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Ethnic Factors and Its Contribution to Interest Rate Disparities

An Analysis of the Norwegian Mortgage Market

Bachelor's thesis

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Abstract

Most Norwegian households are defined as homeowners, owning the houses they live in. The mortgage term thus plays an important role for most Norwegians, being an indicator of their financial welfare. In hopes of stable finances for most households, problems arise when parts of the population achieve less favorable mortgage conditions. Outside of Norway, studies have shown differences in mortgage interest rates, being adverse for ethnic minorities. This paper empirically investigates how ethnicity contributes to the Norwegian mortgage market, looking at a possible interest rate discrepancy between native-born and immigrants. Access to household registries in microdata.no has given the possibility of constructing a panel dataset representing Oslo's homeowners in the years 2015-2020. With regression methods such as Ordinary least squares (OLS) and random effects (FGLS), we were able to estimate a potential interest rate heterogeneity amongst immigrant homeowners. Controlling for time and economic factors, immigrants are shown to pay almost 0.4 percentage points higher interest than native Norwegians. The discrepancy is largest amongst the Asian and African subgroups. Results indicate ethnic factors play a role in the Norwegian mortgage market as well. On this basis, we hypothesize an adverse selection effect from banks classifying immigrants as a riskier client group than natives. This is possibly due to immigrants lacking experience in the housing market, in addition to cultural factors such as language barriers. This affects both immigrants' and bank's behavior. However, further research is needed to both confirm and identify other factors, as little to none of such has been conducted in Norway previously.

Sammendrag

De fleste norske husholdninger er definert som huseiere – eier huset de bor i. Boliglånsrenten spiller en viktig rolle for fleste nordmenn som en indikator på deres finansielle velvære. I håp om finansiell stabilitet for de fleste husholdninger oppstår problemer når deler av befolkningen får mindre gunstige boliglånsvilkår. I andre land viser studier forskjeller i boliglånmarkedets rentenivåer at det er ugunstig for etniske minoriteter. Denne oppgaven undersøker empirisk hvordan etnisitet bidrar til det norske boliglånmarkedet ved å se på en mulig uventet renteforskjell mellom etniske nordmenn og innvandrere. Tilgang til registre for husholdninger i microdata.no har gitt mulighet til å konstruere et panel datasett som representerer Oslos huseiere fra 2015-2020. Med regresjonsmetoder som minste kvadraters metode (OLS) og tilfeldige effekter (FGLS) fikk vi estimert en mulig heterogenitet i boliglånsrenten hos huseiere med innvandrerbakgrunn. Ved å kontrollere for tid og andre økonomiske faktorer får vi et empirisk resultat som tilsier at immigranter betaler rundt 0.4 prosentpoeng høyere rente enn etnisk norske huseiere. Ulikhetene er mest markant hos asiatiske og afrikanske undergrupper. Resultatene indikerer at etniske faktorer også spiller en rolle i det norske boliglånsmarkedet. På basis av dette antar vi en effekt av ugunstig seleksjon fra bankene som klassifiserer innvandrere som mer risikable kunder relativt til etnisk norske. Dette kan være fordi immigranter mangler erfaring i boligmarkedet, i tillegg til kulturelle faktorer som språkbarrierer. Dette påvirker både innvandrernes og bankens oppførsel. Merk at videre forskning er nødvendig for å både bekrefte og identifisere andre faktorer, grunnet at det er nært ingen tidligere norske studier gjennomført på dette temaet.

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1. Introduction

Norway regards itself to be one of the fairest and just countries in the world. Keeping this in mind, we wish to conduct empirical research to find out whether this statement is on par with the level of mortgage rates for immigrants. Access to financial services is a highly relevant aspect of inclusiveness, and ensuring transparency in mortgage rates will act as an indicator of an equal market, which is the basis for our paper. Any significant increase from the mean levels can put you in a far more difficult financial situation compared to the rest of society. This research study looks closely at if people of immigrant background obtain higher mortgage rates relative to native Norwegians. In addition, it questions if potential differences are results of dissimilarities in customs or lack of representation in homeownership. There is not a lot of data regarding the Norwegian market which may be due to the assumption that Norway is less discriminatory than the rest of the world. If false, this results in biased and misleading conclusions. We test this assumption using data spanning from 2015 to 2020.

While extensive research has been done on the relationship between mortgage rates and demographic variables such as race and immigrant status in the United States, there has been scarce attention to the same questions in Norway. It might not be a shocking revelation that this has been a subject of interest in the United States given its history of problematic systematic discrimination, but there could be an argument that the lack of research on this subject in Norway is a missed opportunity. This is especially true given Norway's solid foundations for such research in having access to substantial amounts of registered data. Interestingly though, this issue has recently become more visible within the public debate, as seen by the Ministry of Labour and Social Inclusion's action plan for 2024-2027 on racism and discrimination. In their action plan, one of the stated goals is to map the extent of direct and indirect discrimination in the lending practices of banks.

> *A research initiative has been established to look at the extent of direct and indirect discrimination in banks' lending practices in Norway, including whether people are not offered loans, or receive worse loan conditions than other borrowers in the same financial situation, on the basis of their ethnicity or religion. The investigation will also assess whether there is a need for measures if such discrimination occurs. The report will be*

As mentioned previously there has been a large focus on the issue of discrimination on financial services in the United States, which has led to a collection of legislation being enacted to combat any discrimination. Examples of these protective measures are The Fair Housing Act of 1968 and the Equal Credit Opportunity Act of 1974. The Fair Housing Act is a federal law that prohibits discrimination in the housing market by providers of housing or lending institutions based on race, color, sex, national origin, familial status, or disability (U.S. Department of Justice, 2023). Similarly, the Equal Credit Opportunity Act prohibits discrimination against credit applicants by creditors based on race, color, sex, national origin, marital status, age, or if they receive income from public assistance (U.S. Department of Justice, 2024). In a scenario where the U.S. Department of Justice finds a pattern of mortgage rate discrimination based on national origin; the department could file a suit under both acts.

In contrast to the United States, Norway does not have specific legislation akin to the Fair Housing Act and the Equal Opportunity Act to offer direct protections against mortgage rate discrimination based on race, color, sex, national origin, marital status, age, etc. While Norway does boast strong anti-discrimination laws in general, such as the Equality, and Anti-Discrimination Act, the lack of targeted legislation could open regulatory gaps when it comes to combating discriminatory practices. It is interesting to look further into if the lack of such targeted legislation is due to Norway's reputation as a fair and equal country with high societal trust, being a reason why we both have scarce research into mortgage rate discrepancies and a less targeted legal framework.

To get a broad overview of this topic it is necessary to introduce the current demographic situation in Norway. Statistics Norway defines an immigrant as a person who has physically "migrated" to Norway and who does not have parents or grandparents born in this country. Children born in Norway to two immigrants will be called "Norwegian-born to immigrant parents" (Andreassen, 2018). As per the end of 2023 the population of Norway is estimated to be in the excess of 5,5 million, of which approximately 930 000 or 16,8% are estimated to be categorized as immigrants. In addition, around 220 000 or 4% are Norwegian born to immigrant parents. It would also be amiss to not mention that our data compiled is dated

before the outbreak of the Russia-Ukraine conflict, and thus the consequences of this event on immigration are not considered.

Delving deeper into housing conditions in Norway. According to Statistics Norway's data for 2023, 81.6% of the total population owns the house they live in, either through being a freeholder or part/shareholder. Here there are quite large differences between native Norwegians and other groups. While 85,8% of native Norwegians are either a freeholder or part/shareholder, the share of homeownership for immigrants from the EU/EEA, US, Canada, Australia, and New Zealand is 64,1%. For all other immigrant groups, the percentage of homeownership is 57,1% (Statistics Norway, 2024). Some of these numbers are likely influenced by the fact that a lot of immigrants live in Oslo where due to high housing costs the share of tenants will be higher than the average. This paper aims to look at the housing market situation for immigrants in Oslo.

The paper is organized as follows. Section 2 presents the relevant prior research and a simple theoretical framework. Section 3 explains the empirical methods applied to the research in both a cross-section and panel-data setting. Section 4 presents the evidence from our regression estimates. Section 5 discusses the findings. Section 6 concludes.

2. Theoretical background

As for Norway, we find little to almost no literature in this specific field of studies. Most papers looking at ethnic discrepancies in the mortgage markets are survey based American studies, studying the difference among *Blacks, Hispanics*, *Asians,* etc., more focused on racial/ethnic minorities and not the immigrant-status. As mentioned, discriminatory findings in legal matters are more "popular", hence more important in the United States relative to Norway. Fortunately, research of immigrants and their experiences in the housing market is also available in a European context. In general, the universal empiricism hints in an overrepresentation of immigrants/minorities being a "losing part" in the matter of mortgage terms, both in interest rates and homeownership opportunities. We expect the same principles while conducting our analysis in a Norwegian housing market. Hence, it is contextually pertinent to review the previous literature.

2.1 Methods and previous work

Nova Southeastern University (Baek & Cho, 2023) examined data from the Survey of Consumer Finance (SFC) on mortgage loans originating during the period between 2011 and 2019. Their regression analysis found, with some significance, Blacks and Hispanics paying higher mortgage rates than Whites during the sample period. The disparities among Blacks seemed to decline and diminish over time, an explanation reasons for advances in information technology among banks. For Hispanics, the disparity remained the same without further explanations of why, being a topic for the future. Neil Bhutta & Aurel Hizmo (2020) from the Federal Reserve Board conducted a similar study, finding proximate results for the same two ethnic groups in the interest rates. In contrast to the others, they were able to present some evidence of why. They possessed data on the number of discount points paid by the borrowers. Discount points (dp) are a sort of prepaid interest that mortgage borrowers purchase from their lender, lowering the amount of interest on their subsequent payments. Bhutta & Hizmo found in their regression analysis, using dp as the outcome variable, Blacks and Hispanics paying slightly fewer points than whites and Asians. Depicting a consistent tradeoff between the interest rate and discount points. In conclusion, Blacks and Hispanics tend to choose higher interest rates in return for lower costs upfront of their mortgage. The most recent study (Loya, 2024) used a multinomial logistic regression analysis based on public data from the Home Mortgage Disclosure Act (HMDA). Given the same levels of debt-to-income ratio (DTI), Blacks and Hispanics got outperformed by Whites and Asians obtaining higher-cost loans and rejection rates.

Moving to Europe, a Spanish study (Diaz-Serrano & Raya, 2014) found that immigrants got charged with significantly higher interest rates than their native counterparts in the Spanish housing market, even after controlling for differences in creditworthiness along with other key factors. The authors suggested it is a result of "statistical discrimination" as lenders in a competitive mortgage market view immigrants with familiar characteristics as riskier. It is worth mentioning that this study was only utilized on intermediate mortgages, where the borrower and lender did not deal face to face. A more recent similar Italian paper (Mistrulli et al., 2023) had the same conclusions. With individual characteristics included, it also observed a significantly higher difference in interest rate on mortgages taken up by immigrants. In addition, examining mortgage approvals, immigrants were estimated to have lower probability than natives.

Closer to Norway, a Swedish survey-analysis found hints of discrimination towards self-employed immigrants in association of credit market participation (Aldén & Hammstedt, 2016). The findings suggested non-European immigrants were more likely to have their loan denied and charged higher interest rates.

The closest study of relevance from Norway (Aarland & Santiago, 2023) looked at data from so-called start-up loans provided by The Norwegian State Housing Bank. Start-up loans can be viewed as some sort of low-income homeownership program. Aarland & Santiago analyzed if the number of mortgage arrears, referring to overdue mortgage payments, varied by immigrant background through the lens of these loans. They found evidence suggesting non-Western and Eastern European immigrants are less likely to be in mortgage arrears compared to ethnic Norwegians. However, they hypothesize such an estimation is due to immigrants and refugees having stricter screening criteria than Norwegian applicants. Unfortunately, it is not something their analysis can answer.

2.2 Adverse selection hypothesis

As available literature suggests, ethnic minorities on average pay a higher interest rate on their mortgage. However, we find no consistent empirical reason for the underlying issue-, or its origin. Still, most of the discussed papers hint at banks somehow having more information asymmetry towards ethnic minorities, or at least viewing that customer base as a riskier investment. Cultural shocks from the borrowers and statistical discrimination from the lenders are mentioned as reasons. As a theoretical foundation, we hypothesize asymmetry to also exist in the Norwegian mortgage market. We expect similar discrepancies, where the reason can be shown through a general model of adverse selection.

When the bank does not know whether the borrower is risky or safe, adverse selection might occur. We assume banks are risk neutral, hence, they want to maximize their net expected profit. We set up the following simple adverse selection model, depicting a bank's expected net profit $E(\pi_{bank})$:

$$(2.1)\ E(\pi_{bank}) = \lambda(1+r) \times L + (1-\lambda) \times [p(1+r) \times L + (1-p)D] - L$$

λ denotes a probability of being a "safe" borrower, or non-defaulter. *(1-λ)* being the opposite, a "risky" borrower with a probability of fulfilling their obligation denoted by *p*, and *(1-p)* as a probability of default. If the borrower ends up paying its debt, the bank gets the payoff of *(1+r)L*, where *r* represents the interest rate and *L* being the loan amount. At default, the bank ends up with a recovery *D*, for *D < L*. We call *(1+r)* to represent the interest factor, which multiplied with the loan amount determines the total amount owed after accruing the interest rate.

Due to asymmetry, we assume the bank does not know the borrower type. However, being risk neutral, the bank will provide a loan if the expected payoff is greater than 0:

$$(2.2)\ E(\pi_{bank}) = \lambda(1+r) \times L + (1-\lambda) \times [p(1+r) \times L + (1-p)D] - L \geq 0$$

Assuming a competitive credit market: To see how the interest factor gets determined we solve equation (2.2) for *(1+r)*, holding with equality. For simplicity, we denote the factor as $\hat{R}$, having a larger value than 1 due to the fair assumption of a positive interest rate.

$$(2.3)\ \hat{R} = \frac{1}{\lambda + (1-\lambda)p} - \frac{(1-\lambda) \times (1-p)}{\lambda + (1-\lambda)p}\frac{D}{L} > 1\ (r > 0)$$

To understand what happens if the probability of a safe borrower increases, we derive the expression with respect to λ:

$$(2.4)\ \frac{d\hat{R}}{d\lambda} = \frac{(p-1)}{[\lambda + (1-\lambda)p]^2} - \frac{(p-1)}{[\lambda + (1-\lambda)p]^2}\frac{D}{L} < 0$$

$$0 < p < 1, 0 < \lambda < 1, D < L$$

We notice an increased probability for a "safe" borrower lowers *r*. This implies banks give out lower interest rates if their suspicion of a risky borrower type decreases, and vice versa. Applying this to our case: If banks consider immigrants to somehow be riskier than native with similar financial backgrounds, we expect to find higher interest rates for immigrants.

3. Data, variables, methodology

In contrast to other studies, relying mostly on survey data, our dataset was generated using an anonymized public household registry for the entirety of Norway. It was accessed through the analysis program microdata.no, facilitated by Statistics Norway (SSB). While keeping its anonymity, microdata.no provides Stata-like software built-in its webpage, making it possible to merge registries and perform statistical analysis. We provide the syntax of our dataset and analysis under the attached appendices.

With the newest available information from the tax registry, we look in the years of 2015 - 2020 for individuals with residency in Oslo County. Excluding the tenants, we argue having a population that represents the market of homeownership in Oslo. We possess a distinctive array of observations and variables, which in our understanding, no other similar study has possessed. The observations provided are from adult individuals in Oslo with ownership of their housing and reported debt in their tax returns. This could be sole proprietor, co-owner through a so-called housing association, or shareholder.

In the context of understanding the current housing market situation for immigrants in Oslo, we provide information for the number of homeowners in Table 1.

Table 1. Homeowners in Oslo per 2020

	Homeowners	**Total group**	**% of its group**	**% of Oslo**
Natives	313,307	411,660	76.11 %	54.02 %
Immigrants	88,889	168,310	52.81 %	15.33 %
Total	402,196	579,970		69.35 %

Notes: Numbers are obtained from the registries in microdata.no. *Appendix A* shows the syntax for obtaining the numbers.

From the registries, we observe that 69.35 percent have some sort of ownership of their house. These results are close to the latest that Statistics Norway reported from the 2022 data (Revold, 2023), assuming some deviation from misreporting. We observe that 52.81 percent of immigrants own housing, not far away from the 57 percent reported in the 2022 numbers

by Statistics Norway. With the above in place, we feel confident to have built a sample representing Oslo's housing market.

3.1 Dependent variable

We built our variable of interest using interest costs and total debt reported by the homeowners in their tax returns. Our ideal target variable would be to have access to everyone's mortgage interest. Nevertheless, possessing such information is not possible as the Norwegian tax return is not required to contain detailed information about your type of debt obligation. We acknowledge this as a weakness in our analysis, as the two variables can contain student debt, car loans, mortgage, consumer loans, etc., all merged as a total expenditure of debt.

Constructing our variable of interest we first took the total interest expense divided over total debt times a hundred, obtaining the percentage points (pp). This provided us with the average interest rate payment on the loans for each homeowner. To keep the matter simple, we dropped individuals with reported debt under 100,000 NOK, making sure we are looking at individuals possessing mortgage debt. We considered debt below that level to likely consist of other types of obligations. Further, we dropped observations without any reported interest cost. This left us with a total of 237,538 "mortgage borrowers". In this matter, we have a proxy variable for the mortgage interest rate, which we assume to move in conjunction with the true mortgage rate.

3.2 Explanatory variable of interest

From the registry data, we were able to categorize the individual's ethnic background. A dummy variable was created indicating if the individual went under the "immigrant category", being our main explanatory variable. Statistics Norway defines an immigrant as a person who immigrated to Norway, born abroad by foreign parents, and has 4 foreign grandparents (Dzamarija, 2019). This definition is what we employ throughout the paper. We were also provided with the borrower's origin country, allowing us to categorize immigrants into separate groupings of world regions.

Table 2. Descriptive statistics of the ethnicities

	N	Mean	Std Dev	Description
Immigrant	1,259,967	0.1717	0.3771	Binary indicator if the individual is an immigrant.
Middle East	1,259,967	0.0375	0.1899	Binary indicator if the individual is an immigrant born in the Middle East.
Africa	1,259,967	0.024	0.1531	Binary indicator if the individual is an immigrant born in Africa.
Asia	1,259,967	0.0326	0.1776	Binary indicator if the individual is an immigrant born in Asia (excluding Middle East).
EU	1,259,967	0.0217	0.1456	Binary indicator if the individual is an immigrant born in the EU.

Notes: N being total observation over the years 2015-2020 (*Appendix D*).

We present four subcategories: *Middle East, Rest of Asia, Africa,* and *EU*. Those regions are the largest birth-origins amongst immigrants in Norway (Statistics Norway, 2024). Taken from descriptive statistics of our sample (Table 2), those categories represent almost 70 % of the immigrants, equally distributed, where Asia plus the Middle East is the largest.

We observe a clear differential in average interest rates among the ethnicities. Table 3 depicts average interest rates for the different ethnic backgrounds. On average, immigrants have been paying an interest rate almost 0.7 pp higher than natives. This difference is highest among those with African and Asian (excluding Middle East) origin, showing an average of 3.33 percent and 3.40 percent, compared to the natives' 2.78 percent. In other words, we observe quite a difference.

Table 3. Average interest rates by year and ethnicity

Year	Natives	Immigrant	Middle East	Africa	*Rest of Asia	EU
2015	3.32 %	3.60 %	3.54 %	3.81 %	3.93 %	3.60 %
2016	2.78 %	3.12 %	3.06 %	3.36 %	3.48 %	3.04 %
2017	2.71 %	3.04 %	3.00 %	3.27 %	3.37 %	2.97 %
2018	2.65 %	2.96 %	2.95 %	3.23 %	3.26 %	2.89 %
2019	2.87 %	3.18 %	3.19 %	3.39 %	3.46 %	3.15 %
2020	2.47 %	2.77 %	2.84 %	3.00 %	3.03 %	2.70 %
Average	2.78 %	3.09 %	3.08 %	3.33 %	3.40 %	3.04 %

Notes: Immigrant represents all entities encompassed within the respective category, while Natives represents everyone not classed as Immigrant. The rest of the columns are delineating immigrants based on their respective countries of origin. *Rest of Asia meaning Asia excluding the Middle East.

3.3 Control Variables

We used eleven control variables for the borrowers in total, represented in Table 4 below. Those include economic factors such as *salary, wealth, total debt, market value of primary* and *secondary residencies*, and *unsecured debt* (data only available from 31.12.2019). Wealth serves as a proxy for initial capital, assumed to be represented through its variations. The market value of the primary residence serves as an indicator of the loan size. Other controls include more individual- or household-specific variables such as *stay in Norway, marital status, family size,* and *age.*

Table 4. Descriptive statistics for control variables

Variable	Mean	SD	Observations	Description
Stay in Norway	42.44	17.52	1,259,860	Years stayed in Norway
Married	0.38	0.48	1,259,967	Binary indicator if married
Male	0.51	0.5	1,259,967	Binary indicator if male
Salary income	70.09	51.32	1,259,967	Salary income, measured in 10,000 NOK
Debt	207.54	191.73	1,259,967	Total debt, measured in 10,000 NOK
Wealth	225.46	306.36	1,259,967	Taxable gross wealth, measured in 10,000 NOK
Primary residency	403.41	213.88	1,259,967	Calculated market value of primary residency, measured in 10,000 NOK
Secondary residency	34.06	120.03	1,259,967	Calculated market value of secondary residency, measured in 10,000 NOK
Family size	2.32	1.25	1,259,967	Number of people in the family
Age	46.59	14.99	1,259,860	Individual's age
*Unsecured debt	2.14	6.40	237,550	Debt that is not secured, measured in 10,000 NOK

Notes: *Unsecured debt was not registered until 31.12.2019, thus it is only used in the cross-section analysis of the paper.

Avoiding omitted variable bias as much as possible by controlling for important covariates determining interest rate such as salary, wealth, and housing value are essential. These factors are expected to be heavily correlated with ethnic background. In fact, from 2016 the monthly wage differential between immigrants and the rest of the population has been 15 % (Bye, 2023). This is close to what we observe from Figure 1, illustrating the differential between immigrants and the rest of the population on main economic factors from our sample. We expect such to be a major contributor explaining the observed interest differences.

Figure 1
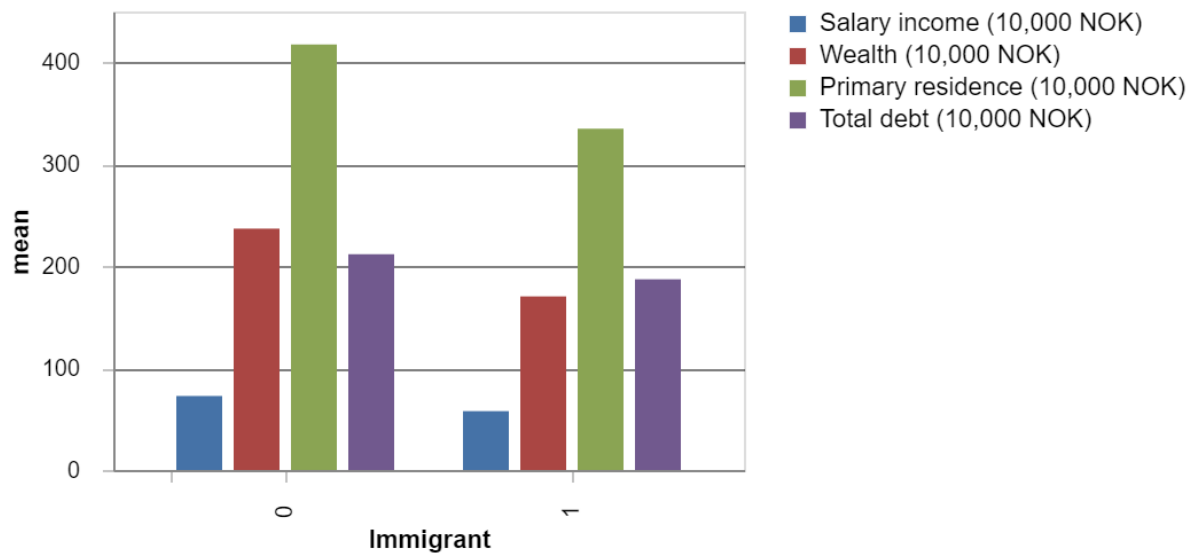
Immigrants score on average lower in all economic metrics. We thus expect to observe a positive bias when omitting such important covariates. That way we get closer to an explained difference revealing the pure effect of being an ethnic minority, holding economic factors equal.

Since the literature has shown individual characteristics being a determinant for loan terms, controlling such factors is necessary. Due to culture, we fairly assume the proportions of marital status and family size to vary among different ethnicities. As for including stay in Norway, we expect newly arrived immigrants to have a worse starting point in getting good loan terms vs. an immigrant with more stay. Age might be an indicator of experience; it can also serve as a variable that addresses our problem with interest-free student loans.

3.4 Model

With regression analysis using the *ordinary least squares* estimator (OLS), we created two model types. The first one is a baseline of observing an ethnic contribution in terms of interest rate, utilizing the cross-section of homeowners in Oslo for 2020. To retrieve the development of potential disparities over time we employed the panel aspects, using time-fixed effects and random effects.

3.4.1 Basis model

The "basic model" utilizes cross-sectional data, incorporating variations observed among homeowners in Oslo of the reported numbers for 2020. Due to scaling and clearer interpretation we denoted interest rate in *basis points*. One basis point (bp) is one 100th of 1 percent, meaning an increase of 10 basis points corresponds to a 0.1 percent increase in the interest rate. For an individual *i* we write:

$$(3.1) \; BP_i = \beta_0 + \beta_1 Immigrant_i + X_i' \gamma + u_i$$

where BP_i is homeowner *i*'s mortgage rate denoted in basis points, $Immigrant_i$ a dummy indicating if *i* is an immigrant or not (1 or 0), and X_i a vector representing individual *i*'s control variables. The term u_i represents the remaining error component.

Interpretation

The interest rate disparity is shown through β_1, depicting the difference in the intercept between immigrants and the Norwegian born group. Here β_0 is denoted as the intercept if $Immigrant_i = 0$. For immigrants we denote it as $\delta_0 = \beta_0 + \beta_1$. A $\beta_1 > 0$, interpreted: for the same levels, immigrants have higher interest rates on their mortgage than natives.

Omitted variable problem

To have an exogenous explanatory variable (Wooldridge, 2021, p. 82) a key assumption is: $E(u|Immigrant) = 0$ to hold. In other words, the error *u* has an expected value of zero given any values of the independent variable. There are three common ways this assumption can be violated: First is measurement error in the explanatory variables, second being simultaneity, and third omitted variables. For our case, the scenario would be the latter. Omitting a variable will lead to bias in our β_1-coefficient (Wooldridge, 2021, p. 84). We mitigate this risk by adding covariates which we expect are associated with $Immigrant_i$. We have shown from Figure 1 how economic factors are correlated with the immigrant status. Thus, through X_i, controlling those factors, we strengthen the assumption to hold true.

There are immeasurable variables such as language barriers, cultural behavior, and knowledge of the loan process. In this model, such factors are captured within the immigrant variable. The same applies to unobtainable factors, such as the number of arrears from a

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borrower. However, our main interest is to see if it in total contributes to disparities in mortgage interest rates. The cause of adverse selection profiling vs. cultural heterogeneity is thus not separated in the model. A walkthrough for a different method that might explain some of it is discussed in section 5. Moving forward we say we are looking at an exogenous explanatory when presenting the model.

3.4.2 Panel regression

With panel data we utilized both the cross-section-, and the time series dimensions (Wooldridge, 2021, p. 427). With the same borrowers over time, we represent the following model:

$$(3.2)\ BP_{it} = \beta_0 + \beta_1 Immigrant_i + X'_{it} + \alpha_i + \lambda_t + \varepsilon_{it}$$

Here BP_{it} denotes individual i's basis point rate for year t, $Immigrant_i$ is the time-invariant dummy taking the value 1 if individual i is an immigrant, and X_{it} being a vector of the time-variant control variables. In addition, we included α_i as individual-specific random effect and λ_t as time-fixed effects. ε_{it} denotes idiosyncratic error varying both across and within entities.

Feasible general least squares

An estimation of this type of model moves us away from regular OLS to what is called *feasible general least squares* (FGLS), implying that we are using random effects. To understand our model selection, we first illustrate a composite error term as $v_{it} = \alpha_i + \varepsilon_{it}$ for regular OLS. We observe a constant time-fixed unit-specific error α_i for unit i, depicting unobserved heterogeneity between borrowers, and an idiosyncratic error ε_{it} for unit i at time t. The most restrictive assumptions with the error term in this model are the following: 1, that our explanatory variable is exogenous relative to ε_{it}. 2, the idiosyncratic is also uncorrelated both within and across units with a constant variance. 3, α_i and ε_{it} are uncorrelated. The last remaining assumption depends if we can interpret the unit-specific error as being somehow correlated within and across units, and have a constant variance, that is: $E(\alpha_i | x_{i1}, x_{i2}, ..., x_{iT}) = 0$ (T being the last time observation). If this assumption is held the equation is a random effects model.

In an opposite case, fixed effects or first differences are more relevant to look at but have no fit in this paper as the main explanatory variable is a dummy. The problem formulation has its main goal to see if non-economic heterogeneity between immigrants and natives, determining the interest rate, can be observed across time. This is something the dummy-coefficient β_1 in equation (3.2) already represents. A method using individual fixed effects becomes pointless as it removes the within variation (Wooldridge, 2021, p. 463). We want to reveal the average time constant variation for immigrants rather than removing it. Through our variables of control, fluctuation in interest rates from economic status gets excluded from our coefficient. We remove the bias as discussed under equation (3.1).

Random effects are thus instead implemented to get more correct standard errors, by removing the serial correlation caused by the remainder of the borrower's unit-specific component. As α_i is in the composite error for each period, regular pooled OLS will struggle with serial correlation (Wooldridge, 2021, p. 470), random effects fixes this.

4. Results

In this section we present the empirical results first on the cross-section model exploring potential evidence of price discrimination. Later in the chapter we display results from the panel estimation and examine how it has developed over time.

4.1 Cross-section estimation

Table 5 presents regression estimates for the cross-sectional data in Oslo for 2020. We show a simplified singular linear regression (1), and regression estimates with the added controls (2). In addition, we present estimates among the different subgroups (3) described previously in Table 2.

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Table 5. Regression estimation for cross-sectional data (year 2020)

	y = basis points		
	(1)	(2)	(3)
Immigrant	28.98*** (2.26)	36.23*** (5.32)	
Middle Eastern			31.35*** (5.04)
African			32.11*** (6.10)
Asian			44.63*** (5.43)
EU			21.79*** (6.27)
Borrower controls		Yes	Yes
Adj. R-squared	.00068	.02905	.02924
N	237,538	237,538	237,538

Notes: Standard errors are in parentheses. Borrower controls include all variables from Table 3. Reference group is natives born in Norway. N indicates the number of observations. For further estimates: See *Appendix A*. * $p < .1$; ** $p < .05$; *** $p < .01$.

Column (1) depicts a significantly higher interest rate among immigrants; however, this estimation consists of bias due to the omitted variable problem. By adding borrower controls, column (2) shows an increase in the interest rate disparity of 0.07 pp. As estimates are depicted in basis points, an interpretation of the estimate says: All else equal, immigrants have a 0.362 pp higher interest rate than native born Norwegians. The number is statistically significant. From column (3) we observe the disparity to be the highest for Asian and African born immigrants, close to the findings of a similar study conducted in Italy (Mistrulli et al., 2023). Asia, Middle East excluded, lies above the estimated average disparity from column

(2), a 0.446 pp higher interest rate than natives. Immigrants from the EU differ the least amount, but are still estimated to have a statistically significant higher interest rate of 0.217 pp. We note that all estimates in column (3) have been conducted with borrower controls.

Estimates from Table 5 show convincing evidence of price discrimination in the mortgage interest rate market based on ethnic status. Thus, it is intriguing to look closer at how this has been over time, and if we observe any sign of improvement or not.

4.2 Panel estimates

To proclaim our findings to be robust, we look at the state and development of the mortgage interest rate differences throughout the years. Even though we lack information, we assume most of the sample population has held its mortgage for an extensive period. With the disparity found in the cross-section above, we should also expect to find comparable results from the panel data estimation. However, we mostly remember 2020 being a year with pandemic and lockdowns. This can have impacted the cross-sectional estimates with bias if the covid-years somehow amplified or impaired the interest rate differences. With the panel we have an advantageous opportunity to control for time-specific trends, eliminating potential biases.

With the years 2015 to 2020 split into two time periods: 2015 - 2017 and 2018 – 2020, we estimate using FGLS equal to equation (3.2) from section 3.4.2. Controlling for time, the two periods should provide equivalent results. Only expecting a small difference in the interest rate disparity due to potential new mortgage borrowers showing up in the data. Next, we utilize the whole sample period by adding interaction terms between immigrants and each year after 2015. This is to see if an observed disparity has increased or decreased from the referenced year.

4.2.1 2015-2017 and 2018-2020

Table 6 report estimates for each half of the sample period. Two regressions have been estimated for each period, one displaying the whole group of immigrants, and the second dividing in subgroups. All estimates include time-fixed effects, borrower random effects, and controls. The estimations are still reported in basis points.

Table 6. Regression estimates of Mortgage Rates: Years 2015-2017 vs. 2018-2020

	y = basis points			
	2015-2017		2018-2020	
Immigrant	41.27*** (4.11)		43.72*** (4.87)	
Middle Eastern		23.19*** (3.87)		39.32*** (4.6)
African		36.69*** (4.62)		38.48*** (5.55)
Asian		51.58*** (4.14)		49.05*** (4.95)
EU		24.89*** (4.91)		25.19*** (5.75)
Borrower controls	Yes	Yes	Yes	Yes
Borrower RE	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
R-squared	.01792	.01811	.00887	.00902
N	582,829	582,829	677,031	677,031

Notes: Standard errors are in parentheses. Borrower controls include all variables from Table 3. Reference group is natives born in Norway. Time fixed effects are represented by year dummies, with year 2015 and 2018 as reference. N indicates the number of observations. For further estimates: See *Appendix B* and *Appendix C*. * $p < .1$; ** $p < .05$; *** $p < .01$.

Both halves estimate a significantly larger interest rate for immigrants, paying around 0.4 pp higher mortgage than natives. We obtain equal results of what we found in the previous section. The inclusion of time trend slightly increases the difference observed in the cross-section. Equivalent results and patterns are shown amongst the subgroups. Asia without the Middle East remains on top with an estimated significant difference around 0.5 pp higher for both periods, all else equal. Immigrants from the EU show the lowest disparity with a significant estimation being around 0.25 pp in both halves. The Middle Eastern group distinguishes itself observing a jump at the disparity at 0.17 pp between the two time periods. Other than that, the estimates stay about the same. With the panel estimates our findings are robust. Controlling for financial situation, time trends, and random effects, we observe a significantly higher interest rate for immigrant homeowners. The likelihood of banks providing higher interest to the group appears to exist.

4.2.2 How does the difference in interest rate change over time?

It is interesting to find out how the disparities have developed over time. The previous panel hints at a slight increase. Using the whole period merged, we create interaction terms between *Immigrant* and the *year* dummies, except for 2015 as we keep it as a reference year. Table 7 reports regression estimates with the included interaction terms using the whole sample period, same controls used as in Table 6.

Table 7. Regression estimates of Mortgage Rates: 2015-2020

	y = basis points
Immigrant	38.55*** (5.05)
Immigrant*year2	7.42* (3.86)
Immigrant*year3	9.64** (3.82)
Immigrant*year4	4.30 (3.79)

Immigrant*year5	7.75
	(3.75)
Immigrant*year6	1.27
	(3.72)
Borrower controls	Yes
Borrower RE	Yes
Time fixed effects	Yes
R-squared	.01238
N	1,259,861

Notes: Standard errors are in parentheses. Borrower controls include all variables from Table 3. Time-fixed effects are represented by year dummies, with the year 2015 as a reference. The reference group is natives born in Norway. N indicates the number of observations. For further estimates: See *Appendix D*. * $p < .1$; ** $p < .05$; *** $p < .01$.

2015 being the year of reference, the estimation shows a significantly higher interest rate at 0.39 pp, all else equal. As hinted in the previous panel, the interaction terms illustrate a positive increasing trend in interest rate disparities, being positive each year prior to the starting year. As two of the subsequent years show a significant increase, the remaining three show insignificance, but still maintain positive coefficients.

These findings contradict Baek & Cho (2023). We depict a different situation for ethnic minorities in Norway vs. Black and Hispanic in America. Our data shows no indication of the disparities being mitigated at all. It stays about the same-, if not slightly increasing. However, Baek & Cho followed the mortgage from its commencement, while we possess no such information in our data. Thus, these findings are not so surprising given that we assume most of our sample borrowers have held the mortgage for a significant period, explaining its status quo. We expect the slight increase being a result of new immigrant borrowers showing up

during the sample period. In this case, our results should be viewed as distinguishable from the American study.

5. Discussion

If true, the results presented above should compel policy makers to be alert to the situation. It alone seems not to fix itself. More research in the field needs to be conducted, checking for similar patterns. Finding such estimations beyond Oslo in other big housing markets as Bergen, Trondheim, and Stavanger, would confirm the validity of our findings. In addition, utilizing more of the general population around various parts of the country across multiple time periods would be a better representation of the current situation nationwide. However, such analysis requires a lot of effort and patience due to its computational scope and time-consuming data processing. It could be considered in a more extensive paper in conjunction with a potential master's thesis, or a selection sent by the authorities.

It is important to note that even though our findings suggest banks give out higher interest rates on mortgage to immigrants, it does not explain the leading mechanisms behind it. Even though we hypothesize about the effects of adverse selection, this remains a hypothesis. Similar methods like Bhutta & Gizmo (2020), looking at the tradeoff between subsequently higher interest rate vs. a better initial starting point can be conducted, as we do not possess the tools in that direction. A deeper look would require more data as we shall not disregard our study's weaknesses: There are omitted factors which could contribute to the magnitude of the effects. Variables such as education, employment contract, credit rating, initial capital, true loan size, number of arrears, type of bank, etc., are some examples. Many of them being information that is unattainable in microdata.no or lack enough observations. To note: Education could be employed to our dataset, but due to complexity in its label codes and the demand of time constructing its tiers, we chose not to include it. However, other than magnitude, we do not have the belief of education to be reversing our estimates. Variables such as income most do catch up a lot of variation from education.

As our results do not separate how much, if at all, the observed disparity originates from discriminatory purposes or cultural variances, we further discuss potential causes for future study points.

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5.1 Discrimination or culture?

Intentional adverse selection effects are one thing, but there can be numerous explanations behind the discrepancy. We further hypothesize language barriers to be a contributing factor. Linguistic challenges might lead to immigrants having far less bargaining power when it comes to negotiating a better mortgage. As cheaper banks are becoming pure digital, one can expect immigrants to choose the traditional banks, often being a more expensive alternative. We believe language barriers make them more dependent on physical meetings with a bank representative rather than going through its online services or phone. We also expect immigrants to have less experience with the credit market. Historically, majority of those with refugee status are originating from Asian and African countries, contrary to most of the migrant workers originating from the EU (Dzamarija & Bjørnskau, 2019). Presuming refugees have less experience with the credit market due to conflicts and wars, it is to no surprise those continents demonstrate the highest interest rates compared to ones originating from EU countries. In addition, it is robust to assume Europeans experiencing less of a cultural shock from both language barriers and credit market proficiency, considering a sizable number of them originate from our neighboring country Sweden (Statistics Norway, 2024). In addition to language, credit history abroad and documentation may be less of a challenge for EU migrants, and attributes more on mortgage applicants originating from countries in conflicts and wars.

Even with a high probability of cultural and linguistic challenges contributing to higher interest rates, we are still not excluding other factors. To evaluate if a cultural-factor hypothesis has some explainable power, we do a similar regression as in Table 7, but now estimate a coefficient on Norwegian born with two immigrant parents, constructing a dummy variable called *second generation*. If language and cultural challenges are key influencers for mortgage disadvantages, we assume disparities on second-generation immigrants to be low, if not insignificant. Some difference is expected but given most of them have been raised and educated in the Norwegian system, the challenges should be mostly eliminated.

Table 8. Regression estimates of Mortgage Rates: 2015 – 2020, with second generation immigrants.

	y = basis points	
	(1)	(2)
Second generation	36.89*** (4.70)	24.26*** (9.00)
Immigrant	45.28*** (4.33)	45.29*** (4.33)
Second generation * year2		14.14 (10.90)
Second generation * year3		11.77 (10.66)
Second generation * year4		17.57* (10.49)
Second generation * year5		18.29* (10.3)
Second generation * year6		10.10 (10.14)
Borrower controls	Yes	Yes
Borrower RE	Yes	Yes
Time fixed effects	Yes	Yes
R-squared	.01247	.01247
N	1,259,861	1,259,861

Notes: Standard errors are in parentheses. Borrower controls include all variables from Table 3. Time-fixed effects are represented by year dummies, with year 2015 as reference. Reference group is natives born in Norway. N indicates the number of observations. For further estimates: See *Appendix D.* * $p < .1$; ** $p < .05$; *** $p < .01$.

Table 8 presents the regression results for the second-generation immigrants. Second generation being the dummy-variable containing the value 1 for sample individuals being native born with two immigrant parents, 0 otherwise. Time-varying interaction terms are added in column (2) checking the development over time. The same controls are used as in previous panels, together with time-fixed effects and borrower random effects.

Column (1) depicts the observed average disparity during the whole sample period. We estimate a significant positive extra constant for second-generation immigrants, not far away from the estimated number on first-generation immigrants. All else equal, second-generation immigrants have paid on average a 0.36 pp higher interest rate than ethnic Norwegians. Equally as in our main finding, the interaction terms in the second column hint at an increasing trend over time. Based on estimates we do not conclude cultural factors being a major contributor in explaining the interest rate difference. Though second-generation immigrants only represent 2 percent of the sample population (*appendix D*), our test demonstrates we cannot exclude other explainable possibilities.

5.2 Hurdles before buying a home?

As presented in section 2, there has been evidence of immigrants facing challenges in the context of even getting their loan application accepted (Aldén & Hammstedt 2016; Loya 2024; Mistrulli et al. 2023). Together with our findings on those who already have a mortgage, we have reason to believe such inequalities apply to the accessibility of owning a house.

To examine this issue, we make further use of our data. Using the entire adult population of Oslo (554,665) from 2020, we apply *homeowner* as a variable of interest, a binary indicator telling if the individual is a homeowner or not. Using logistic regression, we check if the probability of owning a home depends on immigrant status. Table 9 reports the estimates of the binary outcome model, with and without controls.

Table 9. Logit estimates

	y = homeowner	
	(1)	(2)
Immigrant	-0.96***	-0.47***
	(0.01)	(0.02)
Borrower controls	No	Yes
Pseudo R-squared	.03332	.37939
N	554,665	554,665

Notes: Column (1) and (2) depict logit-estimates. Standard errors are in parentheses. Borrower controls include all variables from Table 3. N indicates the number of observations. For further estimates: See *Appendix E.* * p < .1; ** p < .05; *** p < .01.

Consistent with our expectations we report: For a fixed value of economic factors, an immigrant has lower probability of owning a house, all results being statistically significant. It is to no surprise when controlling for economic and demographic factors the difference shrinks but keeping its significance and high effect. To give an interpretation of the results we have to transform the log odds estimate (column (2)) to the probability value, applying the following formula: $p(X) = e^{\beta 0 + \beta 1*X1+...+\beta p*Xp}/(1 + e^{\beta 0 + \beta 1*X1+...+\beta p*Xp})$, where X_p denotes predictor p with its corresponding coefficient β_p (James et al., 2023, p. 137). In addition to estimate predictions of differences in probabilities between the two groups, the initial level of the controls must be added to the formula.

Using their given group sample averages (*Appendix E*), a married native-born male has an approximate 82 percent chance of owning a house. Being an immigrant, we estimate a 71 percent chance. Thus, we observe the average native, married and male, to have an 11 percent higher probability of owning a house vs. the average married male immigrant. However, when we instead fit average characteristics from the whole sample that is, we put in equal values for both groups using the sample average, we find the probability for an immigrant to be approximately 78 percent vs. 80 percent to the native. Thus, we cannot conclude the

difference in likelihood of owning a house is due to purely ethnic characteristics, but rather in the direction of immigrants having initial lower economical characteristics vs. their native counterparts. We still shall not disregard these results as, due to their financial framework, immigrants are observed to have less experience in the housing market.

We still note the importance of understanding that the results do not reflect the current state of loan denial rate by ethnicity. It is rather an indication. However, the results strengthen our assumption of immigrants having less experience in the mortgage market. We further discuss and reason in the same direction. If lack of experience is an issue, a reason for higher mortgage rates might be through both the banks and immigrant mortgage applicants. With less history of immigrant customers, banks might view them differently than natives. As for immigrants, being aware of their housing situation, they might settle with the first mortgage offer they obtain. However, a more comprehensive analysis utilizing loan denials should be in place before jumping to any clear conclusion. Still, the evidence presented in this section strengthens our hypothesis of adverse selection in the mortgage market for ethnic minorities.

6. Conclusion

In this paper we have empirically analyzed mortgage interest rates in a Norwegian mortgage market, looking at interest rate discrepancies towards immigrant borrowers. The analysis was conducted with a uniquely constructed dataset from microdata.no, using Norwegian household data of homeowners in Oslo for the period 2015 to 2020. With both cross-section OLS and panel data regression with FGLS, our findings suggest immigrants are paying significantly higher mortgage rates. Estimates from the panel depicts immigrants to pay 38.55 basis points more than natives, all controls being equal. Analyzing development over time, the differences do not mitigate, but rather increase. We observe Asian and African immigrants, being mostly of refugee status, to have the highest differentials. However, we also observe significant disparity among immigrants from the EU. As language barriers and cultural differences might be an explanation, the same regressions are conducted in the interest of second-generation immigrants. Also giving equivalent results, we do not conclude language and culture to be the sole justification for the results. In the last step we conduct a probability estimation performing logistic regression, classifying who is a registered homeowner. Using the whole Oslo population from 2020, the results indicate immigrants to have lower probabilities of owning their home than natives due to differences in financial

features. However, with the same prerequisites, immigrants and Norwegians seem to have equal probability of owning a house. Based on our findings, we theorize the possibilities of immigrants receiving higher interest rate, being a combination of both cultural factors and an adverse selection effect from the banks. Still, before asserting validity further studies need to be conducted.

7. Literature

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Appendix

The following attached link is supplementary material providing of the command line script from microdata.no, referenced in the paper:

https://drive.google.com/drive/folders/1VHWwuigOrMSwhDlVaZcIbBN6KZq5Ffkw?usp=drive_link