars: life-cycle accounting and regression models. The base of my analysis is detailed, matched AEST and LUE register data of actual transfers and taxes on the individual level.
In the cross group comparison of the average net fiscal contribution (ANFC) for the year 2021 EU migrants contribute more than natives and extra-EU migrants contribute less. Both migrant groups' ANFC is shaped favorably by their age composition.
I have shown that migrants are concentrated in working ages, thus have a fiscally more favorable support ratio. EU migrants on average have a higher education when compared to natives and extra-EU migrants. Both migrant groups however show lower labor market attachment. In the comparison of the ANFC, EU migrants show the highest (5,466 EUR), extra EU migrants the lowest (3,669 EUR). Natives fall between both groups with an ANFC of 4,316 EUR. When comparing the age-conditional fiscal contribution profiles of migrant and native groups I found that the shapes are remarkably similar. The big difference is the level. Here natives show the highest working age plateau followed by EU- and extra EU migrants. In the retirement this ordering reverses due to accumulated pension entitlements. Both, gender and education subsets produce within group gaps that are far larger than the gaps between migrant groups themselves. Critically, during the working ages gaps are almost entirely driven by the contribution side with transfer receipt only becoming salient in education and retirement. The stepwise and sample-split regressions show that once age, education, gender, labor market attachment and other demographic observables are included, the migrant coefficient becomes negative for EU migrants and more negative than the baseline for extra-EU migrants. This is consistent with both groups having a fiscally positive composition which is removed through the controls. The Gelbach decomposition further enhances this picture by attributing the majority of the positive migrant coefficient movement to migrants being underrepresented among pensioners (56% EU migrants, 53% extra-EU migrants).
The overall question must be answered differently for EU migrants than for extra-EU migrants and differently regarding the time-scope. For the year 2021 the ANFC is the central measurement ranking EU migrants highest, followed by natives and extra-EU migrants.

For a more forward-looking perspective, the how and why of the gap becomes more salient. The ANFC in both migrant groups is elevated due to compositional advantages of the groups. They are on average more concentrated in the working ages and thus less likely to be pensioners. When all compositional advantages are removed as in section 7.2 both migrant groups have a lower intercept than natives.

This thesis has examined one component of a larger question: how migration shapes the fiscal sustainability of the welfare state in the coming decades. Promising further investigations include extending the analysis to the household level and including second generation migrants. This shifts the focus from the immediate consequences of migration towards exploring how the welfare state is affected over a longer time-span.

Fiscal accounting is only one input into the debate around migration. Cultural, social, humanitarian and labor market considerations will ultimately determine Austria's character as a society. The fiscal debate, however, illustrates what often goes wrong in how migration is discussed. The implicit framing often focuses on migration as an inconvenience that needs to be addressed and ultimately reduced, rather than a natural process that needs to be shaped by careful policy.

Treating migration as a problem leads to distorted and ultimately ineffective policy measures that try to limit numbers instead of addressing barriers or specific needs in labor market integration, education and social security.

The relevant question is how to design a migration system that turns the current compositional advantages into sustained positive fiscal contributions: faster credential recognition, earlier and fuller labor market integration, and pathways that allow migrants to realize the earnings potential their education would suggest.

The success of migration policy needs to be redefined. Rather than limiting numbers and access to the welfare state, it should be measured by its ability to aid the thousands of young individuals who have migrated to Austria in realizing their economic potential and improving the fiscal sustainability of the Austrian welfare state in the face of rapid demographic aging.

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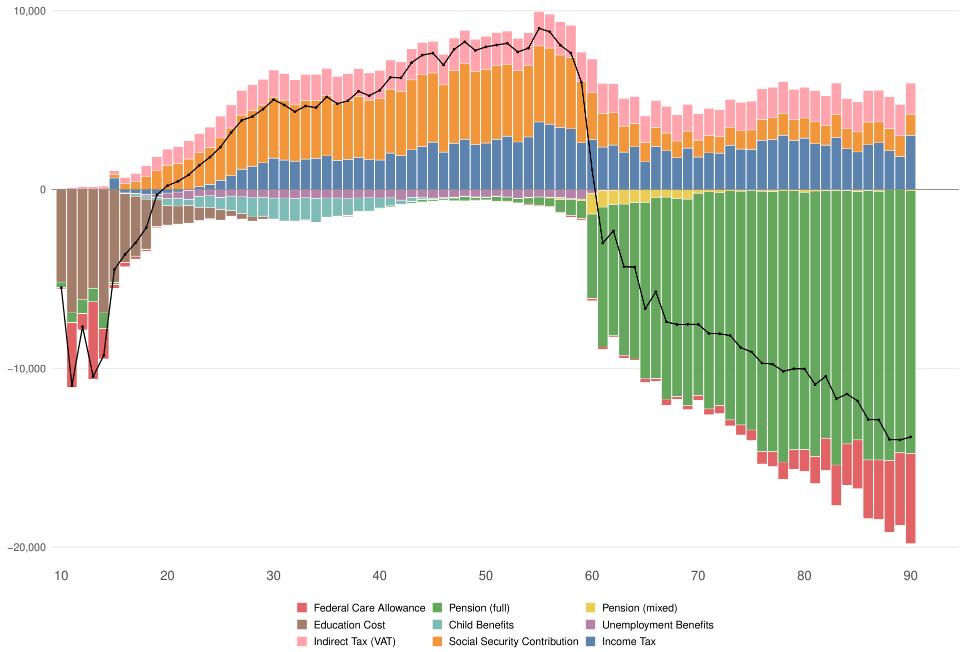
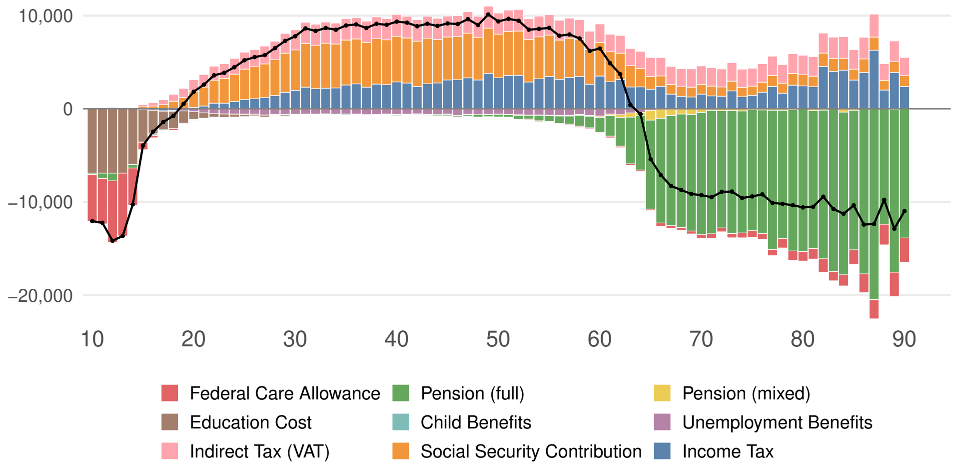
# Appendix

## Detailed Life Cycle Profiles




(a) Female EU Migrants

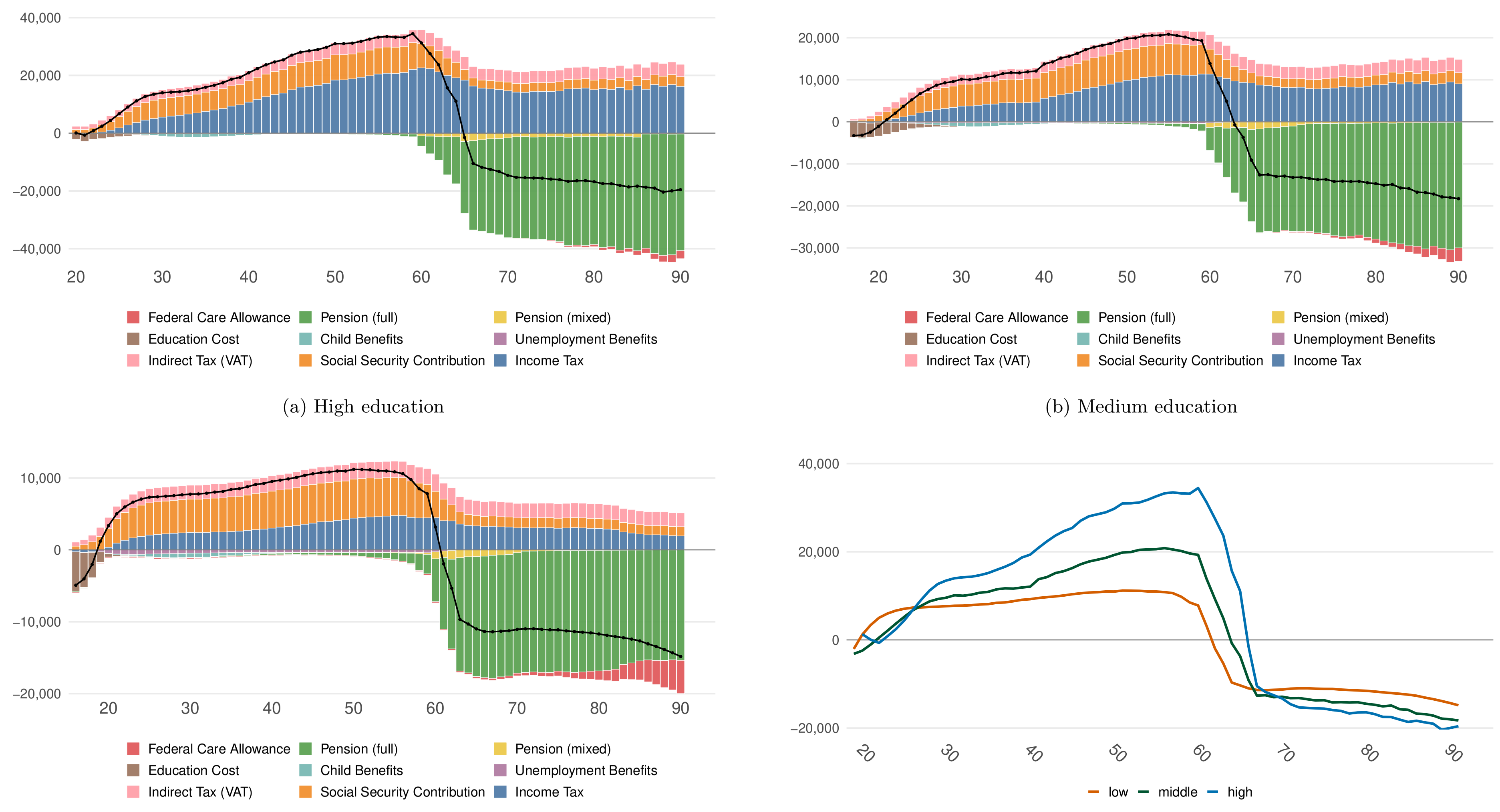



(b) Male EU Migrants

**Figure 18.** Net fiscal contribution life-cycle by gender: EU migrants

*Notes:* Cross-sectional mean net fiscal contribution by age, EUR/person/year, in 2021, restricted to EU-born residents. Stacked bars decompose the NFC into its tax and transfer components; the line marks the net balance.

*Source:* AEST 2021, LUE 2021; author's calculations.




(a) High education

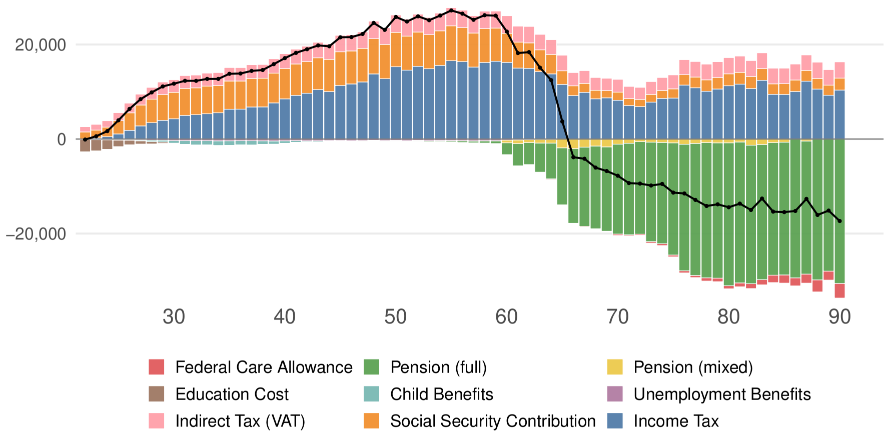
(b) Medium education

(c) Low education

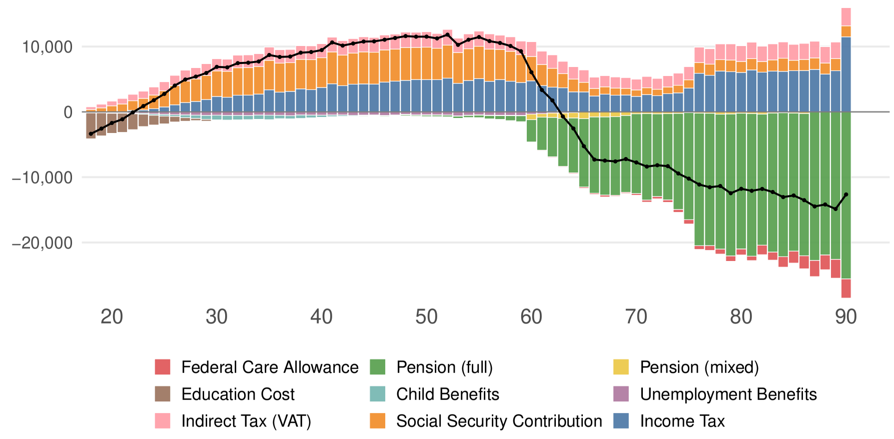
(d) Net balance, all levels

**Figure 19.** Net fiscal contribution life-cycle by education: natives

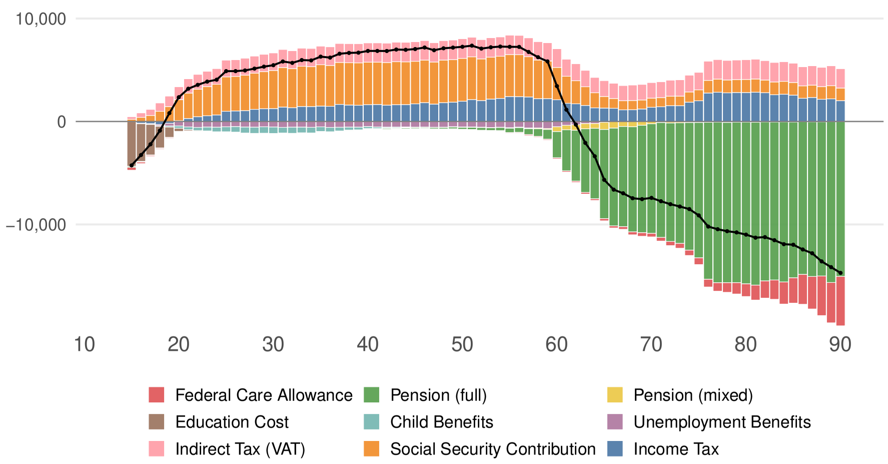
*Notes:* Cross-sectional mean net fiscal contribution by age, EUR/person/year, in 2021, restricted to native-born residents. Stacked bars in panels (a)–(c) decompose the NFC into its tax and transfer components by ISCED level; panel (d) overlays the net balances across education levels.
*Source:* AEST 2021, LUE 2021; author's calculations.



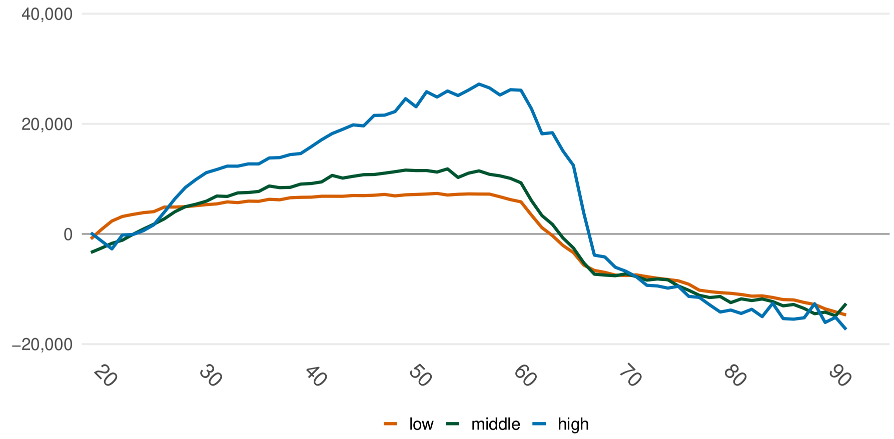

(a) High education




(b) Medium education



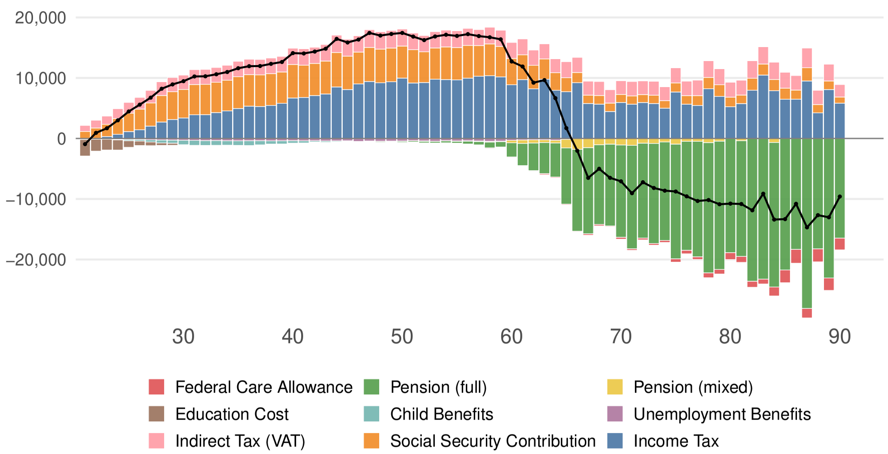

(c) Low education



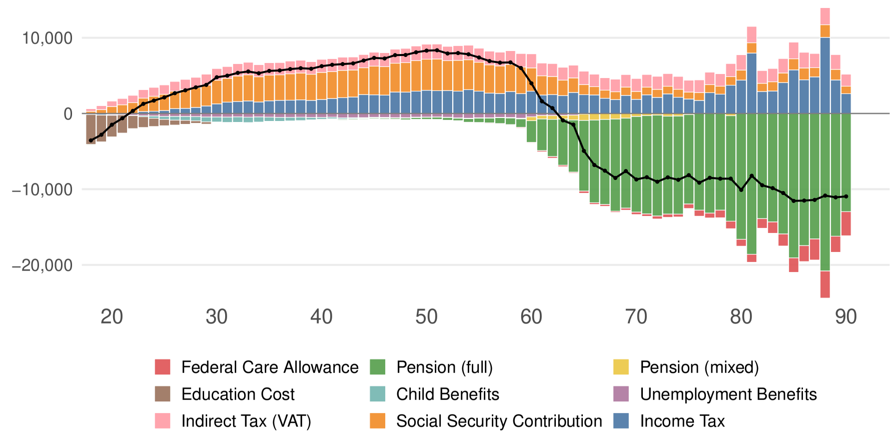

(d) Net balance, all levels

**Figure 20.** Net fiscal contribution life-cycle by education: EU migrants

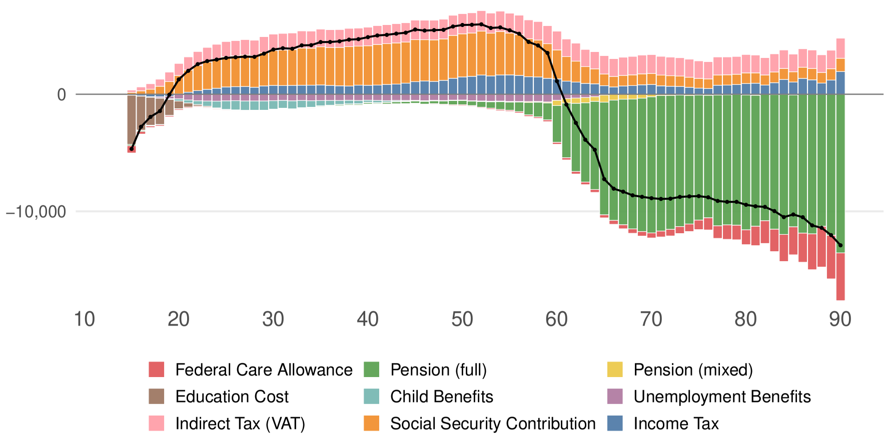
*Notes:* Cross-sectional mean net fiscal contribution by age, EUR/person/year, in 2021, restricted to EU-born residents. Stacked bars in panels (a)–(c) decompose the NFC into its tax and transfer components by ISCED level; panel (d) overlays the net balances across education levels.
*Source:* AEST 2021, LUE 2021; author's calculations.



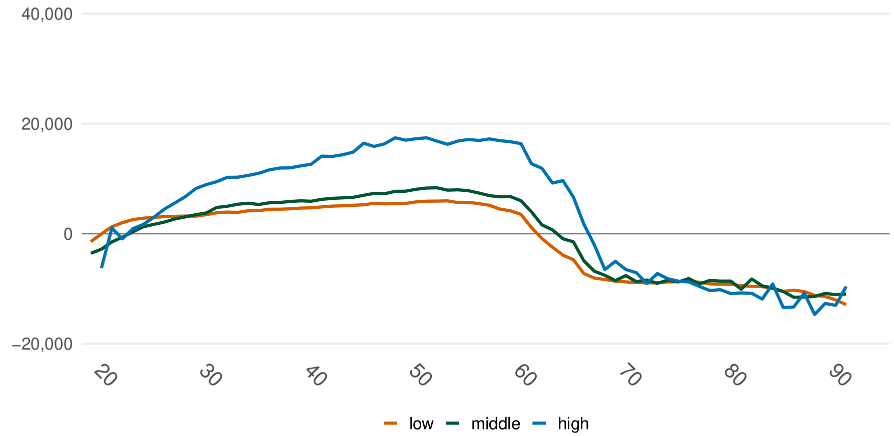

(a) High education




(b) Medium education




(c) Low education




(d) Net balance, all levels

**Figure 21.** Net fiscal contribution life-cycle by education: extra-EU migrants

*Notes:* Cross-sectional mean net fiscal contribution by age, EUR/person/year, in 2021, restricted to extra-EU-born residents. Stacked bars in panels (a)–(c) decompose the NFC into its tax and transfer components by ISCED level; panel (d) overlays the net balances across education levels.
*Source:* AEST 2021, LUE 2021; author's calculations.

# German and Turkish Sample in Stepwise Specification

**Table 7.** Stepwise OLS Regression of Net Fiscal Contributions: Turkish Origin

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| (Intercept) | 4855.805*** | 14101.578*** | 13121.487*** | 16208.274*** |
| | (45.481) | (348.904) | (376.708) | (371.307) |
| Turkish | −1350.953*** | −6564.607*** | −4741.619*** | −4594.378*** |
| | (305.820) | (293.360) | (300.487) | (295.600) |
| Apprenticeship | | | −431.528** | −1389.623*** |
| | | | (135.808) | (133.633) |
| Intermediate VET (BMS) | | | 1284.457*** | −231.378 |
| | | | (155.516) | (153.195) |
| Academic secondary (AHS) | | | 1603.507*** | 450.585* |
| | | | (214.599) | (212.085) |
| Higher VET (BHS) | | | 5366.054*** | 3135.815*** |
| | | | (184.750) | (182.523) |
| Kolleg | | | 3846.235*** | 1394.608** |
| | | | (500.055) | (491.666) |
| Tertiary academy | | | 4721.703*** | 1304.278*** |
| | | | (312.212) | (307.591) |
| University | | | 12875.977*** | 9925.347*** |
| | | | (168.604) | (167.257) |
| Female | | | −6000.089*** | −5019.449*** |
| | | | (87.212) | (86.075) |
| Number of Children 1 | | | −328.324** | −933.126*** |
| | | | (113.287) | (111.422) |
| Number of Children 2 | | | 110.012 | −769.584*** |
| | | | (134.425) | (132.318) |
| Number of Children 3 | | | −294.998 | −1219.618*** |
| | | | (225.026) | (221.224) |
| Number of Children 4 | | | −1144.397* | −1985.019*** |
| | | | (477.788) | (469.489) |
| Number of Children 5 | | | −1194.507 | −2187.368* |
| | | | (1109.409) | (1090.083) |
| Number of Children 6 | | | −1483.983 | −1999.200 |
| | | | (1924.924) | (1891.321) |
| Pension Status: worker+pension | | | | 1694.711*** |
| | | | | (356.936) |
| Pension Status: pension only | | | | −28955.432*** |
| | | | | (226.977) |
| Pension Status: pension+work | | | | −41560.478*** |
| | | | | (342.081) |
| Unemployed | | | | −8919.050*** |
| | | | | (177.982) |
| Active Student | | | | −14617.933*** |
| | | | | (337.083) |
| Num. Obs. | 767069 | 767069 | 767069 | 767069 |
| $R^2$ | 0.000 | 0.086 | 0.103 | 0.134 |
| $R^2$ Adj. | 0.000 | 0.086 | 0.103 | 0.134 |
| $F$ | 19.514 | 919.303 | 949.976 | 1214.558 |
| Age Controls | No | Yes | Yes | Yes |

*Notes:* The table reports OLS estimates from a stepwise specification of individual net fiscal contributions (EUR/year, 2021), estimated on the Turkish-origin and native subsample. Column (1) is the unconditional specification; column (2) adds single-year-of-age dummies; column (3) adds education, gender, and number of children; column (4) adds pension status, unemployment, and active student status. The reference category is a native, male, employed, non-pensioner, non-student with Pflichtschule education and zero children. Standard errors in parentheses. Significance: $^{+}\, p < 0.1$, $^{*}\, p < 0.05$, $^{**}\, p < 0.01$, $^{***}\, p < 0.001$.
*Source:* AEST 2021, LUE 2021; author's calculations.

**Table 8.** Stepwise OLS Regression of Net Fiscal Contributions: German Origin

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| (Intercept) | 4818.804*** | 14189.107*** | 13195.174*** | 16225.417*** |
| | (35.205) | (259.330) | (277.861) | (269.777) |
| German | 4129.758*** | 1665.752*** | 501.498** | −241.621 |
| | (192.278) | (178.117) | (175.909) | (170.350) |
| Apprenticeship | | | −335.221*** | −1266.847*** |
| | | | (101.727) | (98.592) |
| Intermediate VET (BMS) | | | 1299.455*** | −200.176+ |
| | | | (115.727) | (112.292) |
| Academic secondary (AHS) | | | 1284.759*** | 135.180 |
| | | | (157.962) | (153.834) |
| Higher VET (BHS) | | | 5437.317*** | 3245.238*** |
| | | | (137.037) | (133.361) |
| Kolleg | | | 3951.248*** | 1536.954*** |
| | | | (373.455) | (361.675) |
| Tertiary academy | | | 4527.089*** | 1260.766*** |
| | | | (229.905) | (223.071) |
| University | | | 12638.509*** | 9772.712*** |
| | | | (124.206) | (121.359) |
| Female | | | −5885.288*** | −4903.099*** |
| | | | (64.341) | (62.552) |
| Number of Children 1 | | | −289.603*** | −868.502*** |
| | | | (83.609) | (80.992) |
| Number of Children 2 | | | 197.900* | −712.517*** |
| | | | (99.530) | (96.516) |
| Number of Children 3 | | | −612.405*** | −1475.875*** |
| | | | (170.314) | (164.915) |
| Number of Children 4 | | | −1074.802** | −1939.871*** |
| | | | (368.254) | (356.444) |
| Number of Children 5 | | | −1284.965 | −2275.808** |
| | | | (833.979) | (807.185) |
| Number of Children 6 | | | −1429.959 | −2794.993* |
| | | | (1385.686) | (1341.154) |
| Pension Status: worker+pension | | | | 1210.211*** |
| | | | | (262.518) |
| Pension Status: pension only | | | | −28963.759*** |
| | | | | (165.950) |
| Pension Status: pension+work | | | | −42248.971*** |
| | | | | (248.090) |
| Unemployed | | | | −8979.159*** |
| | | | | (130.642) |
| Active Student | | | | −14506.153*** |
| | | | | (243.066) |
| Num. Obs. | 775757 | 775757 | 775757 | 775757 |
| $R^2$ | 0.001 | 0.146 | 0.173 | 0.226 |
| $R^2$ Adj. | 0.001 | 0.146 | 0.173 | 0.226 |
| $F$ | 461.308 | 1674.143 | 1748.415 | 2306.037 |
| Age Controls | No | Yes | Yes | Yes |

*Notes:* The table reports OLS estimates from a stepwise specification of individual net fiscal contributions (EUR/year, 2021), estimated on the German-origin and native subsample. Column (1) is the unconditional specification; column (2) adds single-year-of-age dummies; column (3) adds education, gender, and number of children; column (4) adds pension status, unemployment, and active student status. The reference category is a native, male, employed, non-pensioner, non-student with Pflichtschule education and zero children. Standard errors in parentheses. Significance: $^{+}\,p < 0.1$, $^{*}\,p < 0.05$, $^{**}\,p < 0.01$, $^{***}\,p < 0.001$.
*Source:* AEST 2021, LUE 2021; author's calculations.

# Gelbach Tables

In the following I give the detailed Gelbach results without grouping the age effects into one block. In the second part I give detailed Gelbach decomposition tables for the German and the Syrian migrant communities in Austria in Tables 11 & 12.

**Table 9.** Gelbach decomposition: EU migrants vs. natives, full output

| Covariate | $\beta_K$ | $\gamma$ | $\delta = \gamma\beta_K$ |
|---|---|---|---|
| *Age (baseline: 45–49)* | | | |
| Age 15–19 | −12,507.4 | −0.0243 | 303.3 |
| Age 20–24 | −9,868.2 | −0.0080 | 79.3 |
| Age 25–29 | −8,186.5 | 0.0171 | −140.3 |
| Age 30–34 | −6,822.4 | 0.0447 | −304.9 |
| Age 35–39 | −4,970.3 | 0.0450 | −223.9 |
| Age 40–44 | −2,317.3 | 0.0453 | −104.9 |
| Age 50–54 | 1,281.2 | 0.0019 | 2.4 |
| Age 55–59 | 2,068.3 | −0.0250 | −51.6 |
| Age 60–64 | 3,927.2 | −0.0354 | −139.2 |
| Age 65–69 | 925.9 | −0.0260 | −24.1 |
| Age 70–74 | 235.1 | −0.0299 | −7.0 |
| Age 75–79 | −82.9 | −0.0073 | 0.6 |
| Age 80–84 | −662.9 | −0.0132 | 8.8 |
| Age 85–89 | −1,609.8 | −0.0060 | 9.7 |
| Age 90–94 | −3,604.0 | −0.0042 | 15.0 |
| Age 95–99 | −6,187.7 | −0.0004 | 2.7 |
| | | *Subtotal Age, net $\sum\delta$* | *−574.1* |
| | | *Subtotal Age, $\sum\lvert\delta\rvert$* | *1,417.9* |
| *Education (baseline: Pflichtschule)* | | | |
| Education 1 (below Pflichtschule) | −12,171.7 | −0.0015 | 17.9 |
| Education 2 (Apprenticeship) | −947.5 | −0.0982 | 93.0 |
| Education 3 (Intermediate VET) | 282.4 | −0.0616 | −17.4 |
| Education 4 (AHS) | 368.1 | 0.0469 | 17.2 |
| Education 5 (Higher VET) | 3,515.1 | −0.0341 | −119.7 |
| Education 6 (Kolleg) | 1,656.2 | −0.0013 | −2.2 |
| Education 7 (Tertiary academy) | 1,829.0 | −0.0100 | −18.4 |
| Education 8 (University) | 9,818.6 | 0.0607 | 596.4 |
| | | *Subtotal Education, net $\sum\delta$* | *566.9* |
| | | *Subtotal Education, $\sum\lvert\delta\rvert$* | *882.3* |
| Female | −4,906.6 | 0.0125 | −61.4 |
| *Number of children (baseline: 0)* | | | |
| 1 child | −655.8 | −0.0115 | 7.6 |
| 2 children | −328.2 | −0.0186 | 6.1 |
| 3 children | −1,136.3 | −0.0030 | 3.4 |
| 4 children | −2,076.3 | 0.0006 | −1.3 |
| 5 children | −2,069.3 | 0.0009 | −1.8 |
| 6 children | −1,010.2 | 0.0008 | −0.8 |
| | | *Subtotal Children, net $\sum\delta$* | *13.2* |
| | | *Subtotal Children, $\sum\lvert\delta\rvert$* | *21.0* |
| *Pension status (baseline: no pension, working)* | | | |
| Pension only | −28,503.7 | −0.1312 | 3,739.7 |
| Pension + work | −40,865.6 | −0.0095 | 389.6 |
| Worker + pension | 2,003.4 | −0.0042 | −8.4 |
| | | *Subtotal Pension, net $\sum\delta$* | *4,120.9* |

*continued on next page*

*Table 9 – continued from previous page*

| Covariate | $\beta_K$ | $\gamma$ | $\delta = \gamma\beta_K$ |
|---|---|---|---|
| | | *Subtotal Pension,* $\sum\lvert\delta\rvert$ | *4,137.7* |
| Unemployed | −8,778.7 | 0.0619 | −543.3 |
| Active student | −14,489.0 | −0.0130 | 188.3 |
| Urban residence | 393.6 | 0.2094 | 82.4 |
| | | **Net** $\sum\delta$ | **3,793.1** |
| | | $\sum\lvert\delta\rvert$ | **7,334.4** |
| $N$ | | 846,389 | |

*Note:* Gelbach (2016) decomposition of the change in the EU-migrant coefficient between column (1) (unconditional) and column (4) (full) of Table 2, estimated on the EU + native subsample. $\beta_K$ is the coefficient on covariate $K$ in the full model; $\gamma$ is the coefficient on the EU-migrant indicator in the auxiliary regression of $K$ on migrant status and remaining controls; $\delta = \gamma\beta_K$ is the contribution of $K$ to the change in the migrant coefficient. Net $\sum\delta$ equals $\hat{\beta}_{\mathrm{EU}}^{\mathrm{base}} - \hat{\beta}_{\mathrm{EU}}^{\mathrm{full}}$ by construction; positive $\delta_k$ indicates that adding covariate $K$ to the regression pulls the migrant coefficient downward by $\delta_k$. Block subtotals reported beneath each block; $\sum|\delta|$ is the denominator used for percentage-share statements in the main text.

**Table 10.** Gelbach decomposition: extra-EU migrants vs. natives, full output

| Covariate | $\beta_K$ | $\gamma$ | $\delta = \gamma\beta_K$ |
|---|---|---|---|
| *Age (baseline: 95–99)* | | | |
| Age 15–19 | −5,298.7 | −0.0247 | 131.1 |
| Age 20–24 | −2,600.1 | −0.0041 | 10.6 |
| Age 25–29 | −1,045.8 | 0.0060 | −6.3 |
| Age 30–34 | 280.2 | 0.0449 | 12.6 |
| Age 35–39 | 2,071.5 | 0.0491 | 101.8 |
| Age 40–44 | 4,652.4 | 0.0391 | 181.9 |
| Age 45–49 | 6,904.5 | 0.0320 | 220.7 |
| Age 50–54 | 8,054.2 | 0.0173 | 139.3 |
| Age 55–59 | 8,806.6 | −0.0048 | −41.9 |
| Age 60–64 | 10,458.3 | −0.0213 | −222.8 |
| Age 65–69 | 7,553.6 | −0.0110 | −83.4 |
| Age 70–74 | 6,776.3 | −0.0236 | −159.9 |
| Age 75–79 | 6,251.3 | −0.0307 | −191.7 |
| Age 80–84 | 5,598.8 | −0.0371 | −207.8 |
| Age 85–89 | 4,663.9 | −0.0179 | −83.5 |
| Age 90–94 | 2,618.4 | −0.0094 | −24.7 |
| | | *Subtotal Age, net $\sum\delta$* | *−224.0* |
| | | *Subtotal Age, $\sum\lvert\delta\rvert$* | *1,819.9* |
| *Education (baseline: Pflichtschule)* | | | |
| Education 1 (below Pflichtschule) | −5,021.4 | −0.0015 | 7.3 |
| Education 2 (Apprenticeship) | −944.4 | −0.1369 | 129.3 |
| Education 3 (Intermediate VET) | 212.8 | −0.0891 | −19.0 |
| Education 4 (AHS) | 123.4 | 0.0224 | 2.8 |
| Education 5 (Higher VET) | 3,437.1 | −0.0548 | −188.3 |
| Education 6 (Kolleg) | 1,684.7 | −0.0036 | −6.1 |
| Education 7 (Tertiary academy) | 1,707.4 | −0.0162 | −27.7 |
| Education 8 (University) | 9,788.1 | −0.0140 | −136.6 |
| | | *Subtotal Education, net $\sum\delta$* | *−238.3* |
| | | *Subtotal Education, $\sum\lvert\delta\rvert$* | *517.0* |
| Female | −4,792.3 | −0.0533 | 255.7 |
| *Number of children (baseline: 0)* | | | |
| 1 child | −650.8 | −0.0022 | 1.4 |
| 2 children | −442.9 | 0.0380 | −16.8 |
| 3 children | −1,488.9 | 0.0488 | −72.6 |
| 4 children | −2,555.7 | 0.0191 | −48.9 |
| 5 children | −2,864.8 | 0.0060 | −17.1 |
| 6 children | −2,419.3 | 0.0022 | −5.4 |
| | | *Subtotal Children, net $\sum\delta$* | *−159.4* |
| | | *Subtotal Children, $\sum\lvert\delta\rvert$* | *162.3* |
| *Pension status (baseline: no pension, working)* | | | |
| Pension only | −27,860.4 | −0.1516 | 4,224.8 |
| Pension + work | −39,915.9 | −0.0066 | 263.8 |
| Worker + pension | 2,188.9 | −0.0038 | −8.3 |
| | | *Subtotal Pension, net $\sum\delta$* | *4,480.4* |
| | | *Subtotal Pension, $\sum\lvert\delta\rvert$* | *4,496.9* |
| Unemployed | −8,581.7 | 0.0866 | −743.4 |
| Active student | −14,460.0 | −0.0156 | 225.6 |
| Urban residence | 348.9 | 0.3509 | 122.4 |
| | | **Net $\sum\delta$** | **3,719.0** |
| | | $\sum\lvert\delta\rvert$ | **8,343.2** |
| *N* | | 856,123 | |

*Notes:* See Table 9 for variable definitions and estimation details. Estimated on the extra-EU + native subsample. The omitted age category is 95–99; its $\delta$ contribution is normalized to zero by construction. Note that Table 9 uses Age 45–49 as the omitted category, so absolute values of $\gamma$ on the age dummies are not directly comparable across the two tables; $\delta$ contributions remain interpretable within each table.
*Source:* AEST 2021, LUE 2021; author's calculations.

**Table 11.** Gelbach decomposition: German migrants vs. natives, full output

| Covariate | $\beta_K$ | $\gamma$ | $\delta = \gamma\beta_K$ |
|---|---|---|---|
| *Age (baseline: 95–99)* | | | |
| Age 15–19 | −7,218.6 | −0.0240 | 173.0 |
| Age 20–24 | −4,436.4 | −0.0076 | 33.7 |
| Age 25–29 | −2,791.0 | 0.0266 | −74.2 |
| Age 30–34 | −1,329.9 | 0.0382 | −50.8 |
| Age 35–39 | 569.5 | 0.0348 | 19.8 |
| Age 40–44 | 3,463.1 | 0.0296 | 102.4 |
| Age 45–49 | 6,214.7 | 0.0119 | 74.2 |
| Age 50–54 | 7,119.7 | −0.0005 | −3.3 |
| Age 55–59 | 7,836.7 | −0.0104 | −81.3 |
| Age 60–64 | 9,981.4 | −0.0260 | −259.5 |
| Age 65–69 | 6,870.0 | −0.0267 | −183.7 |
| Age 70–74 | 6,197.5 | −0.0275 | −170.5 |
| Age 75–79 | 5,704.2 | 0.0040 | 22.8 |
| Age 80–84 | 5,243.2 | −0.0050 | −26.3 |
| Age 85–89 | 4,324.5 | −0.0088 | −38.0 |
| Age 90–94 | 2,184.6 | −0.0067 | −14.6 |
| | | *Subtotal Age, net* $\sum\delta$ | *−476.2* |
| | | *Subtotal Age,* $\sum\lvert\delta\rvert$ | *1,328.1* |
| *Education (baseline: Pflichtschule)* | | | |
| Education 1 (below Pflichtschule) | −7,247.9 | −0.0015 | 10.9 |
| Education 2 (Apprenticeship) | −1,332.6 | −0.0457 | 60.8 |
| Education 3 (Intermediate VET) | −176.1 | −0.0413 | 7.3 |
| Education 4 (AHS) | −254.6 | 0.0474 | −12.1 |
| Education 5 (Higher VET) | 3,215.6 | −0.0391 | −125.7 |
| Education 6 (Kolleg) | 1,459.0 | −0.0012 | −1.8 |
| Education 7 (Tertiary academy) | 1,279.9 | −0.0049 | −6.3 |
| Education 8 (University) | 9,578.5 | 0.1453 | 1,391.5 |
| | | *Subtotal Education, net* $\sum\delta$ | *1,324.6* |
| | | *Subtotal Education,* $\sum\lvert\delta\rvert$ | *1,616.3* |
| Female | −5,024.4 | 0.0089 | −44.9 |
| *Number of children (baseline: 0)* | | | |
| 1 child | −719.9 | −0.0389 | 28.0 |
| 2 children | −573.7 | −0.0259 | 14.9 |
| 3 children | −1,043.8 | −0.0041 | 4.2 |
| 4 children | −1,895.4 | −0.0009 | 1.7 |
| 5 children | −1,850.8 | −0.0000 | 0.0 |
| 6 children | −2,759.8 | 0.0002 | −0.6 |
| | | *Subtotal Children, net* $\sum\delta$ | *48.3* |
| | | *Subtotal Children,* $\sum\lvert\delta\rvert$ | *49.5* |
| *Pension status (baseline: no pension, working)* | | | |
| Pension only | −29,184.9 | −0.1189 | 3,469.9 |
| Pension + work | −42,159.1 | −0.0072 | 302.2 |
| Worker + pension | 1,355.6 | −0.0025 | −3.4 |
| | | *Subtotal Pension, net* $\sum\delta$ | *3,768.8* |
| | | *Subtotal Pension,* $\sum\lvert\delta\rvert$ | *3,775.5* |
| Unemployed | −9,004.8 | 0.0268 | −241.6 |
| Active student | −14,390.3 | −0.0035 | 50.1 |
| Urban residence | 402.0 | 0.1326 | 53.3 |
| | | **Net** $\sum\delta$ | **4,482.4** |
| | | $\sum\lvert\delta\rvert$ | **7,159.3** |
| *N* | | 958,315 | |

*Notes:* See Table 9 for variable definitions and estimation details. Estimated on the German + native subsample. The omitted age category is 95–99; its $\delta$ contribution is normalized to zero by construction.
*Source:* AEST 2021, LUE 2021; author's calculations.

**Table 12.** Gelbach decomposition: Syrian migrants vs. natives, full output

| Covariate | $\beta_K$ | $\gamma$ | $\delta = \gamma\beta_K$ |
|---|---|---|---|
| *Age (baseline: 95–99)* | | | |
| Age 15–19 | −7,279.4 | 0.0234 | −170.6 |
| Age 20–24 | −4,327.9 | 0.0860 | −372.4 |
| Age 25–29 | −2,669.8 | 0.1152 | −307.7 |
| Age 30–34 | −1,345.1 | 0.1087 | −146.2 |
| Age 35–39 | 543.8 | 0.0704 | 38.3 |
| Age 40–44 | 3,462.2 | 0.0388 | 134.3 |
| Age 45–49 | 5,821.8 | 0.0006 | 3.3 |
| Age 50–54 | 6,955.5 | −0.0495 | −344.4 |
| Age 55–59 | 7,893.5 | −0.0684 | −540.0 |
| Age 60–64 | 10,310.5 | −0.0780 | −804.0 |
| Age 65–69 | 7,069.3 | −0.0665 | −470.4 |
| Age 70–74 | 6,385.1 | −0.0595 | −380.2 |
| Age 75–79 | 5,971.8 | −0.0455 | −271.7 |
| Age 80–84 | 5,565.7 | −0.0440 | −244.8 |
| Age 85–89 | 4,536.4 | −0.0210 | −95.2 |
| Age 90–94 | 2,401.0 | −0.0109 | −26.2 |
| | | *Subtotal Age, net* $\sum\delta$ | *−3,998.0* |
| | | *Subtotal Age,* $\sum\lvert\delta\rvert$ | *4,349.7* |
| *Education (baseline: Pflichtschule)* | | | |
| Education 1 (below Pflichtschule) | −7,111.2 | 0.0029 | −20.3 |
| Education 2 (Apprenticeship) | −1,386.4 | −0.2672 | 370.5 |
| Education 3 (Intermediate VET) | −277.1 | −0.1303 | 36.1 |
| Education 4 (AHS) | 60.7 | 0.1297 | 7.9 |
| Education 5 (Higher VET) | 3,050.6 | −0.0760 | −231.9 |
| Education 6 (Kolleg) | 1,534.1 | −0.0008 | −1.2 |
| Education 7 (Tertiary academy) | 1,428.2 | −0.0172 | −24.6 |
| Education 8 (University) | 9,801.4 | −0.0042 | −40.7 |
| | | *Subtotal Education, net* $\sum\delta$ | *95.8* |
| | | *Subtotal Education,* $\sum\lvert\delta\rvert$ | *733.1* |
| Female | −4,940.1 | −0.2790 | 1,378.4 |
| *Number of children (baseline: 0)* | | | |
| 1 child | −815.5 | −0.0875 | 71.3 |
| 2 children | −725.3 | 0.0113 | −8.2 |
| 3 children | −1,178.4 | 0.0900 | −106.1 |
| 4 children | −1,952.3 | 0.0657 | −128.3 |
| 5 children | −2,496.7 | 0.0217 | −54.2 |
| 6 children | −2,795.0 | 0.0090 | −25.2 |
| | | *Subtotal Children, net* $\sum\delta$ | *−250.6* |
| | | *Subtotal Children,* $\sum\lvert\delta\rvert$ | *393.3* |
| *Pension status (baseline: no pension, working)* | | | |
| Pension only | −29,546.9 | −0.3071 | 9,072.9 |
| Pension + work | −42,047.5 | −0.0200 | 841.4 |
| Worker + pension | 1,724.8 | −0.0141 | −24.3 |
| | | *Subtotal Pension, net* $\sum\delta$ | *9,890.1* |
| | | *Subtotal Pension,* $\sum\lvert\delta\rvert$ | *9,938.7* |
| Unemployed | −8,863.8 | 0.1242 | −1,101.3 |
| Active student | −14,362.9 | −0.0064 | 91.5 |
| Urban residence | 331.4 | 0.3928 | 130.2 |
| | | **Net** $\sum\delta$ | **6,236.1** |
| | | $\sum\lvert\delta\rvert$ | **18,116.2** |
| $N$ | | 955,759 | |

*Notes:* See Table 9 for variable definitions and estimation details. Estimated on the Syrian + native subsample. The baseline age category is 95–99; its $\delta$ contribution is normalized to zero by construction.
*Source:* AEST 2021, LUE 2021; author's calculations.

## Abstract (deutsch)

Diese Masterarbeit untersucht den fiskalischen Beitrag der in Österreich lebenden Migrant:innen im Vergleich zur in Österreich geborenen Bevölkerung. Datengrundlage sind durch Statistik Austria zur Verfügung gestellte, administrative Registerdaten für das Jahr 2021. Für jede Person wird ein Nettofiskalbeitrag (Net Fiscal Contribution, NFC) als Differenz zwischen geleisteten Steuern und Sozialversicherungsbeiträgen und empfangenen staatlichen Transfers berechnet. Die Analyse kombiniert Lebenszyklus-Profile mit stufenweisen OLS-Regressionen, gruppenweise geschätzten Sample-Split-Regressionen und einer Gelbach-Zerlegung.

Im Querschnitt 2021 weisen EU-Migrant:innen den höchsten durchschnittlichen NFC auf (5.466 EUR), gefolgt von in Österreich Geborenen (4.316 EUR) und außerhalb der EU geborenen Migrant:innen (3.669 EUR). Die altersspezifischen Profile haben für alle Gruppen eine vergleichbare Form, unterscheiden sich jedoch im Niveau. Gruppenunterschiede im Profil entstehen fast ausschließlich auf der Beitragsseite und nicht durch die Inanspruchnahme von mehr oder höheren Transfers.

Die Gelbach-Zerlegung zeigt, dass der günstige aggregierte Befund für beide Migrant:innengruppen primär auf einen Kompositionseffekt zurückgeht: Der Pensionsstatus erklärt 56 Prozent (EU) beziehungsweise 53 Prozent (Nicht-EU) der Veränderung des Migrant-Koeffizienten zwischen Basismodell und vollständiger Spezifikation. Der gegenwärtige fiskalische Vorteil der Migrant:innengruppen ist somit in der aktuellen Höhe überwiegend ein vorübergehendes Kompositionsphänomen und nicht als dauerhaftes strukturelles Merkmal zu interpretieren.

## Abstract (english)

This master's thesis examines the fiscal contribution of migrants residing in Austria relative to the Austrian-born population. The analysis draws on administrative register data provided by Statistik Austria for the year 2021. For each individual, a Net Fiscal Contribution (NFC) is constructed as the difference between paid taxes and social security contributions, and received public transfers. The analysis combines life-cycle profiles with stepwise OLS regressions, group-specific sample-split regressions, and a Gelbach decomposition.

In the 2021 cross-section, EU migrants display the highest average NFC (5,466 EUR), followed by the Austrian-born (4,316 EUR) and extra-EU migrants (3,669 EUR). The age-specific profiles have a comparable shape across groups but differ in level. Group differences in the life-cycle shape arise almost entirely through the contribution side. The sample-split regressions show that a substantial earnings-side level gap between groups persists even after conditioning on all observable characteristics.

The Gelbach decomposition shows that the favorable aggregate position of both migrant groups is primarily driven by a compositional effect: pension status alone accounts for 56 percent (EU) and 53 percent (extra-EU) of the change in the migrant coefficient between baseline and full model. The current fiscal advantage of the migrant groups should therefore be understood as a largely transitory compositional phenomenon rather than a permanent structural feature.