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GENDER AND ETHNIC GAP IN FINANCIAL LITERACY

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Evidence on misogynoir

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Abstract

This paper analyzes the effect of gender and ethnicity on the level of financial literacy using US SCF data. Past research indicates that a high level of economic understanding has a significant positive effects on social mobility and wealth accumulation. Simultaneously, gender and ethnicity could have an impact on the level of financial literacy. Based on this *misogynoir* hypothesis, black women are expected to have a considerably lower level of economic understanding. To test the evidence for financial literacy we apply decomposition analysis to investigate mediation effects. The methodological approaches are theoretically described in details and schematically presented. We find a significantly higher gap in financial literacy between white man and black women than looking at gender and ethnic groups separately. Possible extensions are considered. We conclude by discussing the results at the backdrop of our stated hypothesis and present corresponding policy actions.

Contents

1 Introduction

Life is full of decision making. While some are small and don't really influence future life, others, often financial ones, draw major consequences. As incorrect consumption behavior and debt patterns develop at a young age, understanding basic financial concepts is important for living a self-determined life. Basic economic knowledge entails multiple positive implications. Economic theory even posits: financial knowledge implies higher chances to accumulate wealth. Furthermore, sophisticated individuals are less prone to be trapped or become victim of fraud. Much more, they often detect risks before allowing them to occur, thereby preventing considerable harm through crisis. Furthermore, financially literate people usually aim at fair cohabitation and obey basic rights and laws. A lack of financial education thus not only has a negative impact on ones personal freedom but could harm the welfare state and the stability of the global economy (Lusardi & Mitchell, 2011; Williams & Satchell, 2011). Economic awareness implies not only financial welfare but a strong and equitable society.

Unfortunately, at the latest the detrimental observations during the global financial crisis revealed that a huge part of the society is unaware of basic financial relations and unable to efficiently engage in the financial market. The findings are particularly worrisome considering the counteracting ever growing complexity of financial markets and higher self-responsibility in managing financial issues. Especially in Western societies, changes in social security as well as pension systems increasingly assume people to responsibly self-manage their financial well-being (Bannier & Schwarz, 2018). Defining the diverse field of economic understanding is difficult. Financial literacy, according to Zait and Bertea (2015), the "ability to read, analyze, manage and communicate about the personal financial conditions that affect material well-being", comprises several crucial determinants at the same time. One has to understand that it is more than basic financial knowledge on numbers and interest rates. Several, often behavioral or psychological, aspects cannot be measured in economic terms but are highly relevant for one's financial well-being. Due to such terms and the variety of concepts included, evaluation is challenging. Different literature strands consider various factors, whereas financial literacy, comprising the ability to process economic information and set efficient financial decisions to ensure current and future welfare, is one quite commonly used. Interestingly, already in 1995, Bernheim (1995) claimed that financial literacy is an essential driver of peoples' saving behaviors. Back then, economists had not yet even come up with a reliable way of measurement. Along with the rising awareness of the illiteracy and its risks, the development of a basic measurement framework became of even greater importance. By extensively studying concepts underlying peoples' saving and investment decisions, Lusardi and Mitchell (2014) developed a set of three questions on basic financial concepts to evaluate an individual's level of financial knowledge. The first investigates numeracy and the understanding of interest rate calculations, another evaluates basic inflation knowledge. The third focuses on individuals' understanding of risk diversification concepts. We document the exact wording of the multi-choice questions in the Appendix A.1. Not only enabled the evaluation of those "big three" questions valid and comparable measurement, it simultaneously triggered a boom in investigating the dynamics of financial literacy. On a global level, the questions are nowadays included in most financial surveys, corresponding response data often directly used by economists. Others include further or slightly varied questions to improve estimations and detect deeper relations. Consequently, financial literacy is mostly evaluated by self-indicated survey responses and therefore inherently prone to measurement error. Purely objective measures are basically impossible. Nevertheless, by steadily improved measures as well as consideration of multiple controls, researchers find encompassing evidence for positive effects of financial literacy reaching from savvier saving and investment decisions to greater stock market participation. More prepared retirement planning to ensure old-age well-being is another highly relevant implication (Behrman et al., 2012; Van Rooij et al., 2011). Ultimately, economists report supportive evidence on a positive relationship of financial literacy on the accumulation of (net) wealth, both at the individual as well as well as at the state level. Estimations yielding strongly positive relations were not only conducted in the US (Lusardi & Mitchell, 2008) or Western developed countries (Bannier & Schwarz, 2018), but on a rather global scale; results hold equally for Japan (Sekita, 2013) or Malaysia (Sabri, Wijekoon, et al., 2019).

However, the available literature not only considers the effects of already attained financial literacy but investigates the factors influencing the acquisition of financial literacy. Intuitively, the general educational level impacts on the amount of financial understanding. Related studies confirm that highly educated people are more strongly aware of their financial possibilities, consequently more likely to participate actively in the stock market and efficiently save for their pensions. One could assume that educational attainment levels contribute the most to the individual welfare. But, even controlling for general schooling, the relationship between financial literacy and wealth remains significant (Behrman et al., 2012). Furthermore, financial literacy rises with respondent's age, whereas this relationship is strongly mitigated by higher educational levels among older people. Experience and knowledge, especially in financial issues, primarily come with experience and practice.

As in most financial issues, there is worrying evidence on gender differences. Researchers report overall higher levels among men than women, whereas, at least in financial literacy, the gender gap is quite similar across different age groups (Arellano et al., 2018; Bucher-Koenen et al., 2021; Fonseca et al., 2012). Across-country analyses reveal, that gender differences are more severe in (Western) developed countries than in eastern, former communist regions (Cupák et al., 2018). Deeper inves-

tigations do not perceive the gender gap as solely induced by differences in actual knowledge, but argue that women tend to indicate lower financial literacy scores in surveys due to lower levels of self-confidence. Finances, in general, is still a male-dominated field. Women are supposed to act less efficient, be substantially more worried and insecure about financial decisions. The widespread negative public opinion potentially triggers lower trust of women in their abilities. Decomposition investigations reveal that one third is grounded in lower self-confidence, only two thirds are traceable to actually lower knowledge levels (Bucher-Koenen et al., 2021). Other worrying, but still rarely investigated subgroup effects are ethnic differences. The research available reports evidence that Whites have on average higher levels of financial literacy than minorities. The gap is even found to increase significantly with higher educational levels (Al-Bahrani et al., 2019).
Investigations of interacting effects between gender and ethnicity on financial literacy are basically missing. However, over the last years, discussions on a specific form of discrimination, discussed as *misogynoir*, gain greater importance. The term, coined by Moya Bailey, describes specific hatred, dislike, distrust, and prejudice directed toward Black women (Bailey, 2018; Gassam Asare, 2020).

At the backdrop of the rising relevance, we aim to close the gap in the literature. To enable a detailed decomposition, we first investigate separate subgroup differences by asking: Are women's financial literacy scores different from men's? Do Whites score differently than Blacks? Afterwards, we investigate whether the ethnical differences are intensified by gender to find supporting or contracting evidence for the *misogynoir* hypothesis: To which extent are white men different from black women? To thoroughly investigate our questions of interest, the remainder of this paper is structured as follows: The next section provides an overview over our implemented data. Afterwards, the Oaxaca-Blinder methodology is introduced to decompose the effects on financial literacy. We compute decompositions first in a standard linear OLS approach, then, to infer relative differences, collapse financial literacy to a binary outcome and compute a linear probability model. In the final section, we shortly summarise our findings and infer important policy implications. Potential limitations are considered to motivate future research.

2 Data

2.1 Data construction

For our analyses, we use household data from a publicly available US survey, namely the Survey of Consumer Finances (SCF, 2023). The latest version of the SCF, enabled by the Board of Governors from the Federal Reserve System, was conducted in 2019. A corresponding codebook provides names and descriptions for the variables included as well as a technical summary of the survey design. Moreover, it contains the available answer possibilities given for each survey question, whereas it has to be noted that not every variable in the codebook is actually included in the data set open to the public. Wealth values need to be calculated by hand using a separate codebook. Furthermore, there is a separate file for the replicate weights. They contain necessary informations to enable valid point estimates and corresponding standard errors. We discuss them in more detail afterwards. The SCF data are collected by computer-assisted personal interviewing methods (CAPIs). To evaluate financial household characteristics, they rely, for most parts of the analysis, on the "primary economic unit" (PEU). Whereas for employment, pension and demographic characteristics, respondents and their spouses or partners were asked separately, all other questions are posed on the household level. In our newly created dataset a household size dummy variable (X7001) indicates whether a single household or not was asked. Another dummy on multiple persons households then provides information whether more or less than four persons are considered. Handling of missing response data as well as further details are included in the introductory pages of the codebook. In the following data description, we denote the original variable names in brackets. If at least two numbers are given, the first corresponds to the respondent's, the second to its spouse's or partner's response.

To extract all other necessary variables, we first consider several potentially influencing demographic and socioeconomic characteristics. Besides the age (X13, X18) of the respondents, we implement according dummies for the social groups of primary interest: gender (X8021, X103) and ethnic background (X6809). In accordance with Cupák et al. (2018), we construct four age categories allocating individuals to either a group "below 30", "between 30 and 49", "between 50 and 69" or "above 70" years old. Regarding further control variables, we include education as a quite simplified dummy, grouping respondents into those with and without university education, therefore at least a bachelor's degree (X5931, X6111). The educational attainment level of respondent's parents are equally considered (X6132, X6133). Another dummy on marriage divides the sample into two groups: married and unmarried (X7372). We do not differ further between single, divorced or widowed people. Work status is included as a four-group possibility (X4100, X4700): we grouped together all employed as well as unemployed or at least searching people, those retired or self-employed from two other groups. The fourth includes those not working and not actively trying to participate in the labor market.

In the primary section we want to look at the varying influencors of financial literacy. A reliable measure to evaluate financial knowledge is therefore needed. To do so, we use the "big three" questions, introduced in the previous section (X7558, X7559, X7560). Out of each question we create a dummy, whereas one indicates that the respondent answered correctly, zero otherwise.

Afterwards, the sum of all three questions gives the overall basic financial literacy, ranging on an absolute scale from zero to three. According to (Bucher-Koenen et al., 2021), investigating the impact of staying indecisive about financial questions would be a valuable extension. The three questions used to measure financial literacy, however, always give respondents the possibility to stay indecisive. There is no variant of the SCF available excluding the "do not know" response option; another dataset or an at least adopted survey version would be necessary.
The following histogram 1 provides an overview of the distribution of correct answers among the whole sample. As the "three big questions" are rather simple to make them work in nearly every survey irrespective of environmental circumstances, most respondents prove to understand at least two of three basic financial workings, comprising interest rates, inflation, risk diversification.

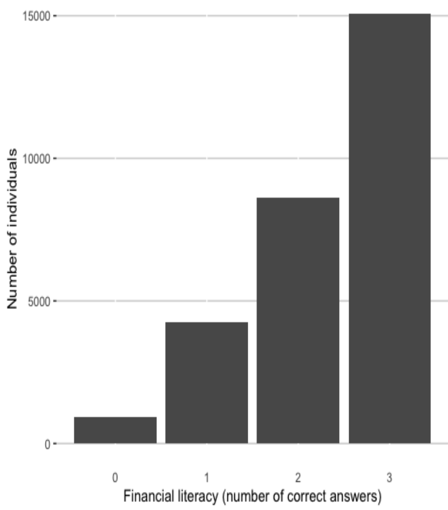


Figure 1: Financial literacy score.

We aim to discuss a potential gender gap in financial literacy, whereas gender is given by a dummy on the question asking for the respondents' sex. To evaluate the moderating impact of ethnicity and, at least in a first evaluation, we look at differences between Blacks and Whites, individuals are grouped based on skin colour, all others are either Hispanic or considered as “Others”.
To enable valuable extensions or as potential control variables, we consider some further financial indicators in our newly created dataset. First, we include a dummy to evaluate respondent's financial dependency (X107) reporting whether the household members share their finances or not. Another potential control considers a scale indication of individual's readiness to take financial risk in investment decisions (7557). We furthermore include responses to an answer on the overall dollars amount

of property income received at the household level (X2010) in the final dataset. Furthermore, beyond looking at the influences on financial literacy, the thereupon influence on wealth is interesting. As already discussed in the literature part, empirical evidence on a significantly positive impact of financial literacy on wealth is already extensive. We therefore suspect the relation to hold and are rather interested in the impact of including wealth in our regression. We are aware of the downside that including it as an additional control could cause an endogeneity issue. Unfortunately, data on net worth, the personal wealth of respondents are not directly available in the public dataset. Using the second, wealth-focused codebook we calculate it by substracting for each respondent all relevant debt values from the summed assets (see Appendix A.2).

2.2 Data overview

Explanatory variable	Original indicator	Variable type	Description
Gender	X8021 X103	Dummy	Male Female
Ethnicity	X6809	Dummies	Black White Hispanic
Age	X13 X18	Categorical	<30 30-49 50-69 >70
Employment	X4100 X4700	Dummies	Employed & Unemployed Retired Self-employed Not working
Education	X5931	Dummy	At least Bachelor´s degree Non-universitarian
Parental education	X6032, X6033	Dummy	
Household size	X7001	Absolute number	0-12

Table 1: Basic explanatory variable overview.

Table 1 provides an overview of the baseline explanatory variables, their original variable names in the SCF dataset as well as a short explanation of the adaptations done. Further considered potential variables are not included. It has to be kept in mind that we grouped or created dummies for most variables. Doing so, the summary statistics therefore loose meaningful interpretation. Intuitively, all dummy variables have minimum zero and a maximum of one. Even though R automatically provides the mean, a value above 0.5 simply means that the dummy variable takes more often the value one. Mean values below can be taken as zero.

Before turning to the empirical analysis, simple plots comparing the group-specific means in financial literacy should provide a first insight into the observable gender and ethnic gap. The simple summary statistics already support our assumed hypothesis. We can clearly see that males, on average, score higher than females (Figure 2). Furthermore, the average financial literacy is higher for white individuals (Figure 3). The gap seems even bigger than between women and men. In this paper, we are especially interested in the different subgroup effects. The two, at least assumed to, most contrary groups should be compared: black women and white men. Plotting again the means, we observe, on average, lower levels of financial literacy for black women than white men. White women, interestingly, seem to perform slightly better than black men. Figure 4 gives us a first insight on the financial literacy gap between these two extreme groups, and therefore on our *mysoginoir* assumption. Using an Oaxaca-Blinder decomposition will enable a statistical comparison, allowing for empirically valid inferences.

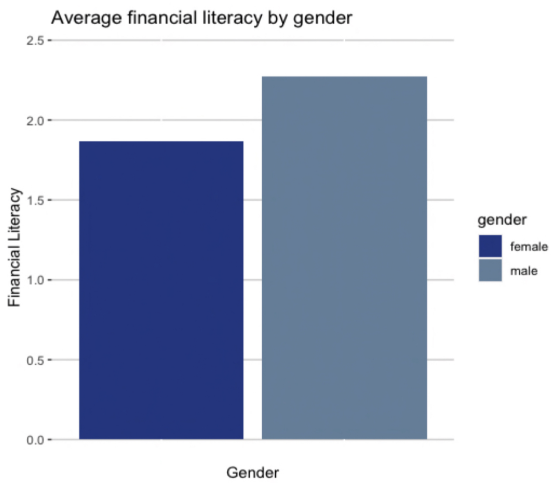


Figure 2: Average financial literacy by gender.

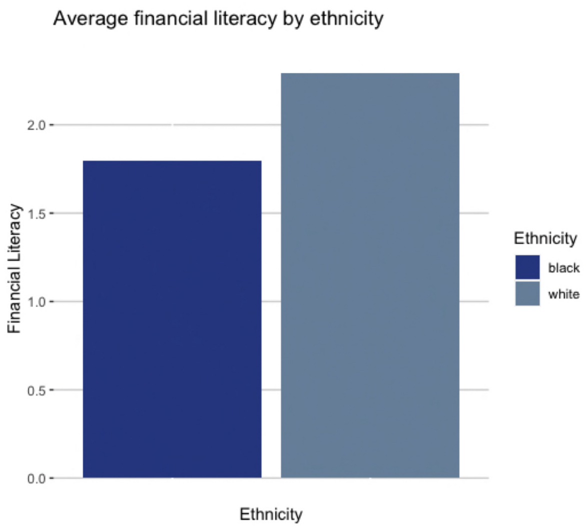


Figure 3: Average financial literacy by ethnic group.

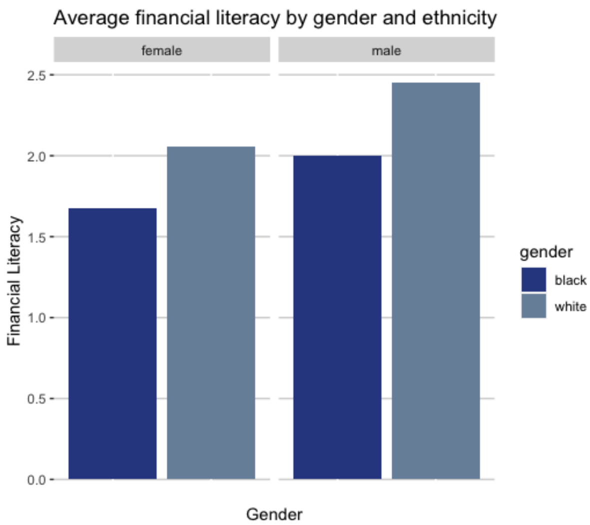


Figure 4: Average financial literacy by ethnic group and gender.

3 Oaxaca-Blinder Decomposition

3.1 Empirical Methodology

After creating the final dataset, in a first, basic analysis, the group-specific influences of gender and ethnicity on an individual's level of financial literacy are of interest. As the analysis is limited to household data, it is not necessary to, in a first step, merge the household with the individual level file. Additionally, all missing values are already taken into account by redefining and grouping the variables in a previous step. Since we use survey data we have to account for the probable bias compared to a random sample. Survey data analysis software enable to take the difference between the design used and a hypothetical, totally random, evaluation into account. The sampling design affects both the calculation of the point estimates and their standard errors. Ignoring it would inflate heavily the results. The main idea behind sampling is that certain values of the input random variables in a simulation have more impact on the parameter being estimated than others. A weighting method is needed to weight the sample back to the population from which the sample was drawn. Only if the "important" values are also emphasized by sampling more frequently, then the estimator variance can be reduced and results will be valid. To do so, we use the publicly provided replicate weights file.

To then investigate subgroup effects, we decided on the quite commonly used Oaxaca-Blinder decomposition. The "svyglm"-function enables a generalised linear model to data from a complex survey design, with inverse-probability weighting and design-based standard errors. Corresponding estimates are the average among the multiple implicates and the point estimates are derived by Rubin's rule. Standard errors are therefore valid, but unfortunately not automatically included in the output of the final estimates. It is not possible to simply sum up the errors obtained from the group specific estimates. Most papers only report point estimates for the decomposition terms, but do not make any indications about the standard errors. The details and calculations of the standard errors are available in Appendix A.3.

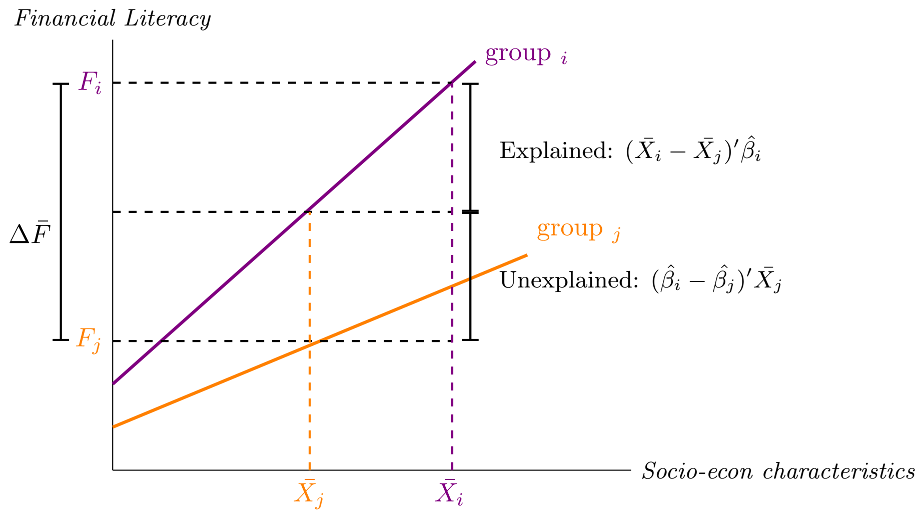
The decomposition consists of two main stages. First, we run group-specific regressions to obtain the beta-coefficient estimates as well as standard errors and confidence intervals. The preliminary output models are included in the Appendices B.1 & B.2. In a second step, we investigate the mean differences in outcomes and the characteristics. Afterwards, we compile all relevant estimates in a single dataframe to finalize the detailed Oaxaca-Blinder decomposition. We split up the sub-group variations in financial literacy, for convenience from now on abbreviated as F, into a part induced by observable or "endowment" differences and another due to unobservable characteristics. The unexplained share of the decomposition is commonly cited as discrimination. In our paper, it would be interpreted as the difference in financial literacy that cannot be explained by differences in socio-economic characteristics such as education or employment. Even though the remaining part might actually be specific discrimination, this can not automatically be derived. Other characteristics, besides those considered as controls, could influence.

Summarily, the final regression equation, in a general version, can be written down as follows (i

being the "privileged group" and j being the "minority group") :

$$\Delta\bar{F} = \bar{F}_i - \bar{F}_j = \underbrace{(\bar{X}_i - \bar{X}_j)'\hat{\beta}_j}_{explained} + \underbrace{(\hat{\beta}_i - \hat{\beta}_j)'\bar{X}_j}_{unexplained} \quad (1)$$

We show separate decompositions for the predictors gender and ethnicity. Doing so enables deeper insight into unexplained part. Since in the summed-up version, the relative contributions of each part are no longer visible, this step beforehand sheds light on the main drivers of the "unexplained" difference. Afterwards, we test our main hypothesis on two subgroups: white men and black women. The graph below illustrates our intended decomposition.



In the detailed decompositions one group respectively needs to be taken as the reference category (the base group at which the endowment differences are evaluated). Which group is chosen crucially matters in terms of interpretations. Using the other subgroup or a weighted average over the two is equally possible and valid, however alters decomposition results. The estimation coefficients quantify differences with respect to the base category. While this is less problematic for the explained part, since the total contribution is unaffected, it is highly problematic for the unexplained part. Referring to another cateogory there alters the overall contribution (Jann et al., 2008). The standard errors are given in brackets, significance levels are, as common, denoted by stars. Details are provided in the legend of the respective tables.

3.2 Results

Table 2: Linear model - decomposition without wealth

	i=Men j=Women	i=White j=Black	i=White men j=Black women
Mean(i)	2.26***	2.29***	2.36***
	(0.023)	(0.022)	(0.023)
Mean(j)	1.91***	1.81***	1.62***
	(0.037)	(0.043)	(0.058)
Mean Difference	0.35***	0.48***	0.74***
Decomposition			
Explained	0.04***	0.15***	0.09***
	(0.006)	(0.018)	(0.021)
Unexplained	0.31*	0.33	0.65***
	(0.185)	(0.225)	(0.208)

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: all results are computed according to Rubin's Rule with 5 implicates and 200 replicate weights.

Looking at the summarizing output table, we can see that the means for Men and Whites are statistically significantly higher than those for the reference categories, females and Whites. The ethnic difference, amounting to 0.48, is even larger than the reported gender gap (0.35). The mean for white males is higher than for the individual subgroups. Additionally, Black women score considerably lower than in the respective subgroups. While their mean score is just 1.62, it is 1.91 for women, 1.81 for Blacks individually. Consequently, comparing white men with black women, the mean difference is the highest (0.74). The significance of the mean differences is computed with a t-test and all of them are significant at the 1% level. Looking at these first mean differences shows that black women are indeed the group with the lower average financial literacy, which supports the mysoginoir assumption.

The decomposition terms give further insight on how much of the gap is explainable by observed characteristics and on the part staying unexplained. The standard errors computation of the explained and unexplained part are described is details in Appendix A.3. In all three cases, the unexplained part largely prevails. Only concerning ethnic differences, at least nearly half of the mean difference is based on explainable characteristics (31.25%). The share of the explained part for the gender gap is only around 11.4%. It means that differences in education, parental education, employment and other socio-economic characteristics account for a larger part of the ethnic gap in financial literacy. All the controls significantly heighten the level of financial literacy as can be seen in Appendix B.1.

The differences in the individual coefficients between the individual output are only minor. Though, due to the standard linear approach, relative comparisons are difficult. So, the first insights are speaking in favor of our *mysoginoir* hypothesis. The mean difference between white men and black women is by far the greatest, the explained share is small (12.0%). We will investigate our conjecture further with different specifications to see whether this difference in explained parts increases or vanishes.
Since the unexplained part is huge in the first specification, we first include wealth as an additional explanatory variable to investigate whether the results change drastically. Empirical evidence already reveals that higher financial literacy contributes to higher chances of wealth accumulation. However, we hypothesize that an reverse impact simultaneously holds. Individual´s wealth, besides the other, mostly sociodemographic controls, could influence an individual´s level of financial literacy. Wealth is retrieved as described in Appendix A.2. We use the inverse hyperbolic sine (IHS) transformation on wealth to deal with the unequal distribution. Additionally to a simple log transformation, it also takes care of zeros and negative values. The transformation is defined as follows: $ihs(w) = log(\sqrt{w^2+1} + w)$.

Table 3: Linear model - decomposition with wealth

	i=Men j=Women	i=White j=Black	i=White men j=Black women
Mean(i)	2.26***	2.29***	2.36***
	(0.023)	(0.023)	(0.022)
Mean(j)	1.91***	1.81***	1.62***
	(0.037)	(0.043)	(0.032)
Mean Difference	0.35***	0.48***	0.74***
Decomposition			
Explained	0.06	0.15***	0.06
	(0.124)	(0.056)	(0.110)
Unexplained	0.29	0.33	0.68
	(0.724)	(0.96)	(0.849)

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: all results are computed according to Rubin's Rule with 5 implicates and 200 replicate weights.

By including wealth, an individual's assets minus all accumulated debts, as an additional explanatory variable in our linear regression, the results do not change drastically. All the relations between the three columns, outlined before, stay unchanged. We can still observe that the explained part is slightly higher for the gender (17.14%), but even lower for the analysis considering gender and ethnicity (8.11%). Including wealth therefore allows to explain a bigger part of the gap in gender differences, but the "discrimination" part gets even larger if we look at gender and ethnicity, which is surprising. Additionally, the standard errors increase for all three analysis, which intuitively makes sense since wealth is heavily unequally distributed among the individuals.

In a third step, we consider a fully interacted model. The reason we do so is to check whether the combination of all the variables in our model leads to different results compared to what we obtained by our previous regression specifications, including only the sum of the individual variables. Though the approach is valid, the explained and the unexplained part of the gap do no longer add up. The estimations for the means as well as the explained part are correct, however, those for the unexplained are inflated by the interactions. Meaningful interpretations would only be possible for variables with a natural zero point (Jann et al., 2008). Nevertheless, we can obtain the unexplained part by substracting the explain part from the total outcome difference. Moreover, since we computed the different interactions by different models, we can not obtain a variance covariance matrix which is necessary to compute the standard errors of the explained and unexplained terms.

As a side note, for the interactions we do no longer show the individual detailed models in the appendix as the models are huge.

Table 4: Linear model with interactions

	i=Men j=Women	i=White j=Black	i=White men j=Black women
Mean(i)	2.26***	2.29***	2.36***
	(0.023)	(0.023)	(0.022)
Mean(j)	1.91***	1.81***	1.62***
	(0.037)	(0.043)	(0.032)
Mean Difference	0.35***	0.48***	0.74***
Decomposition			
Explained	0.12	0.17	0.31
Unexplained	0.23	0.31	0.43

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: all results are computed according to Rubin's Rule with 5 implicates and 200 replicate weights.

Though the discussed problems concerning the unexplained part, results for the explained part and the total mean difference are valid. The decomposition results are therefore interpretable. Compared to the previous two analyses, the explained part of the gap is strongly enlarged taking interactions between all our explanatory variables into account. 34.29% of the difference between females and males and 35.42% of the ethnic gap are now attributable to explainable characteristics. Nearly half of the difference between white men and black women (41.98%) becomes explainable. Whereas we loose standard errors for the final decomposition estimates as described previously, they do not change in the group-specific cases. Even though including interactions increases the explained part, the remaining part is still dominating. Investigating the "discrimination" in financial literacy is therefore of crucial importance.

3.3 Limitations

Though the Oaxaca-Blinder approach enables a detailed decomposition into an unexplained and an explained part, interpretations are limited in several aspects. First, knowledge of non-discriminatory returns to characteristics is assumed. Second, the mechanisms lying behind the relations of interest will stay covered. The explained part refers to statistically observed differences in the characteristics rather than providing theoretical arguments for gender-stereotypical selection into treatment. In general, interpreting the estimations is difficult in terms of probability, as financial literacy is measures on an absolute score according to the amount of right answers, whereas the maximum is three. Comparability to approaches investigating similar questions but using different measures is impossible. Also, as we will discuss below, the distribution of the answers is skewed to the right, meaning that most individuals performed very well in the questions. Another method using a binary response variable could be more suited to this kind of data.

3.4 Linear probability model

3.4.1 Methodological changes

The standard linear Oaxaca-Blinder decomposition already provided insight into the moderating effects of gender and ethnicity. In general, the approach turns out quite useful for separately quantifying individual group differences in continuously measurable characteristics. It is, however, rather unsuited to investigate binary outcomes. As we just mention, a major issue regarding the data is that too many individuals performed very well (see Figure 1), probably due to the easiness of the questions. Therefore, modelling financial literacy as a binary variable and switching from a linear to a linear probability model could lead to more realistic coefficients. Implementing a nonlinear decomposition approach, for example using a logit or probit model, would be a valid, but rather complicated alternative. Investigating the question of interest is equally possible by sticking to a linear approach. We define the binary outcome in the following way: it takes the value one if the individual scores perfectly (i.e. ticks all three questions correctly). If the individual's summed score is below three, we implement the outcome as zero. We do so since perfect scoring in the questions is assumed as the minimum financial literacy required to perform decently in day-to-day financial decisions.

The individual regressions now change from

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + ... + \beta_k X_{ki} + \varepsilon_i \tag{2}$$

to

$$\hat{P}[Y = 1|X] = \hat{Y} = \hat{\beta}_0 + \hat{\beta}_1 X_{1i} + \hat{\beta}_2 X_{2i} + ... + \hat{\beta}_k X_{ki} \tag{3}$$

We now model the dependent no longer as a linear function of the explanatory variables but as the average probability of the binary outcome of interest. Besides, the decompositions are the same as in equation (1), again dividable into a part due to observable and one due to unobservable characteristics. Even though we do not do so in this analysis but the probability interpretation would now enable valid comparisons with other analysis also investigating such relations but probably using a different measurement of financial literacy. While in the standard linear approach, outcomes are denoted in absolute terms, whereas the highest numbers achievable and the concrete composition can strongly vary across different investigations, probability models allow for relative comparisons.

3.4.2 Results

Table 5: Linear probability model - decomposition without wealth

	i=Men j=Women	i=White j=Black	i=White men j=Black women
Mean(i)	0.48***	0.50***	0.54***
	(0.013)	(0.014)	(0.013)
Mean(j)	0.29***	0.27***	0.2***
	(0.019)	(0.022)	(0.016)
Mean Difference	0.19***	0.23***	0.34***
Decomposition			
Explained	0.02	0.06***	0.04***
	(0.023)	(0.011)	(0.012)
Unexplained	0.17	0.17	0.30***
	(0.188)	(0.216)	(0.122)

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: all results are computed according to Rubin's Rule with 5 implicates and 200 replicate weights.

Since we now included financial literacy as a binary dependent variable, taking one if the respondent achieves to answer all three questions correctly, the coefficients are now interpretable as probabilities to score perfectly. This way, all estimates lie between zero and one. The relations between the different estimates, however, is not altered by changing the dependent variable. Additionally, the estimations remain highly significant. The first two columns again show that men (0.48) and Whites (0.50) have higher chances than women (0.29) and Blacks (0.27) to score perfectly. The third columns confirms the higher probability for white men (0.54). Black women, again score considerably lower (0.20) than females and Blacks separately. The outcome difference, looking at gender and ethnicity simultaneously, is therefore again the highest. Concerning the decomposition-specific results, the unexplainable share of the gap is again way larger than the explained. 10.53% of the gender-specific, 26.09% of the ethnic difference are explainable by our considered demographic and socioeconomic control variables. The endowments account for only 11.76% of the large gap between white men and black women.

Table 6: Linear probability model - decomposition with wealth

	i=Men j=Women	i=White j=Black	i=White men j=Black women
Mean(i)	0.48***	0.50***	0.54***
	(0.013)	(0.014)	(0.013)
Mean(j)	0.29***	0.27***	0.2***
	(0.019)	(0.022)	(0.016)
Mean Difference	0.19***	0.23***	0.34***
Decomposition			
Explained	0.04	0.07***	0.05
	(0.072)	(0.034)	(0.045)
Unexplained	0.15	0.16	0.29
	(0.36)	(0.545)	(0.393)

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: all results are computed according to Rubin's Rule with 5 implicates and 200 replicate weights.

As in the standard linear case before we, in a second step, include wealth as an additional explanatory variable in Table 5. Again, some of the unexplained part shifts into the explained. Now, 21.05% of the gap between women and men and 30.44% of ethnic divergences are explainable. Still quite low, but 14.71% of the difference between white men and black women can be related to demographic and socioeconomic characteristics. Wealth therefore indeed influences the group-specific outcome differences in financial literacy. Simultaneously, the standards error for the decomposition again increase due to the unequal distribution of wealth in the sample.

In our third and final model, the one including interactions between all the variables, we again face the problems discussed previously with the unexplained part. As before, we show the unexplained part as the substraction of the explained part from the total mean difference. Standard errors are again lost for the final decomposition analysis.

Table 7: Linear probability model with interactions

	i=Men j=Women	i=White j=Black	i=White men j=Black women
Mean(i)	0.48***	0.50***	0.54***
	(0.013)	(0.014)	(0.013)
Mean(j)	0.29***	0.27***	0.2***
	(0.019)	(0.022)	(0.016)
Mean Difference	0.19***	0.23***	0.34***
Decomposition			
Explained	0.04	0.05	0.15
Unexplained	0.15	0.16	0.19

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: all results are computed according to Rubin's Rule with 5 implicates and 200 replicate weights.

Interestingly, adding the interactions now only increases the explained part for the white men versus black women comparison.

Summarily, the detailed analysis confirm of our hypothesis. The misogynoir theory is strongly present in financial literacy. Black women score lower than white men and, even more, lower than women and black in the group specific analysis. Depending on the analysis, the endowments such as education, parental education or wealth are important to explain this difference. We should still highlight than the unexplained part always accounts for more than 50% of the gaps.

4 Extensions

4.1 RIF regression

Another, rather novel approach, to investigate the relations of interest in a slightly varied sense, is the RIF regression. Using this method, detailed decompositions can be performed for any distributional statistics for which an influence function is computable (Fortin et al., 2011). Again, due to the limited amount of only four possible outcomes for financial literacy it will neither be reliable nor useful to look at quantiles. However, decompositions at the median could yield further insight. To again compare it to the standard case, the dependent would then be replaced by the (recentered) influence function of the statistic of interest. In the simplest case, the conditional expectation of the RIF can be modeled as a linear function of the explanatory variables.

The linearity of the RIF regression has several advantages. The proportion of interest be simply, locally, inverted, by dividing through the density. It is therefore not necessary to focus on the overall impact but one rather obtains path independent and therefore easily interpretable regressions. It really enables estimations of the marginal effects of socioeconomic characteristics on any distributional statistics (Fortin et al., 2011).Unfortunately, every approach comes with limiations, so does the RIF. It is not possible to yield general equilibrium effects. The analysis is limited by the assumed invariance of the conditional distribution. Furthermore, there is some general discussion about the goodness of approximation. We therefore leave this extension for further research.

4.2 Further extensions

Besides methological extensions, it could be interesting to think back to the grouping of certain variables. Remembering the grouping of ethnicity, we simplified the data available to three groups: Hispanics, Black and White. Instead of looking only at Blacks and Whites, we could also compare Hispanics to Whites and investigate whether there are significant differences. Furthermore, the SCF asks in a quite detailed way about the educational attainment. For now, we include it as a simple dummy, dividing the sample into those with at least a bachelor´s degree and those without an universitarian degree. Creating more specified dummies would be possible. By making it more varied, we could therefore infer more details due to educational attainment. Potential differences between tertiary and only secondary educated people as well as varying scores with higher master's or even doctoral degrees stay covered. After all, an outcome comparison to similar analysis could provide further insight into some observations we made but could not infer causality.

5 Discussion

Financial knowledge is critically important for many of today's policy debates. As financial products, the information and decision making about these products became increasingly complex and will become even more complex in the next years, these products will expose people to even higher financial risk. Policy makers are therefore asked to adjust by setting a focus on financial education programs not only in schools but among all age groups, irrespective of socioeconomic background. As previous work shows, not only the economically vulnerable can benefit from higher financial literacy but society as a whole (Mitchell & Lusardi, 2015).

Since the results show the especially Blacks and women have lower levels of financial literacy and thus less chances for upward social mobility, policy makers may set a focus on education programs for these groups. While there are already initiatives targeted especially against women, special actions for Blacks are rare but simultaneously even more difficult to design, especially because of risk of discrimination when confronting them with their worrying lack in financial literacy. Nevertheless, ethnic characteristics, especially skin color should not play a role in economic issues (Bailey, 2018). Concerning the long run, the strongly significant findings on significant gender differences are highly relevant. Starting from a very young age, women face specific financial challenges throughout their lives. Gender role specific social expectations and outdated "traditional" household structures are already cracking, however still fundamentally women´s attitudes and self-determination (OECD, 2021). Females are still usually staying at home to care for the children and fulfill daily household work, while men "bring home the money". Furthermore, as women are socially perceived as less financially sophisticated, they tend to shy away from financial risks and active participation in financial markets (Bumcrot et al., 2011). Household financial planning and decision making is therefore often left to men. In the long run, the financial dependencies and missing abilities to efficiently manage financial assets can cause serious problems. If their partners pass away, women are at a high risk to face old-age poverty. With that in mind, one has to set up programs especially for women that target the break down of these barriers by boosting their confidence to make self determined decisions and actively participate in financial markets to enable higher life chances and well-being.

Though financial literacy is still a rather young field of research it is massively gaining in importance. Further investigations into the large unexplainable share of the gap are decisive to enable ever better tailored and more efficient actions to tackle the observed misogynoir. Though we focused on financial literacy, acccording actions against potential discrimination are needed in various aspects. In foreseeable times it should no longer even be necessary to discuss as women and blacks are equally socially valued and respected.

6 Conclusion

Over the past few years, especially after the financial crisis in 2008, a drastic lack in financial literacy revealed. As it is consdered as a fundamental, lever towards a fair and inclusive economy, investigating the effects of and on financial literacy is therefore crucial to enable efficient policy implications. In this short paper we focus on gender and ethnicity and investigate their mediating influence on financial literacy. We do so using data from the Survey of consumer finances (SCF) in 2019.

Implementing the Oaxaca-Blinder decomposition approach, first in a standard linear followed by a linear probability approach, we find confirming evidence for the empirically reported severe outcome differences. While men score considerably higher than women, an even larger gap reveals between Whites and Blacks. Moreover, our *mysoginoir* hypothesis in financial literacy is confirmed. The mean difference between white men and black women is the highest, and a huge part comes for discrimination or social norms. Besides a slight shift from the unexplained towards the explainable by controlled characteristics share, the results do not fundamentally change by including wealth as an additional control variable. Including interactions between all our controls has a relatively important effect in generally reducing our unexplained part.

Considering further research, especially a deeper look into the varying outcomes between races would lead to a more comprehensive analysis. Policy actions are necessary to fight the highly prevalent gender and ethnicity based differences. Sexual as well as racial characteristics can hardly be individually influenced, the large gaps observed therefore call for according anti-discrimination measures.

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Appendices

Appendix A Details

A.1 Big Three on Financial Literacy

Lusardi and Mitchell (Lusardi & Mitchell, 2014) designed a set of three basic questions to evaluate an indiviual´s basic financial knowledge. The correct question is deoted in bold.

Question 1 (X7559): Suppose you had $100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow?

a) More than $102
b) Exactly $102
c) Less than $102
d) Do not know
e) Refuse to answer

Question 2 (X7560): Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, how much would you be able to buy with the money in this account?

a) More than today
b) Exactly the same
c) Less than today
d) Do not know
e) Refuse to answer

Question 3 (X7558): Please tell me whether this statement is true or false. "Buying a single company's stock usually provides a safer return than a stock mutual fund."

a) True
b) False
c) Do not know
d) Refuse to answer

A.2 Wealth computation

Unfortunately, the publicly available dataset of the SCF, wave 2019, does no longer directly include the calculated net worth based on the survey respondents´ answers given. To come up with a wealth variable, another dataset, additional to the public one, provides the value, substracting all indicated debt positions from all assets. A separate codebook provides information which variables are considered and relevant for the corresponding survey year on both sides of the balance sheet.
To obtain the total assets, financial and nonfinancial values need to be summed up. Afterwards, total debts are substracted.

Financial assets include liquids, mutual funds, stocks, bonds, quasi-liquid retirement accounts, and several others. Vehicles, houses, other estate values or business interests are comprised as nonfinancial assets. total financial assets:
FIN = LIQ+CDS+NMMF+STOCKS+BOND+RETQLIQ+SAVBND+CASHLI+OTHMA+OTHFIN
total nonfinancial asset:
NFIN = VEHIC+HOUSES+ORESRE+NNRESRE+BUS+OTHNFIN
Summed up, total assets are obtained.
ASSET = FIN+NFIN

Total debts include residential property, credit card and several others specific forms of debt:
DEBT=MRTHEL+RESDBT+OTHLOC+CCBAL+INSTALL+ODEBT

Finally we can easily compute net worth, individual´s level of wealth.
NET WORTH = ASSET - DEBT
To adjust the wealth variable for the unequal distribution in the population we use the hyperbolic sine (IHS) transformation on wealth. This method is better than a simple log transformation since it deals also with zeros and negative values. The transformation is defined as follows:
$ihs(w) = log(\sqrt{w^2+1} + w)$.

A.3 Standard errors computation

In the literature, most papers used to pay too little attention to the issue of statistical inference regarding the Oaxaca-Blinder decomposition. They only reported point estimates for the decomposition results but no standard errors (or wrong ones). Jann et al. Jann et al. (2008) were the first to address this issue and argued that since decompositions are based on stochastic regressors, the means also have a sampling variance that has to be taken into account.

The standard errors computation follows Jann et al. Jann et al. (2008) approach.

In our specification we have:

$$\Delta\bar{F} = \bar{F}_i - \bar{F}_j = \underbrace{(\bar{X}_i - \bar{X}_j)'\hat{\beta}_j}_{explained} + \underbrace{(\hat{\beta}_i - \hat{\beta}_j)'\bar{X}_j}_{unexplained} = R \tag{4}$$

The explained part is defined as:

$$Q = (\bar{X}_i - \bar{X}_j)'\hat{\beta}_j \tag{5}$$

The unexplained part is defined as:

$$U = (\hat{\beta}_i - \hat{\beta}_j)'\bar{X}_j \tag{6}$$

We can therefore compute separately the variance of Q and U:

$$\hat{V}(Q) = \hat{V}[(\bar{X}_i - \bar{X}_j)\hat{\beta}_i] = (\bar{X}_i - \bar{X}_j)'\hat{V}(\hat{\beta}_i)(\bar{X}_i - \bar{X}_j) + \hat{\beta}_i{}'[\hat{V}(\bar{X}_i) + \hat{V}(\bar{X}_j)]\hat{\beta}_i + \mathrm{tr}[\hat{V}(\bar{X}_i - \bar{X}_j)\hat{V}(\hat{\beta}_i)] \tag{7}$$

Note that $\lim_{n\to\infty} \mathrm{tr}[\hat{V}(\bar{X}_i - \bar{X}_j)\hat{V}(\hat{\beta}_i)] = 0$ which means that the trace vanishes asymptotically.

Therefore, we have:

$$\hat{V}(Q) = \hat{V}[(\bar{X}_i - \bar{X}_j)\hat{\beta}_i] = (\bar{X}_i - \bar{X}_j)'\hat{V}(\hat{\beta}_i)(\bar{X}_i - \bar{X}_j) + \hat{\beta}_i{}'[\hat{V}(\bar{X}_i) + \hat{V}(\bar{X}_j)]\hat{\beta}_i = \hat{\sigma}_q^2 \tag{8}$$

We can now calculate the variance of the unexplained part:

$$\hat{V}(U) = \hat{V}[\bar{X}_j{}'(\hat{\beta}_i - \hat{\beta}_j)] = \bar{X}_j{}'[\hat{V}(\bar{X}_i) + \hat{V}(\bar{X}_j)]\bar{X}_j + (\hat{\beta}_i - \hat{\beta}_j)'\hat{V}(\bar{X}_j)(\hat{\beta}_i - \hat{\beta}_j) = \hat{\sigma}_u^2 \tag{9}$$

Finally, the total variance can be derived that way:

$$\hat{V}(R) = \hat{\sigma}_r^2 = \hat{\sigma}_q^2 + \hat{\sigma}_u^2 \tag{10}$$

The standards errors can therefore be derived as $\hat{\sigma}_r$. $\hat{\sigma}_q$ is the standard error for the explained part and $\hat{\sigma}_u$ the one for the unexplained part.

Appendix B Additional tables

B.1 Basic - Oaxaca-Blinder

Linear model - Oaxaca-Blinder-decompositions

Table B.1: Gender without wealth

	means_{males}	$\text{means}_{females}$	se_{males}	$\text{se}_{females}$
(Intercept)				
age 18-29	0.117	0.122	0.008	0.012
age 30-49	0.361	0.272	0.010	0.015
age 50-69	0.366	0.355	0.009	0.015
age $>$70	0.139	0.238	0.007	0.016
education	0.644	0.659	0.013	0.019
employment	0.712	0.551	0.011	0.019
ethnicity	0.843	1.209	0.052	0.065
father education	0.258	0.182	0.011	0.016
mother education	0.224	0.166	0.010	0.013
Y:Financial literacy	2.263	1.910	0.023	0.037

Table B.2: Ethnicity without wealth

	means_{Whites}	means_{Blacks}	se_{Whites}	se_{Blacks}
(Intercept)				
age 18-29	0.104	0.144	0.007	0.018
age 30-49	0.306	0.348	0.010	0.020
age 50-69	0.372	0.376	0.010	0.025
age $>$70	0.197	0.121	0.010	0.024
education	0.689	0.582	0.013	0.024
employment	0.652	0.634	0.011	0.029
father education	0.268	0.134	0.012	0.017
mother education	0.220	0.182	0.010	0.020
sex	0.241	0.450	0.010	0.023
Y:Financial literacy	2.294	1.813	0.023	0.043

Table B.3: Gender & Ethnicity without wealth

	$\text{means}_{Whitemales}$	$\text{means}_{Blackfemales}$	$\text{se}_{Whitemales}$	$\text{se}_{Blackfemales}$
(Intercept)				
age 18-29	0.106	0.176	0.009	0.028
age 30-49	0.336	0.320	0.011	0.032
age 50-69	0.371	0.347	0.011	0.032
age $>$70	0.166	0.154	0.010	0.040
education	0.688	0.624	0.014	0.031
employment	0.696	0.594	0.013	0.045
father education	0.285	0.114	0.014	0.022
mother education	0.235	0.163	0.012	0.028
Y:Financial literacy	2.369	1.626	0.023	0.059

Linear model - Oaxaca-Blinder-decompositions including wealth

Table B.4: Gender including wealth

	means_{males}	$\text{means}_{females}$	se_{males}	$\text{se}_{females}$
(Intercept)				
age 18-29	0.117	0.122	0.008	0.012
age 30-49	0.361	0.272	0.010	0.015
age 50-69	0.366	0.355	0.009	0.015
age $>$70	0.139	0.238	0.007	0.016
education	0.644	0.659	0.013	0.019
employment	0.712	0.551	0.011	0.019
ethnicity	0.843	1.209	0.052	0.065
father education	0.258	0.182	0.011	0.016
mother education	0.224	0.166	0.010	0.013
wealth	10.74	7.796	0.169	0.319
Y:Financial literacy	2.263	1.910	0.023	0.037

Table B.5: Ethnicity including wealth

	means_{Whites}	means_{Blacks}	se_{Whites}	se_{Blacks}
(Intercept)				
age 18-29	0.104	0.144	0.007	0.018
age 30-49	0.306	0.348	0.010	0.020
age 50-69	0.372	0.376	0.010	0.025
age >70	0.197	0.121	0.010	0.024
education	0.689	0.582	0.013	0.024
employment	0.652	0.634	0.011	0.029
father education	0.268	0.134	0.012	0.017
mother education	0.220	0.182	0.010	0.020
wealth	10.78	6.88	0.198	0.436
sex	0.241	0.450	0.010	0.023
Y:Financial literacy	2.294	1.813	0.023	0.043

Table B.6: Gender & Ethnicity including wealth

	$\text{means}_{Whitemales}$	$\text{means}_{Blackfemales}$	$\text{se}_{Whitemales}$	$\text{se}_{Blackfemales}$
(Intercept)				
age 18-29	0.106	0.176	0.009	0.028
age 30-49	0.336	0.320	0.011	0.032
age 50-69	0.371	0.347	0.011	0.032
age >70	0.166	0.154	0.010	0.040
education	0.688	0.624	0.014	0.031
employment	0.696	0.594	0.013	0.045
father education	0.285	0.114	0.014	0.022
mother education	0.235	0.163	0.012	0.028
wealth	11.311	5.056	0.207	0.752
Y:Financial literacy	2.369	1.626	0.023	0.059

B.2 Linear probability - Oaxaca-Blinder

Linear probability model - Oaxaca-Blinder-decompositions

Table B.7: LPM - Gender without wealth

	means_{males}	$\text{means}_{females}$	se_{males}	$\text{se}_{females}$
(Intercept)				
age 18-29	0.117	0.122	0.008	0.012
age 30-49	0.361	0.272	0.010	0.015
age 50-69	0.366	0.355	0.009	0.015
age >70	0.139	0.238	0.007	0.016
education	0.644	0.659	0.013	0.019
employment	0.712	0.551	0.011	0.019
ethnicity	0.843	1.209	0.052	0.065
father education	0.258	0.182	0.011	0.016
mother education	0.224	0.166	0.010	0.013
Y:Financial dummy	0.484	0.293	0.013	0.019

Table B.8: LPM - Ethnicity without wealth

	means_{Whites}	means_{Blacks}	se_{Whites}	se_{Blacks}
(Intercept)				
age 18-29	0.104	0.144	0.007	0.018
age 30-49	0.306	0.348	0.010	0.020
age 50-69	0.372	0.376	0.010	0.025
age >70	0.197	0.121	0.010	0.024
education	0.689	0.582	0.013	0.024
employment	0.652	0.634	0.011	0.029
father education	0.268	0.134	0.012	0.017
mother education	0.220	0.182	0.010	0.020
sex	0.241	0.450	0.010	0.023
Y:Financial dummy	0.496	0.265	0.014	0.022

Table B.9: LPM - Gender & Ethnicity without wealth

	$\text{means}_{Whitemales}$	$\text{means}_{Blackfemales}$	$\text{se}_{Whitemales}$	$\text{se}_{Blackfemales}$
(Intercept)				
age 18-29	0.106	0.176	0.009	0.028
age 30-49	0.336	0.320	0.011	0.032
age 50-69	0.371	0.347	0.011	0.032
age >70	0.166	0.154	0.010	0.040
education	0.688	0.624	0.014	0.031
employment	0.696	0.594	0.013	0.045
father education	0.285	0.114	0.014	0.022
mother education	0.235	0.163	0.012	0.028
Y:Financial dummy	0.546	0.209	0.015	0.028

Linear probability model - Oaxaca-Blinder-decompositions including wealth

Table B.10: LPM - Gender with wealth

	means_{males}	$\text{means}_{females}$	se_{males}	$\text{se}_{females}$
(Intercept)				
age 18-29	0.117	0.122	0.008	0.012
age 30-49	0.361	0.272	0.010	0.015
age 50-69	0.366	0.355	0.009	0.015
age >70	0.139	0.238	0.007	0.016
education	0.644	0.659	0.013	0.019
employment	0.712	0.551	0.011	0.019
ethnicity	0.843	1.209	0.052	0.065
father education	0.258	0.182	0.011	0.016
mother education	0.224	0.166	0.010	0.013
wealth	10.74	7.796	0.169	0.319
Y:Financial dummy	0.484	0.293	0.013	0.019

Table B.11: LPM - Ethnicity with wealth

	means_{Whites}	means_{Blacks}	se_{Whites}	se_{Blacks}
(Intercept)				
age 18-29	0.104	0.144	0.007	0.018
age 30-49	0.306	0.348	0.010	0.020
age 50-69	0.372	0.376	0.010	0.025
age >70	0.197	0.121	0.010	0.024
education	0.689	0.582	0.013	0.024
employment	0.652	0.634	0.011	0.029
father education	0.268	0.134	0.012	0.017
mother education	0.220	0.182	0.010	0.020
wealth	10.78	6.88	0.198	0.436
sex	0.241	0.450	0.010	0.023
Y:Financial dummy	0.496	0.265	0.014	0.022

Table B.12: LPM - Gender & Ethnicity with wealth

	$\text{means}_{Whitemales}$	$\text{means}_{Blackfemales}$	$\text{se}_{Whitemales}$	$\text{se}_{Blackfemales}$
(Intercept)				
age 18-29	0.106	0.176	0.009	0.028
age 30-49	0.336	0.320	0.011	0.032
age 50-69	0.371	0.347	0.011	0.032
age >70	0.166	0.154	0.010	0.040
education	0.688	0.624	0.014	0.031
employment	0.696	0.594	0.013	0.045
father education	0.285	0.114	0.014	0.022
mother education	0.235	0.163	0.012	0.028
wealth	11.311	5.056	0.207	0.752
Y:Financial dummy	0.546	0.209	0.015	0.028