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Unobserved heterogeneity and labor market discrimination

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Unobserved Heterogeneity and Labor Market Discrimination

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Researching the causes and consequences of unemployment

Unobserved Heterogeneity and Labor Market Discrimination against Homosexuals

Upjohn Institute Working Paper 18-294

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ABSTRACT

Sexual minorities have historically been subject to many kinds of discrimination. Prejudicial treatment in the labor market could arguably be one of them. Despite that, economic literature has remained mostly silent on the topic. This paper fills that void by leveraging on a novel longitudinal data set that collects detailed information on sexual orientation. I develop an empirical strategy that exploits the fact that sexuality is not a dichotomous trait but rather a wide assortment of sexual preferences. I use empirical models that rely on the identification of unobserved heterogeneity, in the forms of skills and sexual orientation, to allow schooling, employment, and income to be endogenously determined. I find that, after controlling for differences in skills distributions, there are no income gaps against employed homosexuals. However, consistent with the existence of discrimination, homosexuals are 10–20 percentage points less likely to be employed than heterosexuals. These gaps cannot be explained by differences in observable characteristics or skills and are larger among men and the college educated. The results suggest that selection on the employment margin contributes to the elimination of the income gaps as only the highly skilled homosexuals—and thus, higher paid—are employed.

JEL Classification Codes: J15, J24, J71

Key Words: Wage gap, discrimination, unobserved heterogeneity, skills

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The author did not have access to information leading to the identification of individuals. The data analysis was carried out in a secure server.

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1 Introduction

Ever since Becker (1957), labor market discrimination has been a popular topic in economics.[1] In particular, labor economists have devoted substantial effort in analyzing labor market discrimination against women and racial minorities.[2] Some of their findings contributed to the implementation of a number of antidiscriminatory policies around the world. However, much less is known regarding labor market discrimination toward sexual minorities, despite the progress made by this population in securing social rights in recent years (Mucciaroni, 2009; Frank, 2014). Some literature has documented the existence of a sexual minority wage gap. In particular, this literature has shown that homosexual men earn less than their heterosexual counterparts by about 15–30 percent (Badgett, 1995; Black et al., 2003; Carpenter, 2007). Evidence on women is less conclusive. Some studies suggest gay/bisexual women earn less than heterosexual women (Badgett, 1995); others argue the opposite (Berg and Lien, 2002; Black et al., 2003, 2007; Antecol et al., 2007).

Although these studies have made important contributions to our understanding of sexual minorities' labor market outcomes, there are at least two major problems with the existing literature. First, they do not consider that schooling and occupational choices are endogenous and themselves possibly affected by the sexual preferences as well.[3] And second, the income gap might respond to

[1] Defining labor market discrimination is not a simple matter. In this paper, I take a broad view of discrimination defining it in terms of members of the minority group (i.e., the group that suffers discrimination) being subject to inequitable treatment that may lead to disparate outcomes (Cain, 1986).

[2] See, for example, Cain (1986) survey article that collected the extensive evidence available by then on racial and gender labor market discrimination; Mincer and Polachek (1974) link between the family decisions on differential human capital investments across genders and earnings' gap observed later in life, which relates to Neal and Johnson (1996) findings where they account for most of the black-white wage gap by differences in cognitive skills; more recently, Urzua (2008) introduces differentials in abilities rather than test scores as partial determinants of the black-white wage gap, and Lang and Lehmann (2012) who review the existing literature on racial discrimination and evaluate the capacity different theoretical models have to explain the empirical regularities of discrimination we observe today; finally, see Blau and Kahn (2017) for a recent review of the current state of the literature on the gender wage gap, where they suggest that human capital factors are no longer able to explain it.

[3] Evidence suggest that college outcomes are in general different for homosexual men (Carpenter, 2009); that cohabiting homosexuals have significantly higher levels of education than heterosexuals (Allegretto and Arthur, 2001; Antecol et al., 2007); that gay cohabiting men supply less labor than married heterosexual men, while

unobservables, namely skill differentials, not only in productivity terms but also in the way people choose their schooling level or occupation. This paper overcomes these two issues by using an empirical strategy that controls for unobserved heterogeneity, and based on them allows choices and labor market outcomes to be endogenous.

Another problem that plagues this literature is the lack of appropriate data sets. Papers on sexual-preference discrimination have relied mainly on two sources of data: the General Social Survey (GSS) or the census.[4] Each has its own problems. On one hand, the GSS provides a relatively detailed description of sexual preferences but has an extremely small sample size that hinders empirical work on the topic. On the other hand, the census provides a larger sample size, but the definition of who belongs to a sexual minority has important setbacks. Researchers using the census identify homosexuals from people who cohabit with a person of the same gender Clain and Leppel (see, for instance, 2001); Allegretto and Arthur (see, for instance, 2001); Antecol et al. (see, for instance, 2007); Antecol and Steinberger (see, for instance, 2013). Therefore, those identified comprise a selected sample that excludes people who have chosen to remain single (Black et al., 2007). The cultural and legal restrictions imposed to gay marriage give the grounds to claim that the selection into marrying/cohabiting is very different for homosexuals than for heterosexuals, and that it may rely heavily on unobservables that also affect the schooling and occupational choices and the wages earned.[5] I overcome these problems by using a novel longitudinal Norwegian data set that provides very detailed information about sexual preferences, allows me to have an acceptable

lesbians supply more labor than heterosexual women (Tebaldi and Elmslie, 2006)

[4]See Black et al. (2007) for a detailed description of the data sets that contain data on sexual preferences in the United States. Carpenter (2007) uses the National Health and Nutrition Examination Surveys but faces the same problems I describe for the papers that use the GSS. Tebaldi and Elmslie (2006) use the Current Population Survey. These data face issues analogous to the ones I describe for the papers that use the census.

[5]Antecol and Steinberger (2013) show that the gap between primary and secondary earners within a household of cohabiting lesbians is smaller than than found in a heterosexual household. This could relate to differences in selection into marrying/cohabiting across sexual orientation, and thus, be one of the many vehicles through which limiting the sample to partnered adults may be biasing the labor maket outcome estimates.

sample size, and importantly, allows me to measure skills as a latent variable. This way, I do not have to restrict the study to nonsingle homosexuals, and I am able to avoid the source of confoundedness that arise from such a selected sample.

An additional contribution of this paper is that it considers homosexuality a continuous latent variable. This novel approach goes in line with the fact that, widely accepted in psychology, sexuality is not a dichotomous trait but rather a complex assortment of sexual preferences (Laumann et al., 1994). The treatment of homosexuality as an unobserved—to the econometrician—continuous variable provides an opportunity to better understand the effect that different degrees of homosexuality can have on the labor force.

Furthermore, I extend the model of potential outcomes with unobserved heterogeneity used in Heckman et al. (2006) and Urzua (2008) to incorporate the endogenous choice of employment, and thus address selection issues that could affect the estimation of an income gap—namely, that the absence of an income gap does not rule out the existence of discrimination. In fact, it could be the results of discrimination at hiring (Brown, 1984). Income gaps may not be evident within the employed population because only the highly skilled within the minority will manage to get a job. Therefore, quantifying the effect of an entrance barrier to the labor market for sexual minorities becomes particularly relevant.

Gaps against sexual minorities in the probability of being employed could materialize through both the demand and the supply sides of the labor market. Regarding the former, one can extend the Beckerian model of discrimination to include the fact that if the *compensation*—the gap between the wages the employer is willing to pay majority workers over minority ones—needed by the employer to outweigh her distaste for minority workers is big enough, it could cause the wage

offered to minorities to be less than their reservation wage.[6] The latter may be driven by the fact that sexual minorities often have to face hostile workplace cultures (Frank, 2014), and thus, their reservation wages may be higher in order to compensate for that inconvenience when taking on a job.[7] Although both channels differ profoundly, they amount to discrimination as they cause minority agents to behave differently in the labor market, obtaining different outcomes from it.

I find evidence on the existence of labor market discrimination against sexual minorities. My results indicate that discrimination exists at the employment margin and not at the earnings margin for those employed. The overall employment rate is between 10 and 20 percentage points lower for homosexuals than for heterosexuals. I find that this type of discrimination is stronger among men than women. This endogenous selection into employment reduces the income gaps we observe among the employed. Discrimination causes employed homosexuals to be, on average, more skilled than the average employed heterosexual, and the former face extremely high labor market returns to those skills.[8] Hence, the distributions of skills matter. I find that—although their means are not different from each other—the variance of the skills distribution of heterosexuals is greater than that of sexual minorities. Then, if skills of the latter were drawn from a distribution like the one of heterosexuals, the observed income gaps—which range between 9.45 percent and 12 percent—disappear. This happens because a wider skills distribution will increase the fraction of people that surpass the hurdle of becoming employed and face substantially grater returns to those

[6]This intuition on the effect of discrimination on employment is general enough to include specific mechanisms explored recently in the literature like uncertainty in the subjective evaluation of minority workers by majority managers (Ritter and Taylor, 2011).

[7]This angle relates to the one explored by Bond and Lehmann (2018) where black workers lower their reservation wage when they are matched with firms that have black supervisors, as it signals lower firm's prejudice. Black workers are willing to work for less in these firms in order to secure a less prejudiced environment that would yield lower probabilities of being fired.

[8]This challenges the argument of Cain (1986) that states that there should not be employment rate gaps against minorities without the existence of earning gaps, because if minorities are consistently rejected and not hired, they must bid for lower paying jobs.

abilities. Finally, I find that discrimination against sexual minorities differs across genders. Among homosexual men, the college educated ones are less likely to find a job. Among homosexual women, those with no college degree are the ones who do. Also, while employed homosexual men face no wage penalty, employed homosexual women do. In particular, given that the tougher selection occurred on the non-college-educated, employed college-educated nonheterosexual women who get a job earn 10 percent less that heterosexual women.

The paper is organized as follows. Section 2 introduces the definitions of homosexuality used in the paper and presents evidence on the income gap. Section 3 describes the data. Section 4 introduces the empirical strategy. Section 5 presents the first set of results and discusses whether the differences between homosexuals and heterosexuals in terms of income, schooling choices and occupational choices respond to differences in skills. Section 6 presents the analysis of homosexuality as a latent factor. Finally, Section 7 concludes.

2 Background

2.1 Definition of Homosexuality According to the Data

Defining homosexuality is a difficult task, regardless of the data available. Homosexuality is not a dichotomous indicator but a spectrum of preferences that go from being attracted or having had sex with only women to being attracted or having had sex with only men, with a complex assortment of sexual preferences in between these two extremes (Laumann et al., 1994).[9] Defining homosexuality according to the data becomes even more complex as it can be drawn from three

[9] That is why in this paper I sometimes use the term "nonheterosexual" to refer to people whose sexual preferences are away from the heterosexual extreme but anywhere else in the spectrum of preferences.

different concepts (Laumann et al., 1994; Badgett, 1995) . First, the extent to which each gender generates sexual interest (i.e., sexually attracted to, sexual fantasies about) to the respondent. Second, whether the respondent considers herself homosexual to a particular extent. And third, the gender of the respondent's sexual partners. It should be noted that one definition does not imply any of the other two, particularly for individuals of the homosexual or heterosexual extremes.

The data set I use (fully described in Section 3) inquires about the respondents' homosexuality under the three different definitions, and it does so by using a rich set of possible categories to fully capture the wide range of sexual preferences under each definition. The fact that sexuality is not a dichotomous trait but a continuum of degrees of preferences that can be manifested in three dimensions implies that discretizing those measures requires the imposition of *ad hoc* thresholds, one for each definition. One way to use the data is to build three dichotomous variables that split the sample between heterosexual and non-heterosexual respondents. One can construct the first measure according to sexual interests (SI) and considers to be homosexual any individual who is attracted in any degree to people of the same sex. A second measure could be constructed according to self-perception of homosexuality (SP) and considers as homosexual any individual who believes she is homosexual in any degree. Finally, a third measure (SX) responds to whether a person has had sex with someone from the same gender. Note that in the interest of sample size, in creating SI, SP and SX, I imposed the thresholds so as to define as homosexual anyone that claims to be nonheterosexual in any degree.

The left panel in Figure 1 shows the proportion of respondents who are classified as homosexual according to each definition. It shows that the SI and SP definitions are, as expected, very similar to each other, while the definition that relies on actual sexual relations is much more selective. Interestingly, for every definition women are more likely to be classified as homosexuals, but the

difference in the number of men and women identified as homosexual is drastically smaller in the SX definition than in the ones that use self-perception or sexual interest.

Often, individuals classified as homosexuals according to one of the definitions are not classified as such according to other one. Figure 1 presents a Venn's diagram of homosexuality according to each definition. Around two thirds of the sample are considered heterosexual, and only 6.6 percent are considered homosexual according to all three definitions of homosexuality.

Discretizing the measures of sexual preferences is arbitrary and results in some loss of information. To overcome this issue, this paper also incorporates the treatment of homosexuality as a continuous latent variable that can be measured through three manifest scores. Thus, I allow people's *degree of homosexuality* to be an unobserved continuum that affects the answers given to each question regarding sexual preferences. That way, I can reconcile the fact that people may be *less heterosexual* according to one score but *more heterosexual* according to other. That is because the latent *degree of homosexuality* could, for instance, be enough to be manifested in one score, but not in others. This approach, explored in Section 6, also allows the scores to be affected by family contexts that could influence the likelihood of someone *manifesting* a degree of nonheterosexuality.

2.2 The Income Gap

The typical estimation found in the literature on income discrimination for sexual minorities relies on a linear model for labor market outcomes of the form

$$\ln Y = \alpha + \gamma Gay + \beta \mathbf{X} + \sum_{s=1}^{S} \phi_s D_s + \varepsilon \tag{1}$$

where Y is the income measure of interest, $\mathbf{X}$ is a set of observable controls (e.g., age, experience, geographical region), and D_s is a dummy variable that represents the schooling level where $s = \{0, \ldots, S\}$.[10] To capture differences between the effect for lesbians from the effect of homosexual men, Equation (1) is often augmented with an interaction between *Gay* and gender, or the estimations are done separately for each gender. In essence, the parameter of interest of these types of models is γ, which the existing literature interprets as the difference in income between two individuals that have the same observable characteristics and have achieved the same education levels but differ in their sexual preferences.

However, the estimation of (1) requires substantial econometric considerations. The most important one is that unobservable characteristics may influence simultaneously schooling or occupational decisions and income, and those choices themselves can be influenced by the sexual preference of the individual. Models like (1) also assume that ϕ_s does not differ across sexual preferences. Although, we are not interested in the estimates of ϕ_s, this assumption does affect the estimate of γ due to the endogeneity issues just described.

For comparison purposes, Table 1 presents the reduced form results of models of the type described by Equation (1) for each definition of homosexuality. Column 1 presents the unconditional difference in means. Norwegian homosexuals, on average, earn between 11 and 15 percent less than heterosexuals. Adding age and gender controls in Model 2 reduces this gap by about a third. However, the specification that most resembles the one used in the existing literature is that of Model 3 with the introduction of a dummy variable that takes the value of 1 if the respondent had any kind of tertiary education. Also, it incorporates an interaction term between gay and

[10] Berg and Lien (2002) use a multinomial logit because the income on the GSS data is coded in ranges. The intuition and controls used remain the same as in (1)

Table 1: Gap in Yearly Income

	Model 1		Model 2		Model 3		Model 4	
Definition	Coeff.	Std.Err.	Coeff.	Std.Err.	Coeff.	Std.Err.	Coeff.	Std.Err.
SI	-0.139***	(0.045)	-0.104**	(0.045)	-0.166*	(0.086)	-0.149*	(0.090)
SI×*female*					0.089	(0.101)	0.075	(0.105)
SP	-0.157***	(0.046)	-0.107**	(0.046)	-0.146*	(0.081)	-0.138	(0.085)
SP×*female*					0.056	(0.098)	0.072	(0.103)
SX	-0.113**	(0.057)	-0.089	(0.056)	-0.058	(0.086)	-0.064	(0.090)
SX×*female*					-0.055	(0.113)	-0.020	(0.116)
Age & gender			X		X		X	
College					X			
Test scores							X	

Note: *** p<0.01, ** p<0.05, * p<0.1. All estimations were drawn from different regressions with the dependent variable being the natural logarithm of yearly income among the employed population in wave four of the survey. Age enters in a quadratic polynomial. The College variable takes the value of 1 when the person has undertaken any kind of tertiary education in colleges (*høyskole*) or universities (*universitetet*). This includes three- or four-year college studies or studies in the university with the same length. The estimations with test scores include six scores, one related to school grades (Math, Norwegian, and English), two of them relate to agreeableness and the ease to make friends, the others relate to positivism, leadership, and scholastic competence. All of them collected in the first wave of the survey. Number of observations in Model 1: 1,964, Model 2: 1,964, Model 3: 1,964, and Model 4: 1,861. *Source*: Own calculations.

female to identify a differential effect on lesbians. The income gap in this specification ranges from 6 percent to 16.6 percent depending on the homosexuality definition. Model 4 presents the estimation results of a model *a la* Neal and Johnson (1996). That is, introducing test scores as proxies of abilities instead of the schooling attainment.[11] The results are very similar to those obtained in Model 3. These gaps amount to half of what similar estimations have found in the U.S. labor market. This could respond to differences in the types of samples used in the analyses or to structural features in the Norwegian labor market *vis-a-vis* the United States. Interestingly,

[11] Neal and Johnson (1996)—when exploring racial wage gaps—argue that they can bypass the endogeneity between race and education attainment on the measurement of income gaps using the stock of skills accumulated up until mandatory schooling ends instead of controlling for schooling attainment *per se*. They argue that the educational and occupational choices made during adulthood that end up affecting income are themselves consequences of the stock of skills—proxied by test scores—agents had when they started making those decisions. Hence, this approach claims that, conditional on the skill levels, the income gap is fixed across educational levels or occupational sectors. As Urzua (2008) shows in the case of racial income gaps, I show that this approach is not appropriate to describe the existing labor market differences between homosexuals and heterosexuals, as the size of these gaps differ across educational choices.

Table 2: Gap in Yearly Income (Heckman Selection Model)

	Model 1		Model 2		Model 3	
Definition	lnIncome	Pr(Empl=1)†	lnIncome	Pr(Empl=1)†	lnIncome	Pr(Empl=1)†
SI	-0.004	-0.230***	-0.030	-0.359***	0.020	-0.411***
	(0.040)	(0.067)	(0.076)	(0.124)	(0.078)	(0.128)
SI×*female*			0.028	0.194	-0.025	0.294*
			(0.090)	(0.147)	(0.091)	(0.150)
SP	-0.047	-0.156**	-0.076	-0.170	-0.053	-0.145
	(0.041)	(0.069)	(0.072)	(0.122)	(0.074)	(0.126)
SP×*female*			0.039	0.004	0.036	0.007
			(0.087)	(0.148)	(0.089)	(0.152)
SX	-0.038	-0.120	-0.022	-0.039	0.008	-0.063
	(0.049)	(0.083)	(0.077)	(0.136)	(0.079)	(0.139)
SX×*female*			-0.032	-0.140	-0.053	-0.029
			(0.100)	(0.172)	(0.102)	(0.176)
College				X		
Test Scores						X

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. All estimations were drawn from different Heckman selection models with the dependent variable being the natural logarithm of yearly income among the employed population in wave four of the survey. Omitted controls for the selection equations are age in a quadratic polynomial, gender, whether as a child the person lived with one parent, a remarried parent or with no parents, BMI in wave one of the survey, whether the person practiced sports, skipped school or was excluded from a class during childhood. Omitted controls in the income equations are age in a quadratic polynomial, gender, dummies for mother's education, dummies for mother's SES and municipality size. The College variable takes the value of 1 when the person has undertaken any kind of tertiary education in colleges (*høyskole*) or universities (*universitetet*). This includes three-year, four-year college studies or studies in the university with the same length. The estimations with test scores include six scores, one related to school grades (Math, Norwegian and English), two of them relate to agreeableness and the ease to make friends, the others relate to positivism, leadership and scholastic competence. All of them collected in the first wave of the survey. The number of observations for Model 1: 2,326, Model 2: 2,326, and Model 3: 2,204. *Source*: Own calculations.
† Coefficients. Not marginal effects.

there seems to be no differential effect for lesbians. Furthermore, the mean comparisons of college attendance presented in Table G.1 in the Appendix G show that there seems to be no systematic evidence of either group being more likely to go to a tertiary education institution. If anything, these results suggest that lesbians are less likely to go less to college than heterosexual women.

2.3 The Importance of Endogenous Selection into Employment

The findings in Table 1 are obtained from a selected sample—namely, those who are employed. There are many reasons to believe those employed are not representative of the whole sample, as they may have observable and unobservable characteristics that contribute to their sorting (or not) into employment (Mroz, 1987), including—probably—homosexuality. If those characteristics correlate with income, the estimates in Table 1 are biased. To address this issue and provide a more comparable benchmark for the estimates provided by the models I estimate later in this paper, I present in Table 2 the results obtained from estimating models that allow for selection (Heckman, 1979). That is, I allow selection into employment to endogenously determined.

The results indicate that income gaps presented in Table 1 disappear once I allow endogenous selection into employment, regardless of the homosexuality definition and the controls used. It provides evidence on the fact that differences in the labor market against sexual minorities may take place at the time of getting a job and not by working for a lower wage. This result will be fully explored in the subsequent chapters, paying especial attention to how endogenous choices that are critical in determining income—like employment and schooling—could be affected by differences in characteristics, both observable and unobservable, across sexual preference groups.

3 Data

This paper uses a novel data set that has not been explored by the economic literature. The Young in Norway (YiN) is a longitudinal data set product of a research project headed by the Program for Adolescent Research (Ungforsk) in 1990.[12] YiN collects detailed information about

[12]The project had four main goals. First, it was designed to produce studies of the entire population, not just specific groups. For that, the study's design needed to have a high response rate and national representativity.

the characteristics, attitudes, and choices of a cohort of Norwegians. In particular, it has four features that makes it the best data set currently available to study sexual minority labor market discrimination. First, it is longitudinal; therefore, I am able to observe respondents' characteristics when young. This improves over existing literature that explores income gaps of sexual minorities using nonlongitudinal surveys, which in turn prevents researchers from differentiating away time-invariant unobservables that might bias the results. Second, it collects scores on personality traits and academic performance as children. I use these measures to identify the unobserved skills, a key feature of my empirical strategy. Third, it collects detailed information about sexual preferences and practices. This way, I do not run into absurdly small sample sizes, I can include single people in the analysis, and I can construct a model with a continuous measure of unobserved heterogeneity on homosexuality. Finally, YiN collects information about the job market including ISCO88 coded occupations and yearly income. See the descriptive statistics in Appendix Table A.1.

YiN has four waves of data. The first wave was collected in 1992, when 12,287 students of lower and upper secondary school pupils, from 67 schools in grades 7–12 (age 13–18) were interviewed. The sampling allowed for each grade to be represented equally, and the sampling unit was the school. Wave 2 was collected two years later. By then, the older members of the sample had already graduated. Thus, the younger cohorts answered wave 2 in school (n=3,844), while the older ones were contacted through the mail. The study was originally planned to end after wave 2. However, a spin-off of the study continued in 1999 but only for the younger cohorts, those who had answered the wave 2 questionnaire in school and not by mail. 2,923 people were interviewed. Wave 4 was collected between May 2005 and August 2006, with the target population being the

Second, the study wanted to provide researchers tools to find causal relations. Finally, the study had to be comprehensive enough to be able to provide information of adolescents across different social arenas (Strand and von Soest, 2008).

same as in wave 3. In this wave, data were collected for 2,890 people. There is a great overlap between those wave 3 and wave 4 respondents; in total, 2,562 responded both surveys. Following advice from the experts at NOVA, the agency responsible for the data, I do not include in my analysis respondents that were not followed up in waves 3 or 4. This leaves a final sample of 2,991.

3.1 Skills

The empirical strategy used in this paper relies on the identification of unobserved skills. Such identification and the subsequent estimations based on this unobserved heterogeneity pose heavy requirements on sample size. The number of observations required increases geometrically with the number of unobserved dimensions of skill to be estimated. Given that the sample size of homosexuals in every definition is not large, I estimate the models with one unobserved factor. This factor will comprise both cognitive and noncognitive skills in one construct.

To identify the unobserved skills factor, I use six scores; all of them were collected in the first wave of the survey, when the respondents were in their early to mid teens. The first four measures come from the Self-Perception Profile for Adolescents (SPPA) (Harter, 1988). These are self evaluations that take into account the perceived competence and the relative importance the respondent gives to specific areas of life (Wichstraum, 1995). First, two of the measures relate to agreeableness, one in the area of social acceptance—being able to get others to accept and like oneself—and another one measuring how easy it is for the respondent to build close social relationships. The third measure relates to self-esteem; similar to the widely used Rosenberg self-esteem scale, but its wording is more appropriate to adolescents. The fourth score measures scholastic competence, understood as the perceived cognitive competence related to schoolwork (Harter, 2012). The fifth score relies on a scale that measures qualities like leadership and strong-

mindedness—makes decisions easily, is independent, willing to take a stand. Finally, the sixth scale uses school grades in Math, Norwegian, and English.

3.2 Income Measures

The YiN data set is was not conceived as a labor force survey and thus does not contain a measure of hourly wage. Instead, it asks about pretax personal yearly income. In addition, time worked is not recorded. Hence, halftime workers could be earning less just because they are working less hours. To overcome this, I compare the results I obtain on the whole sample with those I obtain on the sample of full-time workers, for whom the income reported is more likely to come from their work.[13] Note that income measures were collected when the cohort in the sample was around 30 years old. Thus, this study focuses on labor market discrimination at relatively early stages in their carrer. However, evidence shows that wage gaps in other contexts widen with age (Manning and Swaffield, 2008; Bertrand et al., 2010). Hence, finding gaps at early ages is indicative of gaps later in life.[14]

[13]In addition, there is a chance part of the income comes from rehabilitation, disability, or unemployment benefits. However, I find that homosexuals are equally as likely to receive social benefits as heterosexuals, regardless of the definition of homosexuality. Therefore, there is no reason to believe that any leakage in the income measures constructed could bias the results in either direction.

[14]In fact, Weinberger and Kuhn (2010) suggest that the reduction of the gender wage gap observed in the last half of the twentieth century responds more to disappearing differentials in the factors that determine initial wage than changes in relative wage growth after labor market entry.

4 Empirical Strategy

4.1 Identifying Unobserved Heterogeneity

Works like Murnane et al. (1995), Heckman et al. (2006) and Espinoza et al. (2014) show that unobserved heterogeneity (e.g., skills) is as relevant in determining life choices and adult outcomes as other characteristics like gender or household composition. Thus, I model the outcomes $\mathbf{Y}$ we are interested in (e.g., wage, schooling, employment) as the results of observable characteristics $\mathbf{X_Y}$ (e.g., gender, tenure, local labor market) and the unobserved heterogeneity $\mathbf{\Theta}$, which in the case of this paper can contain up to two dimensions: skills and the latent degree of homosexuality. That is,

$$\mathbf{Y} = \mathbf{X}_Y \beta^Y + \alpha^Y \mathbf{\Theta} + \mathbf{e^Y} \tag{2}$$

where $\mathbf{Y}$ is a $M \times 1$ vector of outcome variables, $\mathbf{X}_Y$ is a matrix with all observable controls for each outcome variable, and $\mathbf{e^Y} \perp (\mathbf{\Theta}, \mathbf{X_Y})$ is a vector of error terms with distributions $f_{e^{ym}}(\cdot)$ such that $e^{y_i} \perp e^{y_j}$ for every $m = 1, \ldots, M$. Given that $\mathbf{\Theta}$ is unobserved, the estimation of (2) is not straightforward. To begin with, unobserved heterogeneity factors are not well defined entities with established scales or units of measurement. Instead they are latent variation that needs to be inferred from variation captured in manifest variables they affect (Bartholomew et al., 2011). The manifest variables are assumed to be the result of a linear production function of scores whose inputs are both observable characteristics and the unobserved heterogeneity of the form

$$\mathbf{T} = \mathbf{X}_T \beta^T + \alpha^{\mathbf{T}} \mathbf{\Theta} + \mathbf{e^T} \tag{3}$$

where $\mathbf{T}$ is a $L \times 1$ vector of measurements (e.g., test scores, answers to the sexual preferences questionnaire), $\mathbf{X}_T$ is a matrix with all observable controls that affect each score, and $\mathbf{e^T} \perp (\mathbf{\Theta}, \mathbf{X}_T)$ is a $L \times 1$ vector of mutually independent error terms that have associated distributions $f_{e^h}(\cdot)$ for every $h = 1, \ldots, L$. Hence, I am effectively disjoining the manifest measures we observe on the data ($\mathbf{T}$) from the true latent heterogeneity ($\mathbf{\Theta}$). In particular, in the case of the answers to the sexual preferences questionnaire, I am able to estimate a latent factor clean from characteristics or contexts that may have affected the answers we do observe, but should not change the true underlying homosexuality.

I use measurement system (3) (i.e., the variation observed in the manifest variables) to identify $f_\theta(\cdot)$, the underlying distribution of the unobserved factors—that is, I do not assume a particular functional form. Instead, I use a two-component mixture of normals $\theta \sim \omega\mathcal{N}(\mu_1, \sigma_1^2) + (1-\omega)\mathcal{N}(\mu_2, \sigma_2^2)$ to estimate the true—and usually nonnormal—underlying distribution $f_\theta(\cdot)$ for each dimension of unobserved heterogeneity.[15] The estimation of the parameters that govern $f_\theta(\cdot)$ is crucial for the estimation the complete semistructural model because such distributions allow me to integrate away the latent heterogeneity in all the outcomes, choices, and scores associated with the model, while still being able to retrieve the coefficients related with it in every equation.

Identification of $f_\theta(\cdot)$ requires the identification of the loadings $\alpha^{\mathbf{T}}$. Carneiro et al. (2003) show that their identification requires three assumptions: first, that $L \geq 2k+1$, where k is the number of unobserved factors in the model; second, that in the case when $k > 1$, the latent factors are orthogonal to each other; and third, that we normalize one of the loadings associated to each factor to 1. To observe how the assumptions work for identification, take for instance the case

[15] The mixture of normals allows me to not only replicate a wide range of distributions but also integrate numerically using the Gauss-Hermite quadrature, which is particularly useful for calculating $\int f(X)\,dx$ when $X \sim \mathcal{N}(\mu, \sigma^2)$ (Judd, 1998). For a more detailed analysis regarding the estimation of the skills' distributions see Sarzosa and Urzua (2016).

when $k = 1$, requiring $L \geq 3$. Thus, system (3) would become

$$T_1 = \mathbf{X}_T \beta^1 + \alpha^1 \theta + e^1$$

$$T_2 = \mathbf{X}_T \beta^2 + \alpha^2 \theta + e^2$$

$$T_3 = \mathbf{X}_T \beta^3 + \theta + e^3$$

where $\alpha^3 = 1$ is the nummeraire. Note that $\frac{COV(T_1,T_2|\mathbf{X}_T)}{COV(T_1,T_3|\mathbf{X}_T)} = \alpha^2$ and $\frac{COV(T_1,T_2|\mathbf{X}_T)}{COV(T_2,T_3|\mathbf{X}_T)} = \alpha^1$. Then, having identified the loadings, we can write model (3) as $\mathbf{J} = \mathbf{\Theta} + \tilde{\mathbf{e}}^{\mathbf{T}}$ where $\mathbf{J} = \frac{\mathbf{T} - \mathbf{X}_T \beta^T}{\alpha^T}$ and $\tilde{\mathbf{e}}^{\mathbf{T}} = \frac{\mathbf{e}^{\mathbf{T}}}{\alpha^T}$, and together with the fact that $\mathbf{e}^{\mathbf{T}} \perp \mathbf{\Theta}$ rely on the Kotlarski Theorem which shows that using the joint distribution of $(J_1, J_2, \ldots, J_L)$ one can nonparametrically identify the distributions of $\mathbf{\Theta}$ and $\tilde{\mathbf{e}}^{\mathbf{T}}$—and thus $\mathbf{e}^{\mathbf{T}}$—up to one normalization (Kotlarski, 1967).

The complete structure of the model, including the parameters that describe the distributions of the underlying factor $f_\theta(\cdot)$, is estimated using maximum likelihood estimation (MLE). The likelihood function will be the following:

$$\mathcal{L} = \prod_{i=1}^{N} \int \left[\begin{array}{c} f_{e^{y_1}}(\mathbf{X}_{Y_1}, Y_1, \zeta) \times \cdots \times f_{e^{y_M}}(\mathbf{X}_{Y_M}, Y_M, \zeta) \\ \times f_{e^1}(\mathbf{X}_{T_1}, T_1, \zeta) \times \cdots \times f_{e^L}(\mathbf{X}_{T_L}, T_L, \zeta) \end{array} \right] dF_\theta(\zeta) \tag{4}$$

In Section 2.3, I showed the importance of taking selection into account. The model presented in Equation (2) can accommodate such outcomes by expanding vector $\mathbf{Y}$ to include an indicator E of selection into employment and a censored income measure Y that takes positive values when $E = 1$.

$$\mathbf{Y} = \left[\begin{array}{c} E \\ Y \end{array} \right] = \left[\begin{array}{c} \mathbb{1}\left[\mathbf{X}_E \beta^E + \alpha^E \theta + e^E > 0\right] \\ E\left(\mathbf{X}_Y \beta^Y + \alpha^Y \theta + e^Y\right) \end{array} \right] \tag{5}$$

where $\mathbb{1}[A]$ denotes an indicator function that takes a value of 1 if A is true. Thus, I am effectively using a type-II Tobit model (Amemiya, 1985, p. 385) in the presence of unobserved heterogeneity, allowing endogenous choices of employment to depend on observable characteristics and unobserved traits like skills or latent homosexuality.[16]

4.2 Roy Model: Allowing for Endogenous Choice of Schooling

Norway has a relatively high tertiary education enrollment rate; around 62 percent of people in the sample go to a tertiary education institution of some sort. A vast literature on returns to schooling shows that differences in access to tertiary education is critical in determining difference in earned income (Mincer, 1958; Becker and Chiswick, 1966; Card, 2001). Therefore, part of the sexual preference income gap could be explained by differences between homosexuals and heterosexuals in enrollment rates in tertiary education. A model of potential outcomes that endogenizes schooling choices inspired by the Roy model (Roy, 1951) can easily be introduced as a special case of the setup presented above in subsection 4.1. For that, suppose vector $\mathbf{Y}$ in Equation (2) is comprised by five rows (i.e., $M = 5$), where one row contains a binary choice D (e.g., going to college $D = 1$ or not $D = 0$) and the other four contain the outcomes of interest that depend on such choice (e.g., wage and employment for those that went to college (Y_1, E_1) and wage and employment for

[16]System (5) can be effectively estimated as a Heckman selection model by estimating $y = \mathbf{X}_Y\beta^Y + \alpha^Y\theta + \psi IMR + e_c^Y$ on the selected sample, where $IMR = \phi(\mathbf{X}_E\hat{\beta}^E + \hat{\alpha}^E\theta)/\Phi(\mathbf{X}_E\hat{\beta}^E + \hat{\alpha}^E\theta)$ is the Inverse Mills Ratio obtained from a probit on the selection equation.

those that did not (Y_0, E_0)). Hence, (2) becomes

$$\mathbf{Y} = \begin{bmatrix} D \\ E_1 \\ Y_1 \\ E_0 \\ Y_0 \end{bmatrix} = \begin{bmatrix} \mathbb{1}\left[\mathbf{X}_D \beta^{Y_D} + \alpha^{Y_D} \boldsymbol{\Theta} + e^D > 0\right] \\ D\left(\mathbb{1}\left[\mathbf{X}_E \beta^{E_1} + \alpha^{E_1} \boldsymbol{\Theta} + e^{E_1} > 0\right]\right) \\ D\ E_1\left(\mathbf{X}_Y \beta^{Y_1} + \alpha^{Y_1} \boldsymbol{\Theta} + e^{Y_1}\right) \\ (1-D)\left(\mathbb{1}\left[\mathbf{X}_E \beta^{E_0} + \alpha^{E_0} \boldsymbol{\Theta} + e^{E_0} > 0\right]\right) \\ (1-D)\, E_0\left(\mathbf{X}_Y \beta^{Y_0} + \alpha^{Y_0} \boldsymbol{\Theta} + e^{Y_0}\right) \end{bmatrix} \tag{6}$$

where $\mathbf{X}_D$ represents a set of exogenous or predetermined observables that affect the choice. $\mathbf{X}_D$ and $\mathbf{X}_Y$ could share elements. An exclusion restriction (i.e., a source of variation present in $\mathbf{X}_D$ but not in $\mathbf{X}_Y$) would secure identification of the model without the need to rely on its nonlinearity.

An important feature of the Roy model is that individuals must choose between two sectors, for example, treated and not treated depending on their comparative advantage (Heckman and Honore, 1990). Therefore, both the decision and the outcomes are endogenous based on observable and unobservable characteristics of the individuals. This feature is key in the development of counterfactuals in Section 5.3. The empirical strategy assumes that after controlling for the unobserved heterogeneity $\boldsymbol{\Theta}$, the remaining error terms are independent (i.e., $e^D \perp e^{Y_1} \perp e^{Y_0} \perp e^{E_1} \perp e^{E_0}$) and thus can be modeled through independent contributions to likelihood function. That is:

$$\mathcal{L} = \prod_{i=1}^{N} \int \begin{bmatrix} \left[\left(1 - f^D\left(\mathbf{X}_D, Y_D, \zeta\right)\right)\left[f_{e^{Y_0}}\left(\mathbf{X}_Y, Y_0, \zeta\right) f_{e^{E_0}}\left(\mathbf{X}_E, E, \zeta\right)\right]^{E_0}\left(1 - f_{e^{E_0}}\left(\mathbf{X}_E, E, \zeta\right)\right)^{1-E_0}\right]^{1-D} \\ \left[f^D\left(\mathbf{X}_D, Y_D, \zeta\right)\left[f_{e^{Y_1}}\left(\mathbf{X}_Y, Y_1, \zeta\right) f_{e^{E_1}}\left(\mathbf{X}_E, E, \zeta\right)\right]^{E_1}\left(1 - f_{e^{E_1}}\left(\mathbf{X}_E, E, \zeta\right)\right)^{1-E_1}\right]^{D} \\ f_{e^1}\left(\mathbf{X}_{T_1}, T_1, \zeta\right) f_{e^2}\left(\mathbf{X}_{T_2}, T_2, \zeta\right) \times \cdots \times f_{e^L}\left(\mathbf{X}_{T_L}, T_L, \zeta\right) \end{bmatrix} dF_\theta\left(\zeta\right)$$

5 Results: Homosexuality as Dichotomous Variables

5.1 General Distribution of Skills

Let me introduce the unobserved heterogeneity and the Roy model of potential outcomes in a context where one general distribution of skills is estimated. Putting it in terms of (6), I estimate the following system:

$$\mathbf{Y} = \begin{bmatrix} D \\ E_1 \\ Y_1 \\ E_0 \\ Y_0 \end{bmatrix} = \begin{bmatrix} \mathbb{1}\left[\gamma_D Gay + \mathbf{X}_D \beta^{Y_D} + \alpha^{Y_D}\theta + e^D > 0\right] \\ D\mathbb{1}\left[\gamma_{E_1} Gay + \mathbf{X}_E \beta^{E_1} + \alpha^{E_1}\theta + e^{E_1} > 0\right] \\ DE_1\left(\gamma_{Y_1} Gay + \mathbf{X}_Y \beta^{Y_1} + \alpha^{Y_1}\theta + e^{Y_1}\right) \\ (1-D)\,\mathbb{1}\left[\gamma_{E_0} Gay + \mathbf{X}_E \beta^{E_0} + \alpha^{E_0}\theta + e^{E_0} > 0\right] \\ (1-D)\,E_0\left(\gamma_{Y_0} Gay + \mathbf{X}_Y \beta^{Y_0} + \alpha^{Y_0}\theta + e^{Y_0}\right) \end{bmatrix}$$

where θ comes from a distribution estimated using the complete sample.[17] In this case, the parameters of interest are γ_D, γ_{E_0}, γ_{E_1}, γ_{Y_0} and γ_{Y_1}.[18]

Table 3 presents the results. First, it shows that, even after controlling for skills, college attendance does not differ across sexual preferences. It also shows that discrimination takes place in accessing jobs and not in the pay itself, and that these gaps are larger among college educated than among those with no college education. Table 3 indicates that college-educated homosexual men according to the SI definition are 18 percentage points less likely to be employed and 30 percentage points less likely to have a full time job than comparable heterosexuals. SI homosexual men without

[17] See the estimation of the measurement system of test scores for the whole sample from which the distribution of the latent skills θ are identified in Table E.1 and the estimated distribution of skills θ in Figure E.1 in Appendix E.

[18] For completeness, I estimate a model without an education choice equation—which is the closest to the reduced form estimates in the existing literature—and present its results in Appendix B.

college education are 10 percentage points less likely to be employed and 15.6 percentage points less likely to have a full-time job than comparable heterosexuals.

Among women, Table 3 also shows an employability gap against lesbians. In particular, against the college educated ones, with gaps ranging between 7.3 and 13 percentage points.

The results of Table 3 attest to the importance of a model that allows for endogenous choices and separate estimates for two different sectors. This way, I find particular sectors where discrimination is stronger, namely among the higher educated workers.

5.2 Separate Distributions: Unobserved Abilities

The main drawback of the empirical strategy used above is that it restricts the estimates of the model to be the same for homosexuals and heterosexuals. If there are any differences in the skill distributions, or in the labor market returns to observable and unobservable characteristics, the results presented above could be misleading. Therefore, in this subsection, I present the results of models that allow to estimate a complete set of different parameters for heterosexuals and homosexuals, including the skills' distributions.

Table 3: Effect of Homosexuality on Annual Income, Employment and College, Roy Model With Overall Distribution

	SI		SP		SX	
	Coeff.	Std.Err.	Coeff.	Std.Err.	Coeff.	Std.Err.
College†						
Gay	0.089	(0.203)	0.105	(0.192)	0.346*	(0.205)
GayXFemale	-0.017	(0.240)	-0.152	(0.234)	-0.784***	(0.272)

	SI		SP		SX	
	Income	Employed	Income	Employed	Income	Employed
Employed						
No College						
Gay	9.320	-0.457*	9.879	-0.296	-4.722	-0.287
	(23.098)	(0.250)	(19.766)	(0.240)	(21.987)	(0.271)
GayXFemale	-2.829	0.186	4.223	0.085	22.883	0.038
	(25.114)	(0.304)	(23.204)	(0.296)	(26.865)	(0.334)
College						
Gay	-5.995	-0.640***	-32.440	-0.404**	1.765	-0.130
	(24.034)	(0.157)	(19.811)	(0.161)	(17.996)	(0.173)
GayXFemale	0.418	0.487***	17.293	0.291	-27.863	-0.017
	(23.615)	(0.185)	(21.409)	(0.194)	(22.636)	(0.223)
Obs.(N|Cnsrd)	2274	1821	2280	1828	2283	1827
FullTime4						
No College						
Gay	14.468	-0.432*	10.439	-0.251	-22.528	-0.055
	(23.809)	(0.239)	(20.205)	(0.230)	(21.501)	(0.269)
GayXFemale	-38.460	0.632**	-1.006	0.329	18.503	0.232
	(32.498)	(0.282)	(27.802)	(0.274)	(31.324)	(0.323)
College						
Gay	13.425	-0.772***	-3.184	-0.625***	11.515	-0.260
	(30.958)	(0.152)	(27.221)	(0.154)	(20.460)	(0.162)
GayXFemale	-29.256	0.807***	-15.434	0.600***	-41.058	0.351*
	(33.421)	(0.176)	(28.976)	(0.182)	(27.361)	(0.208)
Obs.(N|Cnsrd)	2335	1409	2340	1415	2345	1414

Note: *** p<0.01, ** p<0.05, * p<0.1. The coefficients presented are the ones associated with the homosexuality indicators. The College variable takes the value of 1 when the person has undertaken any kind of tertiary education in colleges (*høyskole*) or universities (*universitetet*). This includes three-year, four-year college studies or studies in the university with the same length. The controls used in the College choice equation and not presented in the Table are: age, age squared, gender, dummies for father's education, dummies for mother's education, whether as a child the person lived with one parent, a remarried parent or with no parents, number of books available at home as a child, and the unobservable factor of skills. The controls used in the income equations and not presented in the Table are age, age squared, gender, dummies for Father SES, population of the municipality, height and the unobservable factor of skills. *Source*: Own calculations.
† Coefficients, not marginal effects.

Figures 2 presents the estimated skill distributions for heterosexuals and homosexuals according to each definition of homosexuality.[19] It is easy to see that not assuming normality and instead empirically estimating the distributions pays off as they are far from normally distributed, especially the ones from homosexuals. Figures 2 show that skills among homosexuals are more tightly distributed. While the standard deviation of skills among heterosexuals is around 0.33, it is between 0.12 to 0.22 for homosexuals. This interesting difference in the distribution of unobserved skills may have important consequences on schooling and occupational sorting and also in the income obtained when adults.

By construction, all the estimated distributions of unobserved ability are centered at zero.[20] However, Urzua (2008) shows that with a minor linearity assumption, one can use the difference between the estimated constants of the test score equations that contain the nummeraire loadings to infer the difference in means of the skill distributions of two groups. Figure 2 is depicted in a way such that the centers of the skills distributions of homosexuals are shifted to represent the difference in means with respect to those of heterosexuals. Importantly, none of these differences in the means of skill distributions between homosexuals and heterosexuals are statistically significant.

Effect of Skills on Outcomes. With different estimated distributions of skills for every subpopulation, I am able to estimate different models of potential outcomes and endogenous choices

[19] Because of sample size issues I can only estimate this kind of models for homosexuals according to the SI and SP definitions of homosexuality.

[20] This comes from the fact that I estimate $f_\theta(\cdot)$ using a mixture of Q normals that will be combined using weights ω_q. The weight of the last normal needs to fulfill $\omega_Q = 1 - \sum_{q=1}^{Q-1} \omega_q$. In the same way, given that all equations contain intercepts, the mean of the last normal μ_Q is one such that $\sum_{q=1}^{Q} \omega_q \mu_q = 0$. That is, $\mu_Q = \sum_{q=1}^{Q-1} \omega_q \mu_q / 1 - \sum_{q=1}^{Q-1} \omega_q$.

for each group. Therefore, I estimate the following models:

$$\begin{bmatrix} D \\ E_1 \\ Y_1 \\ E_0 \\ Y_0 \end{bmatrix} = \begin{bmatrix} \mathbb{1}\left[\mathbf{X}_D\beta^{Y_D^S} + \alpha^{Y_D^S}\theta_S + e^{D,S} > 0\right] \\ D\mathbb{1}\left[\mathbf{X}_E\beta^{E_1^S} + \alpha^{E_1^S}\theta_S + e^{E_1^S} > 0\right] \\ DE_1\left(\mathbf{X}_Y\beta^{Y_1^S} + \alpha^{Y_1^S}\theta_S + e^{Y_1^S}\right) \\ (1-D)\,\mathbb{1}\left[\mathbf{X}_E\beta^{E_0^S} + \alpha^{E_0^S}\theta_S + e^{E_0^S} > 0\right] \\ (1-D)\,E_0\left(\mathbf{X}_Y\beta^{Y_0^S} + \alpha^{Y_0^S}\theta_S + e^{Y_0^S}\right) \end{bmatrix}, \quad \begin{bmatrix} D \\ E_1 \\ Y_1 \\ E_0 \\ Y_0 \end{bmatrix} = \begin{bmatrix} \mathbb{1}\left[\mathbf{X}_D\beta^{Y_D^G} + \alpha^{Y_D^G}\theta_G + e^{D,G} > 0\right] \\ D\mathbb{1}\left[\mathbf{X}_E\beta^{E_1^G} + \alpha^{E_1^G}\theta_G + e^{E_1^G} > 0\right] \\ D\left(\mathbf{X}_Y\beta^{Y_1^G} + \alpha^{Y_1^G}\theta_G + +e^{Y_1^G}\right) \\ (1-D)\,\mathbb{1}\left[\mathbf{X}_E\beta^{E_0^G} + \alpha^{E_0^G}\theta_G + e^{E_0^G} > 0\right] \\ (1-D)\left(\mathbf{X}_Y\beta^{Y_0^G} + \alpha^{Y_0^G}\theta_G + e^{Y_0^G}\right) \end{bmatrix} \tag{7}$$

where the parameters labeled with S correspond to heterosexuals and the ones labeled with G correspond to homosexuals. Tables C.1 and C.2 in the Appendix present the estimates of the sexual preference-specific coefficients associated with skills for income, employment and tertiary education. They show that skills are important determinants of sorting into tertiary education regardless of the sexual orientation. Interestingly, skills have significant positive returns only for those that undertook some sort of tertiary education. However, the results also show that the returns to skills do differ between heterosexuals and homosexuals, supporting the use of a model that allows different parameters across sexual preferences. The numbers in Tables C.1 and C.2 indicate that skills have stronger effects on income for homosexuals than for heterosexuals. In particular, while a one standard deviation increase in skills among college-educated heterosexuals causes yearly income to increase by around 8.8 percent to 11.7 percent, the yearly income increase due to a one standard deviation increase in skills among college educated homosexuals ranges between 14 and 39 percent.[21]

Goodness of Fit of the Model. Tables C.3 and C.4 in Appendix C present evidence on the models' goodness-of-fit on the first and second moments for annual income, college enrollment and

[21]To obtain these figures, I take the loadings from Tables C.1 and C.2, normalize them using the standard deviation of the skills distributions, and divide them by the relevant yearly income mean that can be found in Table 4. For instance, the returns to one SD of skills among college-educated heterosexuals under the definition SI is 76.439*0.33/287.018=8.8 percent.

employment. They are a product of 40,000 simulations of the model based on as many different draws from the distributions of skills. The models do very well in predicting the means and standard deviations for each definition of income and homosexuality. The performance of the models predicting income for homosexuals is remarkable considering the reduced sample size the models are facing.

5.3 Gaps in Labor Market Outcomes

From the results I have provided so far, it is possible to argue three facts: 1) that unobserved skills are important determinants of choices and income earned, 2) that the way skills affect those labor market outcomes depends on the sexual preference of the individual, and 3) that skills follow different distributions for homosexuals and heterosexuals. Hence, based on these three facts, one could hypothesize that the income and employment gaps observed could respond to these estimated differences in skill distributions, and that the portion of the gap that is not explained by such differences—or differences in observable characteristics—could be attributed to plain discrimination.

One can use the structure of the model to evaluate these claims (Urzua, 2008). In particular, it is possible to use the model to simulate the outcomes that homosexuals would have obtained if their skills came from the heterosexual skills distribution and/or if they had the observable characteristics heterosexuals have.[22] This way, I can tease out the differences in labor market outcomes that are due to differences in the skills available across the groups from the differences that are due to plain discrimination. It is evident from Figure 2 that the distribution of skills

[22]See the differences in observable characteristics across groups in Table G.3 in Appendix G.

among homosexuals has a higher mean, but a lower variance than that of heterosexuals.[23] This makes the counterfactual exercise even more compelling: it is not clear the direction outcomes will change—or if they will change at all—as there will be on average a lower stock of skills, but at the same time, there will be people with substantially higher and lower stocks of skills than before.

Using the same notation as in Equation (7), let

$$Y^H\left(\mathbf{X}_Y^{H_X},\mathbf{X}_E^{H_X},\mathbf{X}_D^{H_X},\theta^{H_\theta}\right)=D^H\left(\mathbf{X}_D^{H_X},\theta^{H_\theta}\right)E_1^H\left(\mathbf{X}_E^{H_X},\theta^{H_\theta}\right)Y_1^H\left(\mathbf{X}_Y^{H_X},\theta^{H_\theta}\right)$$
$$+\left[1-D^H\left(\mathbf{X}_D^{H_X},\theta^{H_\theta}\right)\right]E_0^H\left(\mathbf{X}_E^{H_X},\theta^{H_\theta}\right)Y_0^H\left(\mathbf{X}_Y^{H_X},\theta^{H_\theta}\right)$$

be the income given by observable characteristics $\mathbf{X}_Y^{H_X}$, $\mathbf{X}_E^{H_X}$ and $\mathbf{X}_D^{H_X}$ and unobservable skills θ^{H_θ}. The supra-index denotes the sexual preference group (i.e., $H_\cdot=\{S,G\}$). Hence, for instance, income for heterosexuals is given by $Y^S\left(\mathbf{X}_Y^S,\mathbf{X}_E^S,\mathbf{X}_D^S,\theta^S\right)$, while income for homosexuals is given by $Y^G\left(\mathbf{X}_Y^G,\mathbf{X}_E^G,\mathbf{X}_D^G,\theta^G\right)$. These are the values presented in Tables C.3 and C.4. I can use this notation to identify the simulation of counterfactuals. For instance, $Y^G\left(\mathbf{X}_Y^G,\mathbf{X}_E^G,\mathbf{X}_D^G,\theta^S\right)$ denotes the simulated income earned by homosexuals when given skills drawn from the heterosexuals' skills distribution but keeping the observable characteristics as they are. Consequently, the simulated income earned by homosexuals when given the skills and observable characteristics of heterosexuals is denoted by $Y^G\left(\mathbf{X}_Y^S,\mathbf{X}_E^S,\mathbf{X}_D^S,\theta^S\right)$.

The fact that choices $D^H\left(\mathbf{X}_D^{H_X},\theta^{H_\theta}\right)$ and $E_D^H\left(\mathbf{X}_E^{H_X},\theta^{H_\theta}\right)$ are endogenous is an important feature of the model that affects the simulation of counterfactuals. That is, when counterfactuals are simulated, their new results are a product not only of direct changes in the outcome equations $Y_1^H\left(\mathbf{X}_Y^{H_X},\theta^{H_\theta}\right)$ and $Y_0^H\left(\mathbf{X}_Y^{H_X},\theta^{H_\theta}\right)$ but also of indirect changes through the schooling and employ-

[23] Why the moments of the distributions of skills would differ is outside the scope of this paper. It may be due to the different contexts homosexuals have to face while growing up, being more likely to be bullied or harassed, which end up affecting the stock of skills with which they reach adulthood (Sarzosa, 2015).

ment decisions. For instance, when simulating the model for homosexuals but giving them skills drawn from the heterosexuals's distribution, the choices become $D^G\left(\mathbf{X}_D^G,\theta^S\right)$, $E_0^G\left(\mathbf{X}_E^G,\theta^S\right)$ and $E_1^G\left(\mathbf{X}_E^G,\theta^S\right)$. This materializes the very important fact that education and employment decisions are taken based on observable and unobservable characteristics, and once these change, people might choose differently. Hence, the measure of the total income gaps between the two groups need to incorporate the differences that arise from both the direct and indirect channels. That is, the different gaps measured—depending on the counterfactual used—are provided by

$$
\begin{aligned}
&E\left[Y^S\left(\mathbf{X}_Y^S,\mathbf{X}_E^S,\mathbf{X}_D^S,\theta^S\right)\right]-E\left[Y^G\left(\mathbf{X}_Y^{H_X},\mathbf{X}_E^{H_X},\mathbf{X}_D^{H_X},\theta^{H_\theta}\right)\right]\\
&\quad=\Pr\left[D^S\left(\mathbf{X}_D^S,\theta^S\right)=1\right]\Pr\left[E_1^S\left(\mathbf{X}_E^S,\theta^S\right)=1\left|D^S\left(\mathbf{X}_D^S,\theta^S\right)=1\right.\right]E\left[Y_1^S\left(\mathbf{X}_Y^S,\theta^S\right)\left|D^S\left(\mathbf{X}_D^S,\theta^S\right)=1\right.\right]\\
&\quad+\Pr\left[D^S\left(\mathbf{X}_D^S,\theta^S\right)=0\right]\Pr\left[E_0^S\left(\mathbf{X}_E^S,\theta^S\right)=1\left|D^S\left(\mathbf{X}_D^S,\theta^S\right)=0\right.\right]E\left[Y_0^S\left(\mathbf{X}_Y^S,\theta^S\right)\left|D^S\left(\mathbf{X}_D^S,\theta^S\right)=0\right.\right]\\
&-\Pr\left[D^G\left(\mathbf{X}_D^{H_X},\theta^{H_\theta}\right)=1\right]\Pr\left[E_1^G\left(\mathbf{X}_E^{H_X},\theta^{H_\theta}\right)=1\left|D^G\left(\mathbf{X}_D^{H_X},\theta^{H_\theta}\right)=1\right.\right]E\left[Y_1^G\left(\mathbf{X}_Y^{H_X},\theta^{H_\theta}\right)\left|D^G\left(\mathbf{X}_D^{H_X},\theta^{H_\theta}\right)=1\right.\right]\\
&-\Pr\left[D^G\left(\mathbf{X}_D^{H_X},\theta^{H_\theta}\right)=0\right]\Pr\left[E_0^G\left(\mathbf{X}_E^{H_X},\theta^{H_\theta}\right)=1\left|D^G\left(\mathbf{X}_D^{H_X},\theta^{H_\theta}\right)=0\right.\right]E\left[Y_0^G\left(\mathbf{X}_Y^{H_X},\theta^{H_\theta}\right)\left|D^G\left(\mathbf{X}_D^{H_X},\theta^{H_\theta}\right)=0\right.\right]
\end{aligned}
\tag{8}
$$

Notice that differences in schooling or employment choices across groups (i.e., $\Pr\left[D^S\left(\mathbf{X}_D^S,\theta^S\right)=1\right]$ versus $\Pr\left[D^G\left(\mathbf{X}_D^{H_X},\theta^{H_\theta}\right)=1\right]$ and $\Pr\left[E_D^S\left(\mathbf{X}_E^S,\theta^S\right)\left|D^S\left(\mathbf{X}_D^S,\theta^S\right)=D\right.\right]$ versus

$\Pr\left[E_D^G\left(\mathbf{X}_E^{H_X},\theta^{H_\theta}\right)\left|D^G\left(\mathbf{X}_D^{H_X},\theta^{H_\theta}\right)=D\right.\right]$) are important in determining the overall income gap because they mediate the way income differences between homosexuals and heterosexuals for each level of education or employment choice enter in the overall gap calculation.

Table 4 presents the results using two counterfactual simulations on college enrollment, employment, and yearly income.[24] For reference, I present the fitted values of the model for heterosexuals (i.e., $\Pr\left[D^S\left(\mathbf{X}_D^S,\theta^S\right)=1\right]$, $\Pr\left[E^S\left(\mathbf{X}_E^S,\theta^S\right)=1\right]$ and $E\left[Y^S\left(\mathbf{X}_Y^S,\theta^S\right)\right]$). I present both the censored and the uncensored income means. With the label *basic*, I present the fitted

[24]Results using full time employment are available upon request.

Table 4: Heterosexual and Homosexual Annual Income and College Enrollment Under Different Assumptions

	College Enrollment			
	Heter.	Homosexuals		
	Basic	Basic	Eq Gender	Het. Unobs
SI	0.654	0.719	0.710	0.613
SP	0.665	0.662	0.657	0.645

	Income and Labor Market Participation								
	SI								
	No College			College			Overall		
	Empl.	CensY	Y	Empl.	CensY	Y	Empl.	CensY	Y
Het.	0.854	281.422	240.357	0.793	285.450	226.475	0.814	283.990	231.276
Hom.	0.731	257.434	188.752	0.694	256.336	177.723	0.704	257.142	181.236
Hom. (Eq Gender)	0.758	278.577	211.919	0.656	260.026	170.396	0.685	266.456	182.852
Hom. (Het. Unobs)	0.553	277.621	156.301	0.662	282.267	188.795	0.620	286.945	177.971
	SP								
	No College			College			Overall		
	Empl.	CensY	Y	Empl.	CensY	Y	Empl.	CensY	Y
Het.	0.860	280.631	241.409	0.789	287.072	226.563	0.813	284.782	231.543
Hom.	0.745	263.791	196.365	0.694	240.754	167.424	0.712	250.464	178.354
Hom. (Eq Gender)	0.750	280.686	210.683	0.671	244.829	164.535	0.699	259.086	181.223
Hom. (Het. Unobs)	0.744	277.236	205.895	0.692	286.362	202.311	0.710	296.529	214.757

Note: The values presented are result of 40,000 simulations for each *basic* model and 200,000 simulations for each counterfactual model. *Empl.* stands for probability of being employed. *CensY.* is the censored income. Y stands for the uncensored income (i.e., including the zeros of the unemployed). *Het.* presents the fitted values of the model for heterosexuals (i.e., $\Pr\left[D^S\left(\mathbf{X}_D^S, \theta^S\right) = 1\right]$, $\Pr\left[E^S\left(\mathbf{X}_E^S, \theta^S\right) = 1\right]$ and $E\left[Y^S\left(\mathbf{X}_Y^S, \theta^S\right)\right]$). The label *basic* presents the fitted values for the homosexual sample with their own characteristics (i.e., $\Pr\left[D^G\left(\mathbf{X}_D^G, \theta^G\right) = 1\right]$, $\Pr\left[E^G\left(\mathbf{X}_E^G, \theta^G\right) = 1\right]$ and $E\left[Y^G\left(\mathbf{X}_Y^G, \theta^G\right)\right]$). *Eq Gender* presents a counterfactual in which the gender proportion in the homosexuals' samples is equated to the one in the heterosexuals' samples. Label *Het. Unobs* presents the simulated means of homosexuals when the gender distribution and the unobservables are taken from the heterosexual sample (i.e., $\Pr\left[D^G\left(\mathbf{X}_D^G, \theta^S\right) = 1\right]$, $\Pr\left[E^G\left(\mathbf{X}_E^G, \theta^S\right) = 1\right]$ and $E\left[Y^G\left(\mathbf{X}_Y^G, \theta^S\right)\right]$). *Source*: Own calculations.

Table 5: Gap of Annual Income and College Enrollment of Homosexuals Under Different Assumptions

	College Enrollment		
	Homosexuals		
	Basic	*Eq Gender*	*Het. Unobs*
SI	-0.065***	-0.056**	0.041*
SP	0.003	0.008	0.020

Income and Labor Market Participation

SI

	No College			College			Overall		
Hom.	Empl.	CensY	Y	Empl.	CensY	Y	Empl.	CensY	Y
Basic	0.123***	23.989**	51.604***	0.100***	29.113***	48.752***	0.110***	26.848***	50.040***
Eq Gender	0.096**	2.845	28.438*	0.138***	25.424***	56.079***	0.129***	17.534***	48.424***
Het. Unobs	0.301***	3.801	84.055***	0.131***	3.182	37.679***	0.194***	-2.955	53.305***

SP

	No College			College			Overall		
Hom.	Empl.	CensY	Y	Empl.	CensY	Y	Empl.	CensY	Y
Basic	0.115***	16.840	45.045***	0.095***	46.318***	59.139***	0.102***	34.318***	53.189***
Eq Gender	0.110***	-0.056	30.727**	0.118***	42.243***	62.028***	0.115***	25.696***	50.320***
Het. Unobs	0.117***	3.395	35.514**	0.098***	0.710	24.252**	0.103***	-11.747	16.786*

Note: *** p<0.01, ** p<0.05, * p<0.1. The values presented are result of 40,000 simulations for each *basic* model and 200,000 simulations for each counterfactual model. *Empl.* stands for probability of being employed. *CensY.* is the censored income. Y stands for the uncensored income (i.e., including the zeros of the unemployed). *Het.* presents the fitted values of the model for heterosexuals (i.e., $\Pr\left[D^S\left(\mathbf{X}_D^S,\theta^S\right)=1\right]$, $\Pr\left[E^S\left(\mathbf{X}_E^S,\theta^S\right)=1\right]$ and $E\left[Y^S\left(\mathbf{X}_Y^S,\theta^S\right)\right]$). The label *basic* presents the fitted values for the homosexual sample with their own characteristics (i.e., $\Pr\left[D^G\left(\mathbf{X}_D^G,\theta^G\right)=1\right]$, $\Pr\left[E^G\left(\mathbf{X}_E^G,\theta^G\right)=1\right]$ and $E\left[Y^G\left(\mathbf{X}_Y^G,\theta^G\right)\right]$). *Eq Gender* presents a counterfactual in which the gender proportion in the homosexuals' samples is equated to the one in the heterosexuals' samples. Label *Het. Unobs* presents the simulated means of homosexuals when the gender distribution and the unobservables are taken from the heterosexual sample (i.e., $\Pr\left[D^G\left(\mathbf{X}_D^G,\theta^S\right)=1\right]$, $\Pr\left[E^G\left(\mathbf{X}_E^G,\theta^S\right)=1\right]$ and $E\left[Y^G\left(\mathbf{X}_Y^G,\theta^S\right)\right]$). *Source*: Own calculations.

values for the homosexual sample keeping their own characteristics (i.e., $\Pr\left[D^G\left(\mathbf{X}_D^G, \theta^G\right) = 1\right]$, $\Pr\left[E^G\left(\mathbf{X}_E^G, \theta^G\right) = 1\right]$ and $E\left[Y^G\left(\mathbf{X}_Y^G, \theta^G\right)\right]$). Under the label *Equalizing Gender*, I present the simulations correcting for the fact that there are more women than men defined as homosexuals (see Table 1), and if women earn consistently less than men, the gaps I calculate could be confounding the effect of belonging to a sexual minority with the effect of being a woman. By equalizing the gender distributions across groups, I prevent gender discrimination biasing the comparisons. Under the label *Het. Unobs*, I present the simulated college enrollment, employment, and income means of homosexuals when the gender distribution and the unobservables are taken from the heterosexual sample (i.e., $\Pr\left[D^G\left(\mathbf{X}_D^G, \theta^S\right) = 1\right]$, $\Pr\left[E^G\left(\mathbf{X}_E^G, \theta^S\right) = 1\right]$ and $E\left[Y^G\left(\mathbf{X}_Y^G, \theta^S\right)\right]$).

Table 5 presents the estimated gaps between heterosexuals and homosexuals under the counterfactuals described above and using the intuition of Equation (8). Table 5 shows that relative to heterosexuals, homosexuals are 6.5 percent more likely to achieve tertiary education, they are 10 percentage points less likely to be employed, and once employed they earn 9.45 percent (SI) and 12 percent (SP) less.[25] Going into detail, the results show that the income gaps are larger among college-educated workers, who earn 10.2 percent (SI) and 16 percent (SP) less than comparable heterosexuals.

Table 5 also shows that the only effect equalizing the gender distribution in the sexual minority groups is the elimination of the earning gaps among workers with no college education.

When I equate skills distributions and gender rations across sexual preferences, income gaps disappear for those employed. The effect is evident regardless of the tertiary education choice. This is due to the high returns skills have among homosexuals, and it happens despite the fact that

[25]Figures obtained from dividing the gap calculated on the censored income by the mean income of heterosexuals under each definition. For instance, the proportional gap under the SI definition is given by 9.45 percent=26.848/283.99.

in this scenario, homosexuals would be 4.1 percent less likely to go to college than heterosexuals. However, homosexuals remain less employable by 19 and 10 percentage points for the SI and SP definitions, respectively. That is, the overall probability of getting a job would worsen by 6.5 percentage points in the case of the SI definition, relative to the counterfactual where only the gender proportions were equalized. This effect would come mainly from the further deterioration that would take place in the probability of being employed among people that would not have gone to college. The gap in employment probability against non-college-educated homosexuals would amount to 30.1 (SI) and 11.7 (SP) percentage points.

The results of the last counterfactual simulation indicate that there is no evidence of income discrimination among people that are working. However, becoming employed is the difficult part for homosexuals. The counterfactual simulations show that there is a 10.3–19.4 percentage point difference in the probability of being employed that cannot be explained due to differences of skills and gender composition. That gap is discrimination. And this is where the flexibility of the model with endogenous choices helps interpreting how the mechanisms that create the gaps work. Based on the loadings presented in Table C.2, it is evident that highly skilled homosexuals will sort into college, and among those, due to discrimination, the most highly skilled will be able to sort into employment. Hence, the ones who end up college-educated and employed are a very select group who face high returns to their high stocks of skills. That way, I can reconcile the fact that, in the last counterfactual, homosexuals were provided with a distribution of skills that had greater variance with the elimination of the gap among those who managed to get a job. The barrier homosexuals face is getting a job—a barrier that becomes taller for those who did not sort into college education simply because they have fewer skills than the ones who did.

6 Homosexuality as a Latent Continuous Variable

6.1 Identification of the latent homosexuality factor

Homosexuality is not a dichotomous variable, but a continuum of sexual preferences and perceptions. To incorporate that definition, I develop a model in which homosexuality is an additional source of unobserved heterogeneity. Such an approach is particularly well suited in this case as homosexuality is often veiled and only in some cases it is openly manifested or inferred by others. In that sense, homosexuality is a continuous characteristic—unobserved to the econometrician—that influence the answers given to the the sexual preferences/perceptions questionnaire, resembling the relation between latent skills and manifest scores presented in Section 4.1. Furthermore, latent factor models allows pro- or antigay contexts in which the respondent lives to mediate the answers to the questionnaire. Hence, I use the reported answers to the questions on sexual preferences, sexual interest, and gender of sexual partners as three manifest scores that are affected by the true latent homosexuality ϖ and societal, household or personal or contexts $\mathbf{X}_S$

$$
\begin{aligned}
S_{SX} &= \mathbf{X}_S \beta_{SX} + \lambda_{SX} \varpi + \epsilon_{SX} \\
S_{SP} &= \mathbf{X}_S \beta_{SP} + \lambda_{SP} \varpi + \epsilon_{SP} \\
S_{SI} &= \mathbf{X}_S \beta_{SI} + \lambda_{SI} \varpi + \epsilon_{SI}
\end{aligned}
\tag{9}
$$

where $\epsilon_{SX} \perp \epsilon_{SP} \perp \epsilon_{SI}$. Then, using the framework presented in Section 4.1, I identify the underlying distribution of the unobserved degree of homosexuality $F_{\varpi}(\cdot)$ clean from observable contexts that could affect the *answers* collected in the sexual preferences/perceptions questionnaire.

In practice, however, a complication arises because answers to the questionnaire are not

smoothly spread out across the possible categories. The majority of respondents locate themselves at the heterosexual extreme in each question. In consequence, measurement system (9) needs to be modified to accommodate such skewed distributions of the answers. To do so, I allow S_{SX} and S_{SP} to be binary scores that take the value of one if the respondent chose any answer different to the extreme heterosexual option. I allow S_{SI} to be a left-tailed censored variable for which there is a mass at the heterosexual extreme and number of individuals in each of the other categories that report increasing levels of homosexuality. It is important to note that while the manifest sores are not continuous, the latent score is. Therefore, measurement system (9) becomes:

$$
\begin{aligned}
S_{SX} &= \mathbb{1}\left[\mathbf{X}_S\beta_{SX} + \lambda_{SX}\varpi + \epsilon_{SX}\right] \\
S_{SP} &= \mathbb{1}\left[\mathbf{X}_S\beta_{SP} + \lambda_{SP}\varpi + \epsilon_{SP}\right] \\
S_{SI} &= \begin{cases} 0 & \text{if } \mathbf{X}_S\beta_{SI} + \lambda_{SI}\varpi + \epsilon_{SI} \leq 0 \\ \mathbf{X}_S\beta_{SI} + \lambda_{SI}\varpi + \epsilon_{SI} & \text{if } \mathbf{X}_S\beta_{SI} + \lambda_{SI}\varpi + \epsilon_{SI} > 0 \end{cases}
\end{aligned}
\tag{10}
$$

Assuming that ϵ_{SX}, ϵ_{SP}, and ϵ_{SI} follow a standard normal, then the estimation entails a system comprised by two probits and a type-I Tobit model—in Amemiya (1985, p. 384) parlance—with unobserved heterogeneity. Identification of all parameters in the system, including the ones that determine $F_{\varpi}(\cdot)$, require the normalization $\lambda_{SI}/\sigma_{\epsilon_{SI}} = 1$.

6.1.1 Complete Sample

Table 6: Identification of Homosexuality as a Latent Factor

	Sex. Partner[a]		Self Perception[b]		Sex. Interest[c]	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Complete Sample (Obs.=2859)						
Age	-0.355	(0.303)	0.358	(0.375)	0.311	(0.360)
Age Sq.	0.010	(0.010)	-0.016	(0.012)	-0.012	(0.012)
Female	0.279***	(0.091)	0.892***	(0.107)	1.431***	(0.114)
MotherSES: High	0.412***	(0.154)	0.375**	(0.166)	0.657***	(0.179)
LivesBothParents	-0.369***	(0.101)	-0.363***	(0.107)	-0.223*	(0.115)
Latent Homosex.	0.578***	(0.047)	0.774***	(0.070)	1	
Constant	1.449	(2.330)	-3.427	(2.853)	-4.150	(2.766)
Men (Obs.=1291)						
Age	0.048	(0.557)	0.547	(0.747)	1.923	(1.244)
Age Sq.	-0.002	(0.018)	-0.022	(0.025)	-0.066	(0.042)
MotherSES: High	0.660**	(0.265)	1.032***	(0.296)	2.090***	(0.528)
LivesBothParents	-0.400**	(0.165)	-0.597***	(0.192)	-0.328	(0.269)
Latent Homosex.	0.417***	(0.059)	0.578***	(0.084)	1	
Constant	-2.179	(4.261)	-5.434	(5.641)	-18.127**	(9.128)
Women (Obs.=1568)						
Age	-0.510	(0.357)	0.232	(0.385)	0.078	(0.413)
Age Sq.	0.015	(0.011)	-0.011	(0.012)	-0.003	(0.013)
MotherSES: High	0.423**	(0.197)	0.209	(0.192)	0.538**	(0.238)
LivesBothParents	-0.351***	(0.126)	-0.252**	(0.119)	-0.200	(0.149)
Latent Homosex.	0.495***	(0.055)	0.567***	(0.065)	1	
Constant	2.891	(2.751)	-1.766	(2.935)	-1.350	(3.190)

Note: *** p<0.01, ** p<0.05, * p<0.1. *Source*: Own calculations.
[a]Binary Score. Takes the value of one if respondent has ever had at least one sexual partner of the same gender. Estimated as a probit.
[b]Binary Score. Takes the value of one if respondent considers he/she is non-heterosexual in any degree. Estimated as a probit.
[c]Left-tail censored variable. Estimated as a tobit.

Table 6 presents the estimated parameters of the measurement system (10) used to identify the latent factor of homosexuality for the complete sample. It shows that the latent factor presented in Figure 3 greatly affects the scores purveyed by the answers to the sexual preferences/perceptions questionnaire. In fact, my findings suggest that the factor loadings are large and statistically different from zero at the 1 percent level. Furthermore, as expected, some contexts matter in

the determination of the answers to the questionnaire. The results in Table 6 show that women and people that come from a high SES household tend to report higher homosexuality *scores*, while those that live with both parents as a child tend to do the opposite. These are interesting findings as they epitomize the role contexts play in determining the answers to the sexual preferences/perceptions questionnaire. They show that people of higher SES have less trouble with revealing a nonzero degree of homosexuality in all three measures, while people with biparental households during childhood have a harder time doing so.

6.1.2 Identification of Gender-Specific Homosexuality Factors

The empirical approach I follow in this section allows me to further explore differences in discrimination against homosexuals depending on the gender of the worker. Not finding any discrimination could be a misleading result that masks the possibility of the existence of gender-specific effects of discrimination. To overcome this, I identify gender-specific unobserved homosexual heterogeneity distributions, using the measurement system whose estimates are also presented in Table 6. They show that SES and household composition affect the homosexuality scores reported independently from the gender of the sample used.

6.2 Homosexuality Factor, Education, and Labor Market

Having estimated the distribution from which the latent homosexuality heterogeneity is drawn, I can use it to estimate the effect that latent variable has on different outcomes. Furthermore, I keep controlling for the other source of unobserved heterogeneity: skills that I identified for the complete and the gender-specific samples using the measurement system (3). Hence, the labor

market variables can be analyzed using a model like (2) as follows:

$$\mathbf{Y} = \mathbf{X}_Y \beta^Y + \alpha_\theta^Y \theta + \alpha_\varpi^Y \varpi + \mathbf{e}^{\mathbf{Y}}$$

where $\mathbf{\Theta} = [\theta, \varpi]$ are the dimensions of unobserved heterogeneity and θ are the latent skills and ϖ is the unobserved homosexuality factor. The usual assumptions for the error terms hold. That is, $\mathbf{e}^{\mathbf{Y}} \perp (\tau, \varpi, \mathbf{X_Y})$ distributed following $f_{e^{y_m}}(\cdot)$ such that $e^{y_i} \perp e^{y_j}$ for every $m = 1, \ldots, M$.

6.2.1 Models without Endogenous Choice of Schooling

As with the previous models used in this paper, I would like to start the analysis of the effect of homosexuality as unobserved heterogeneity using a model that allows for endogenous choices on employment but without the endogenous choice of education. That is, models of the form

$$E = \mathbb{1}\left[\alpha^E + \beta^E \mathbf{X}_E + \alpha^E \theta + \lambda^E \varpi + \epsilon > 0\right]$$

$$Y = \alpha + \beta \mathbf{X}_Y + \psi IMR + \alpha^Y \theta + \lambda^Y \varpi + \varepsilon \qquad \text{if } E = 1$$

Table 7 presents the results for the complete sample and for the gender specific samples. In particular, it shows that discrimination against homosexuals happens at the time of obtaining a job and not at the income earned itself. It is evident that the homosexuality factor is negatively related with the probability of being employed, while that is not the case for the income earned.[26] To analyze the dimensions of those gaps, I use the estimates to predict employment and income

[26] Table G.2 in the Appendix presents further evidence on the effect of the homosexuality factor on labor-market-related choices. They are the results of estimating models with latent skills on a number of choices like labor market participation, employment, full time employment and working in a white collar occupation. In line with previous results, they indicate that people with a higher degree of homosexuality are less likely to be economically active and employed. Also, it shows no relation between the homosexuality factor and the likelihood of working in a white collar occupation.

Table 7: Homosexuality Factor in Model with Selection Equations

	Overall Sample		Males		Females	
	Income	Employed	Income	Employed	Income	Employed
IncomeEmpl						
Latent Homosex.	-2.325	-0.080***	-3.602	-0.065***	-2.609	-0.061**
	(2.776)	(0.019)	(2.642)	(0.021)	(2.807)	(0.026)
Latent Skills	29.734*	0.415***	39.490**	0.272	19.398	0.502***
	(15.663)	(0.135)	(18.402)	(0.189)	(19.711)	(0.173)
Obs.(N|Censored)	2214	1781	971	803	1243	978
IncomeFullTime4						
Latent Homosex.	-3.695	-0.075***	-2.401	-0.075***	-6.764**	0.022
	(2.890)	(0.020)	(2.995)	(0.020)	(3.036)	(0.022)
Latent Skills	24.375	0.447***	29.363	0.287	9.903	0.282*
	(17.671)	(0.145)	(19.906)	(0.175)	(20.836)	(0.154)
Obs.(N|Censored)	1816	1383	982	738	1293	645

Note: *** p<0.01, ** p<0.05, * p<0.1. The controls used in all the equation and not presented in the Table are: age, age squared, gender (complete sample only), dummies for father's education, whether as a child the person lived with one parent, a remarried parent or with no parents, and the Inverse Mills Ratio. *Source*: Own calculations.

for each level of the homosexuality factor by simulating them with 40,000 draws of each source of unobserved heterogeneity.[27]

Figure 4 shows the results of the simulations on the employment margin—those on the income part of the model can be found in Figure F.1 in Appendix F. They indicate that going from the heterosexual extreme to the homosexual extreme of the homosexuality factor distribution—holding everything else constant—decreases the probability of being employed by 14.76 percentage points, a number consistent with the gaps measured in Section 5 based on the dichotomous definitions of homosexuality. The same pattern is observed when analyzing full-time workers. High levels of the latent factor of homosexuality face a probability of being full-time employed 9 percentage points

[27]Tables D.1 and D.2 in the Appendix show that the models do a good job fitting the means and standard errors of the actual labor market variables.

lower.

As mentioned above, one of the advantages of analyzing homosexuality as a source of unobserved heterogeneity is that I can estimate gender-specific homosexuality factors and analyze discrimination against gay men separately from discrimination against lesbians. Using the gender specific model whose results I also present in Table 7, and whose goodness-of-fit I also check in Tables D.1 and D.2 in the appendix, I predict the probability of employment and income for each level of the homosexuality factor.

Gender-Specific Model, Men: Figure 5 analyzes labor market discrimination against gay men. They show a steep negative gradient between the level of latent homosexuality and the chances of getting a job. In fact, extreme homosexual men are 18.11 percentage points less likely to be employed and 25.54 percentage points less likely to hold a full-time job than extreme heterosexual men.

Gender-Specific Model, Women: Discrimination against homosexual women is different. Figure 6 shows that the employment situation of women depends on whether they are full time employed or not. Homosexual women face a 13.57 percentage points lower probability of finding *a* job than extreme heterosexual women. However, lesbians have the same probability of finding a full-time job as heterosexual women. Due to this lack of selection and contrary to the men's situation, homosexual women do face discrimination in terms of income in full-time jobs. Women with high values of the homosexuality factor receive, on average, an income from their full-time jobs that is 16.39 percent shorter that what comparable heterosexual women receive.

6.2.2 Models with Endogenous Choice of Schooling (Roy Model)

Now, I consider a full Roy model of endogenous college choice. It allows me to see any differential effects of homosexuality on income and employment by education level. The estimated model is very similar to the system of equations presented in (6), with an extension to include two dimensions of unobserved heterogeneity: skills and homosexuality.

Table 8 presents the main results of the estimation on the complete and the gender-specific samples.[28] It shows that homosexual men are more likely to go to college than their heterosexual counterparts by about 15.7 percentage points—the figure comes from comparing those in the first decile of the homosexuality factor to those in the top decile. Such a phenomenon is not present among women. Although Table 7 shows that homosexuality affects the chances of getting both *a* job and a full-time job, Table 8 reveals that the selection channels in each margin differ: while homosexuality diminishes the probability of being employed regardless of the education level (by about 12 percentage points according to Figures 7), it does so only to the college educated in the full-time job margin (by about 10 percentage points).[29]

Table 8 also documents gender-specific effects. In fact, in Section 6.2.1 I already showed that labor market discrimination for homosexual women works differently than the discrimination against homosexual men. The Roy model with endogenous education choices allows me to check the extent to which discrimination varies across levels of educational attainment at each gender. I find that the employment discrimination against homosexual men documented in Table 7 is driven mainly by the employment discrimination against college-educated homosexual men. In

[28] Goodness-of-fit of the models is presented in Tables D.1, D.2 and D.3 in the Appendix. The models perform extremely well in fitting the first and second moments of the variables observed in the data.

[29] For the sake of brevity, I do not present the simulations to every outcome in each subsample in the main text. They can be found in Appendix F.

Table 8: Homosexuality Factor in a Roy Model with Selection Equations

	College†	Income		Employed†	
		NoCollege	*College*	*NoCollege*	*College*
IncomeEmpl					
Overall					
Latent Homosex.	0.019	1.998	-4.329*	-0.077**	-0.065***
	(0.020)	(2.929)	(2.391)	(0.037)	(0.024)
Latent Skills	0.380***	23.894	47.461***	0.166	0.659***
	(0.133)	(17.191)	(16.953)	(0.238)	(0.176)
Males					
Latent Homosex.	0.043**	-0.944	-3.098	-0.040	-0.070***
	(0.019)	(2.785)	(2.621)	(0.038)	(0.027)
Latent Skills	0.349**	25.439	71.259***	-0.006	0.593**
	(0.173)	(21.779)	(25.955)	(0.324)	(0.261)
Females					
Latent Homosex.	-0.012	3.417	-4.137	-0.075	-0.038
	(0.026)	(2.976)	(2.788)	(0.050)	(0.030)
Latent Skills	0.532***	10.660	27.472	0.315	0.663***
	(0.181)	(19.457)	(19.879)	(0.305)	(0.221)
IncomeFullTime4					
Overall					
Latent Homosex.	0.021	0.273	-3.077	0.000	-0.035
	(0.020)	(3.397)	(2.589)	(0.034)	(0.022)
Latent Skills	0.350***	33.182	36.756*	0.147	0.415***
	(0.129)	(20.183)	(19.080)	(0.216)	(0.155)
Males					
Latent Homosex.	0.047**	-1.047	-1.238	-0.032	-0.084***
	(0.019)	(2.996)	(2.793)	(0.035)	(0.025)
Latent Skills	0.331*	34.831	41.267	-0.116	0.660***
	(0.170)	(22.595)	(27.263)	(0.301)	(0.244)
Females					
Latent Homosex.	-0.012	0.372	-4.553	0.046	0.021
	(0.025)	(3.345)	(3.103)	(0.044)	(0.026)
Latent Skills	0.477***	8.148	29.693	0.316	0.247
	(0.173)	(23.676)	(22.790)	(0.279)	(0.194)

Note: *** p<0.01, ** p<0.05, * p<0.1. Controls used in the college choice equation are: age, age squared, gender (in the overall sample), municipality population, mother's and father's education, indicators of skipping school, taken out of classroom and police contact while teenager. Controls in the selection equations are: age, age squared, gender (in the overall sample), whether as a child the person lived with both parents, indicator for practicing sports while teenager and male labor force participation rate in the 25 to 39 age bracket in the municipality. Controls in the income equations are: age, age squared, gender (in the overall sample), father's SES, and mother's education. The College variable takes the value of 1 when the person has undertaken any kind of tertiary education in colleges (*høyskole*) or universities (*universitetet*). This includes three-year, four-year college studies or studies in the university with the same length. Total observations for overall, male and female employed sample: 2,127, 937 and 1,190. Total observations for overall, male and female full time sample: 2,218, 951 and 1,267. *Source*: Own calculations. †Coefficients, not marginal effects.

fact, Figures 8 suggest that the employment gap between college educated heterosexual men and college-educated men with high values of the homosexuality factor is 22 percentage points. The gap balloons to 31 percentage points if we consider full-time employment. Consistent with previous results, I find no effect of latent homosexuality on the income earned on the job, regardless of the education choice.

The results in Table 8 indicate that the gap in the probability of employment against homosexual women documented in Table 7 is due mainly to the discrimination faced by homosexuals without college education. It also shows that college-educated lesbians are the ones who face the income penalty documented above. In fact, the simulated income earned once employed for each level of homosexuality factor presented in Figures 9 show that employed homosexual women earn 10.7 percent less than the extreme heterosexual ones, and 11.37 percent if they are employed full time.

7 Conclusions

This paper incorporates differences in skill distributions and tastes for schooling and employment into the analysis and quantification of the gaps in labor market outcomes observed against homosexual workers. In the process, I extend the Roy model with unobserved heterogeneity to account for endogenous choices of employment. The results from the model indicate that there are in fact differences in the variance distribution of unobserved skills characteristics between homosexual and heterosexual workers, and that these traits have different effects on education and employment choices, as well as different returns in terms of income across different sexual preferences groups. In particular, skills are more rewarded in terms of income among homosexuals than among hetero-

sexuals. All these results indicate that there are several forces working simultaneously in opening the income gaps observed.

My findings indicate that homosexuals face a probability of finding a job that is 10–20 percentage points lower than the probability faced by a heterosexual. I find that the gap is not explained by differences in the stock of skills or gender composition. I also find that once employed, homosexuals face no income gap because the ones that get a job are highly skilled, and the market rewards those skills profusely. In a second model, I incorporate homosexuality as a latent continuous construct. My findings corroborate the ones obtained from the previous models, attesting to the fact that the biggest hurdle homosexuals face in the labor market is getting a job. Furthermore, the second model allows me to analyze gender-specific outcomes. I find that discrimination in getting a job is greater for homosexual men, but lesbians are also penalized through the income earned, especially the college-educated who manage to get a full-time job.

This is the first paper to incorporate endogenous decisions and unobserved heterogeneity in the analysis of income discrimination against homosexuals. My results show that the overall income gaps observed come entirely from a significant difference in the probability of being employed. Thus, future research is required to improve our understanding of the reasons behind these employability differences. That way, economic research will provide arguments that will help to push forward equality, as barriers against sexual minorities continue to fall in other aspects of life.

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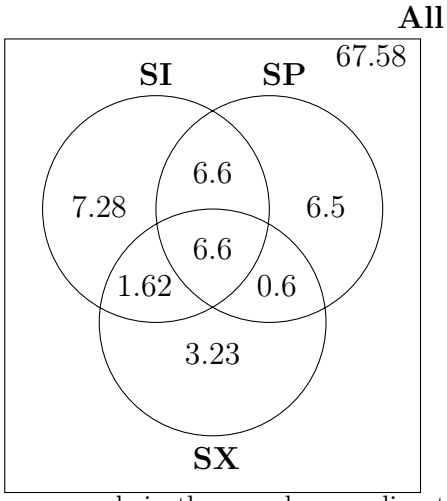
Figures

Figure 1: Homosexuals According to Each Definition

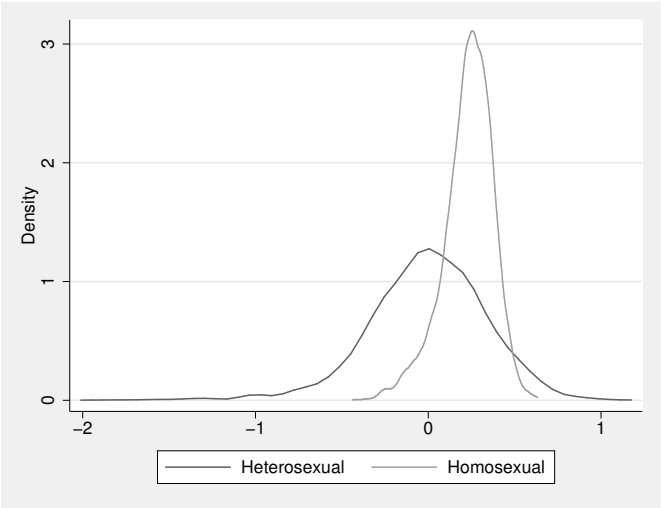
	SI	SP	SX
Observations	644	591	350
% of Population			
Overall	22.0	20.2	11.9
Males	11.4	12.9	10.2
Females	30.7	26.1	13.3



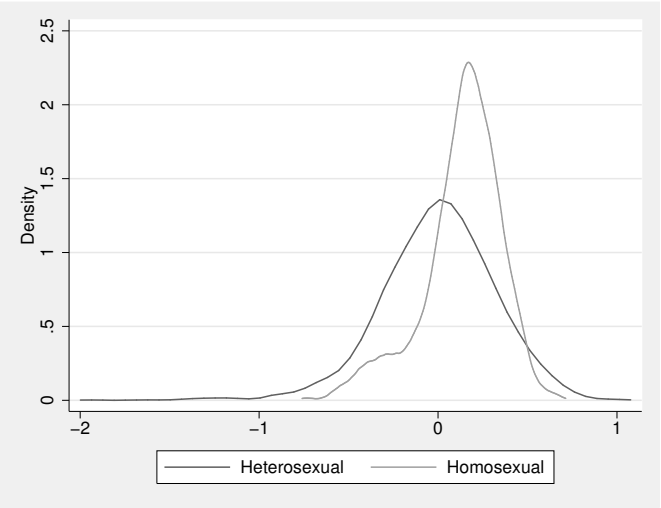
Note: The left panel presents the number and proportion of homosexuals in the sample according to each definition of homosexuality. The right panel presents the Venn's diagram of those observations and definitions in the data. *SI* corresponds to sexual interests and considers to be homosexual any individual that is attracted in any degree to people of the same sex. *SP* corresponds self-perception considers as homosexual any individual that believes he or she is homosexual in any degree. *SX* corresponds to whether a person has had sex with someone from the same gender. *Source*: Own calculations.

Figure 2: Distribution of Unobserved Abilities by Sexual Preference

(a) According to SI Definition



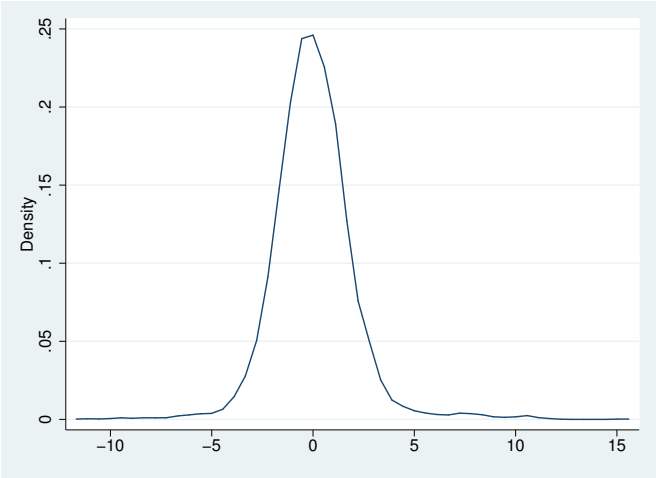
(b) According to SP Definition



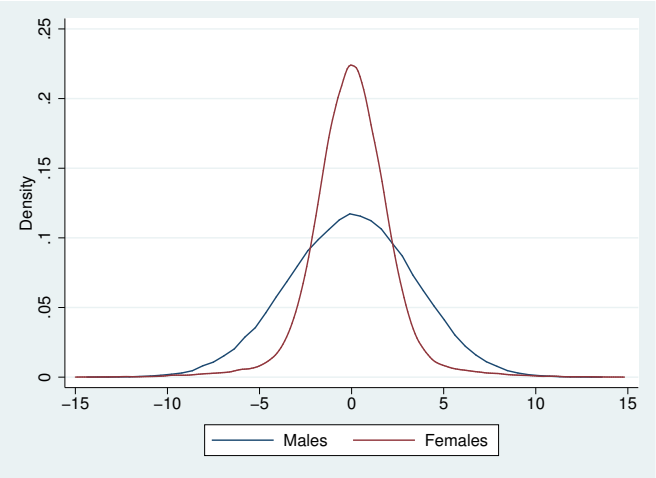
Note: Estimated from measurement systems presented in Tables E.2 to E.5 in Appendix E. Each estimation use the mixing of two normals. Left densities are estimated for those defined as homosexual and heterosexual according to the SI definition. The distributional parameters for the skills of the homosexuals are given by $\mu_1 = -0.153$, $\sigma_1 = 0.174$, $\mu_2 = 0.044$, $\sigma_2 = 0.107$, and the mixing probability is 0.223. The distributional parameters for the skills of the heterosexuals are given by $\mu_1 = -0.585$, $\sigma_1 = 0.483$, $\mu_2 = 0.032$, $\sigma_2 = 0.296$, and the mixing probability is 0.051. Right densities are estimated for those defined as homosexual and heterosexual according to the SP definition. The distributional parameters for the skills of the homosexuals are given by $\mu_1 = -0.450$, $\sigma_1 = 0.142$, $\mu_2 = 0.057$, $\sigma_2 = 0.157$, and the mixing probability is 0.113. The distributional parameters for the skills of the heterosexuals are given by $\mu_1 = -0.690$, $\sigma_1 = 0.450$, $\mu_2 = 0.024$, $\sigma_2 = 0.290$, and the mixing probability is 0.033. *Source*: Own calculations.

Figure 3: Homosexuality Factor

(a) Full Sample

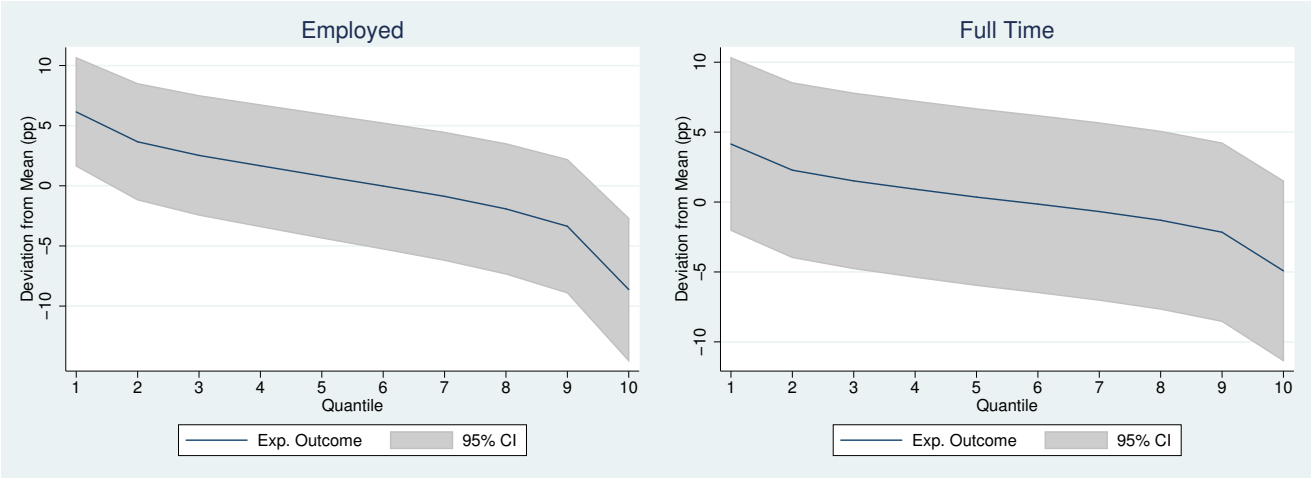


(b) Gender Specific Samples



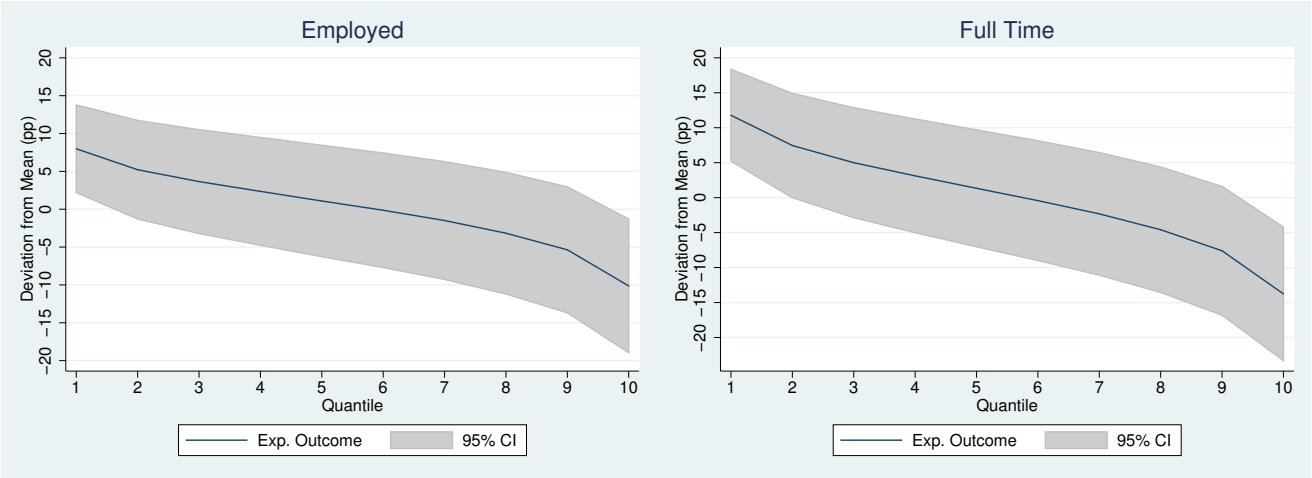
Note: Estimated from measurement systems presented in Table 6. Estimations use the mixing of two normals. Left density is estimated for the complete sample. $\mu_1 = 0.969$, $\sigma_1 = 4.318$, $\mu_2 = -3.264$, $\sigma_2 = 1.429$, and the mixing probability is 0.104. The right figure presents the gender-specific densities. For males: $\mu_1 = 0.825$, $\sigma_1 = 3.115$, $\mu_2 = -2.274$, $\sigma_2 = 3.089$, and the mixing probability is 0.734. For women: $\mu_1 = -0.033$, $\sigma_1 = 4.441$, $\mu_2 = 0.005$, $\sigma_2 = 1.617$, and the mixing probability is 0.133. *Source*: Own calculations.

Figure 4: Probability of Employment at Levels of Homosexuality
Complete Sample



Note: Simulated incomes and employment probabilities using the estimated parameters and 40,000 draws from each dimension of unobserved heterogeneity. *Source*: own calculations.

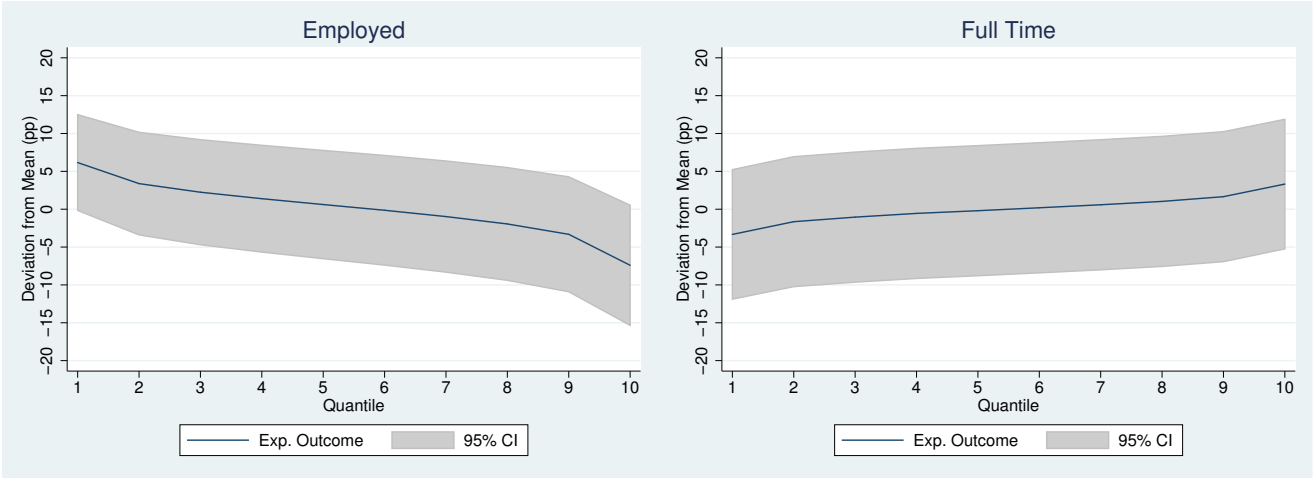
Figure 5: Probability of Employment at Levels of Homosexuality
Men



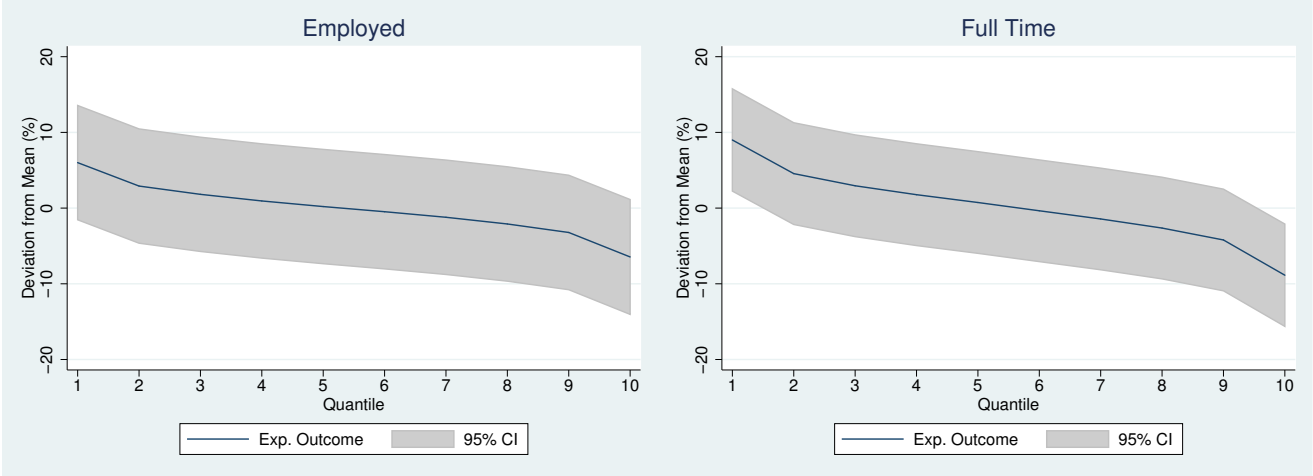
Note: Simulated incomes and employment probabilities using the estimated parameters and 40,000 draws from each dimension of unobserved heterogeneity. *Source*: own calculations.

Figure 6: Women

(a) Women: Probability of Being Employed



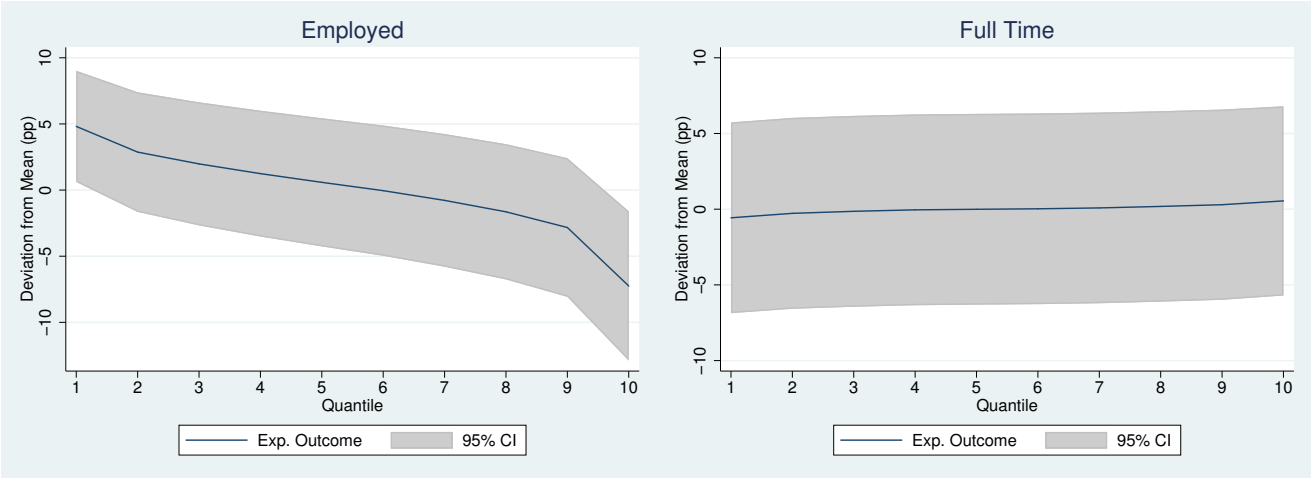
(b) Women: Income (Censored)



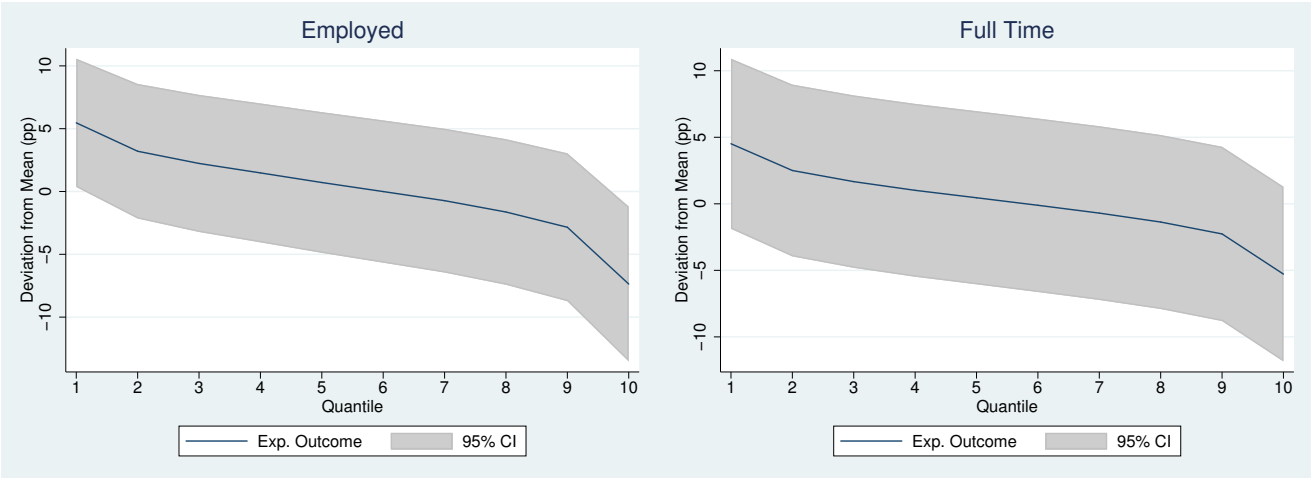
Note: Simulated incomes and employment probabilities using the estimated parameters and 40,000 draws from each dimension of unobserved heterogeneity. *Source*: own calculations.

Figure 7: Probability of Being Employed

(a) Highest Education Level Achieved: No College

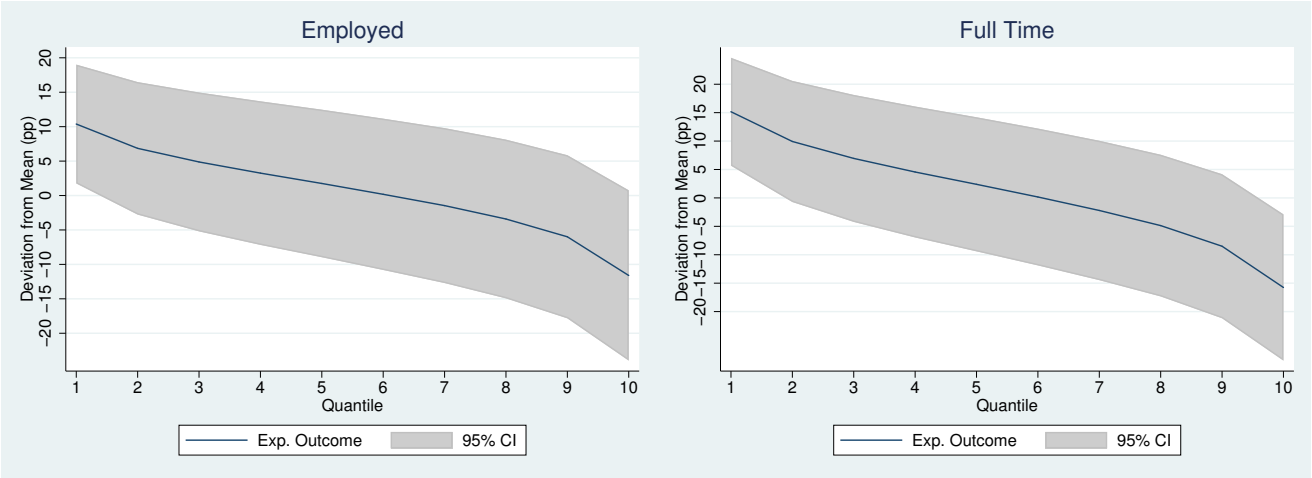


(b) Highest Education Level Achieved: College



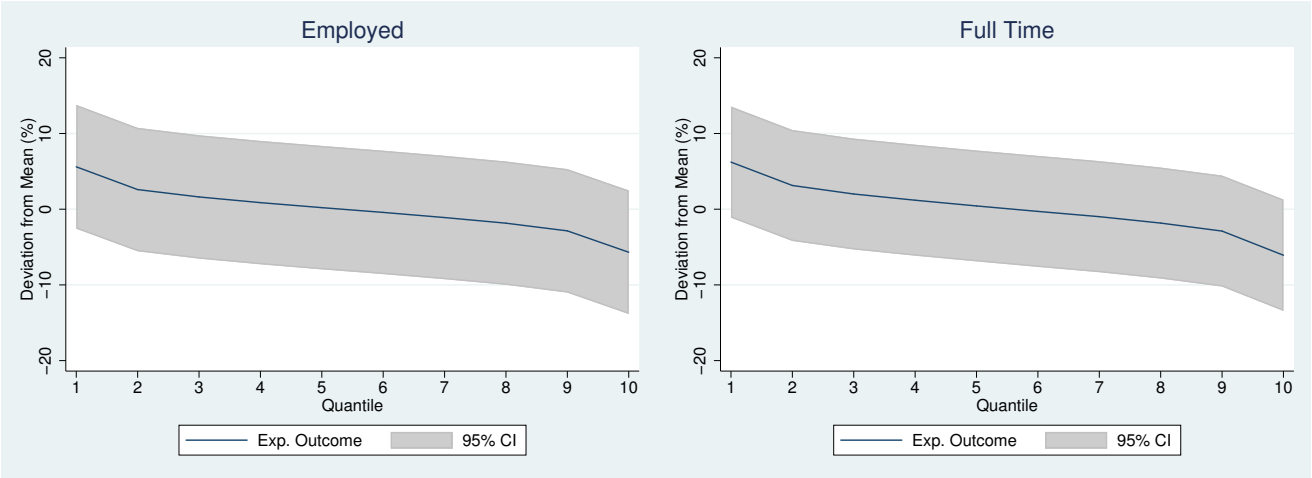
Note: Simulated incomes and employment probabilities using the estimated parameters and 40,000 draws from each dimension of unobserved heterogeneity. *Source: own calculations.*

Figure 8: Men: Probability of Being Employed
Highest Education Level Achieved: College



Note: Simulated incomes and employment probabilities using the estimated parameters and 40,000 draws from each dimension of unobserved heterogeneity. *Source: own calculations.*

Figure 9: Women: Income (Censored)
Highest Education Level Achieved: College



Note: Simulated incomes and employment probabilities using the estimated parameters and 40,000 draws from each dimension of unobserved heterogeneity. *Source:* own calculations.

Appendix

A Descriptive Statistics

Table A.1: Sample Characteristics

		Overall		Males		Females		Heterosex.	
Variable	N	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Demographic									
Age *(Wave 4)*	2958	27.465	1.844	27.384	1.788	27.531	1.886	27.538	1.860
Female *(%)*	2958	0.548	0.498					0.465	0.499
Father's Educ (Wave 1, %)									
University	2958	0.153	0.361	0.153	0.360	0.154	0.361	0.148	0.355
3yr College	2958	0.090	0.286	0.092	0.289	0.088	0.283	0.086	0.281
Vocational	2958	0.138	0.345	0.134	0.341	0.141	0.348	0.141	0.349
Mother's Educ (Wave 1, %)									
University	2958	0.073	0.260	0.073	0.259	0.073	0.261	0.064	0.244
3yr College	2958	0.204	0.403	0.203	0.403	0.204	0.403	0.199	0.399
Vocational	2958	0.038	0.191	0.037	0.190	0.038	0.192	0.039	0.193
Household Composition (Wave 1)									
Siblings	2958	1.720	1.095	1.694	1.094	1.742	1.096	1.727	1.062
Single Parent *(%)*	2958	0.124	0.330	0.128	0.334	0.121	0.326	0.116	0.320
Remarried *(%)*	2958	0.054	0.226	0.052	0.221	0.056	0.230	0.047	0.211
No Parents *(%)*	2958	0.046	0.210	0.040	0.195	0.052	0.222	0.045	0.207
Father's SES (Wave 1, %)									
High	2958	0.268	0.443	0.271	0.445	0.266	0.442	0.263	0.441
Skilled	2958	0.139	0.346	0.135	0.341	0.143	0.350	0.141	0.349
Mother's SES (Wave 1, %)									
High	2958	0.069	0.253	0.076	0.264	0.064	0.244	0.060	0.238
Skilled	2958	0.014	0.118	0.012	0.109	0.016	0.126	0.014	0.116
Scores (Wave 1)									
Soc. Accept.	2892	0.000	0.720	-0.012	0.717	0.010	0.722	0.012	0.714
Sympathetic	2891	-0.001	0.731	-0.173	0.735	0.140	0.697	-0.014	0.737
Self-esteem	2893	0.000	0.733	0.142	0.722	-0.117	0.722	0.038	0.730
Leadership	2836	-0.002	0.581	0.034	0.599	-0.031	0.564	-0.007	0.572
Grades	2726	0.066	1.897	-0.145	1.923	0.241	1.857	0.096	1.931
Scholastic	2892	-0.001	0.673	0.066	0.677	-0.056	0.665	0.025	0.672
College & Labor Mkt (Wave 4, %)									
Any College	2958	0.622	0.485	0.561	0.496	0.673	0.469	0.617	0.486
Active	2626	0.863	0.344	0.886	0.318	0.845	0.362	0.884	0.320
Employed	2626	0.816	0.387	0.829	0.377	0.807	0.395	0.841	0.366
Full Time	2626	0.626	0.484	0.757	0.429	0.524	0.500	0.661	0.474

Note: *University* (*universitetet*) includes program of four or more years. *3yr College* corresponds to the *høyskole*. *Remarried* takes the value of 1 if the person—at that time of wave 1—lived with a parent who remarried. *High SES* describes parents who have a high administrative or academic job. *Soc. Accept.* (social acceptance), *Sympathetic* (capable of building close friendships), *Self-esteem*, *Leadership* and *Scholastic Competence* are measures that come from SPPA scales (Harter, 1988). *Grades* correspond to a demeaned aggregation of school grades (Math, Norwegian and English). The *Any College* variable takes the value of 1 when the person has undertaken any kind of tertiary education in colleges (*høyskole*) or universities (*universitetet*). *Employed* presents the proportion of people employed out of the whole sample, and not out of only those active. The same holds for *Full Time*. *Source*: Own calculations.

B General Distribution of Skills: Income Gap Controlling for Unobservables

In this appendix, I introduce the unobserved skills in a labor market outcome model similar to those of the existing literature. The idea is to expand the reduced-form results to incorporate unobserved heterogeneity. Hence the equation I estimate is

$$Y = \alpha + \gamma Gay + \beta \mathbf{X} + \psi IMR + \lambda\theta + \varepsilon$$
$$E = \alpha_E + \gamma_E Gay + \beta_E \mathbf{X} + \lambda_E \theta + \epsilon$$

where θ is the unobserved skills that are drawn from a general distribution estimated using the complete sample. Like with the reduced-form results, I am interested in the estimates of γ and γ_E. The results are presented in Table B.1 for each definition of homosexuality and each measure of yearly income. These results are similar to the reduced-form results from the third column of Table 2. They suggest that the greatest differences between heterosexuals' and homosexuals' job market rewards are in terms of the access to a job rather than in the amount payed once they have a job. Interestingly, once I control for skills, I find that, unlike homosexual males, lesbians face no difference in the probability of being employed compared to their heterosexual counterparts.

Table B.1: Income Gap Controlling for Skills with Selection Equations

	SI		**SP**		**SX**	
	Income	Employed	Income	Employed	Income	Employed
IncomeEmpl						
Gay	-14.272	-0.623***	-24.379	-0.374***	-14.154	-0.231
	(19.590)	(0.130)	(15.335)	(0.130)	(14.324)	(0.142)
Gay × Female	9.963	0.431***	17.429	0.236	5.909	0.060
	(18.366)	(0.155)	(16.021)	(0.159)	(17.214)	(0.182)
Obs.(N|Cnsrd)	2259	1806	2266	1814	2270	1814
IncomeFullTime4						
Gay	4.083	-0.699***	-4.790	-0.526***	9.011	-0.266**
	(46.164)	(0.124)	(38.594)	(0.123)	(31.953)	(0.134)
Gay × Female	-46.725	0.768***	-30.537	0.520***	-52.915	0.367**
	(52.697)	(0.145)	(43.168)	(0.147)	(43.874)	(0.169)
Obs.(N|Cnsrd)	2368	1442	2374	1449	2378	1447

Note: *** p<0.01, ** p<0.05, * p<0.1. The controls used in all the equation and not presented in the Table are: age, age squared, gender, dummies for father's education, whether as a child the person lived with one parent, a remarried parent or with no parents. Constants not shown. *Source*: Own calculations.

C Models With Dichotomous Definitions of Homosexuality

C.1 Loadings of Latent Factors

Table C.1: Skill Loadings: Income and Employment (Heterosexuals), Roy Model

	SI		SP	
	Coeff.	Std.Err.	Coeff.	Std.Err.
College†	2.078***	(0.350)	1.992***	(0.341)
	SI		SP	
	Income	Employed	Income	Employed
Employed				
No College	35.540	0.043	29.974	0.483
	(22.786)	(0.329)	(25.782)	(0.325)
College	102.116***	0.624*	76.439**	0.516
	(32.114)	(0.352)	(31.290)	(0.341)
Obs.(N|Cnsrd)	1746	1438	1825	1493

Note: See note in Table C.2. *Source*: Own calculations.

Table C.2: Skill Loadings: Income and Employment (Homosexuals), Roy Model

	SI		SP	
	Coeff.	Std.Err.	Coeff.	Std.Err.
College†	6.717	(4.905)	6.922	(5.268)
	SI		SP	
	Income	Employed	Income	Employed
Employed				
No College	124.351	5.537	105.036	-0.112
	(255.394)	(4.412)	(91.294)	(1.268)
College	300.241	0.502	428.380***	0.952
	(250.011)	(2.686)	(157.841)	(1.798)
Obs.(N|Cnsrd)	518	373	446	326

Note: *** p<0.01, ** p<0.05, * p<0.1. Controls used in the college choice equation are: age, age squared, gender, municipality population, mother's and father's education, indicators of skipping school, taken out of classroom and police contact while teenager. Controls in the selection equations are: age, age squared, gender, whether as a child the person lived with both parents, indicator for practicing sports while teenager and male labor force participation rate in the 25 to 39 age bracket in the municipality. Controls in the income equations are: age, age squared, gender, father's SES, and mother's education. The College variable takes the value of 1 when the person has undertaken any kind of tertiary education in colleges (*høyskole*) or universities (*universitetet*). This includes three-year, four-year college studies or studies in the university with the same length. *Source*: Own calculations. †Coefficients, not marginal effects.

C.2 Goodness-of-Fit

Table C.3: Goodness of Fit - Annual Income by Schooling level and Sexual Preference Definition Roy Model, Heterosexuals Sample

	College	**Employment**		**Income**	
	Means	Means	Std.Dev.	Means	Std.Dev.
SI					
1. Model Without Endogenous Education Choice					
Actual		0.824	0.381	235.909	154.010
Model		0.821	0.383	235.954	155.524
2. Model With Endogenous Education Choice					
Actual	0.649				
Model	0.654				
No College					
Actual		0.863	0.344	242.878	142.006
Model		0.854	0.352	240.357	145.003
College					
Actual		0.805	0.396	230.578	161.850
Model		0.793	0.405	226.475	163.426
SP					
1. Model Without Endogenous Education Choice					
Actual		0.817	0.386	234.355	155.464
Model		0.815	0.388	234.145	156.276
2. Model With Endogenous Education Choice					
Actual	0.665				
Model	0.665				
No College					
Actual		0.864	0.343	242.863	143.266
Model		0.860	0.346	241.409	145.566
College					
Actual		0.796	0.403	228.534	162.795
Model		0.789	0.408	226.563	163.909

Note: *** p<0.01, ** p<0.05, * p<0.1 indicate the probability of rejecting the null hypothesis of the model predictions being different to the actual moments provided by the data. The model predictions are the result of 40,000 simulations of the estimated models. *Source*: Own calculations.

Table C.4: Goodness of Fit - Annual Income by Schooling level and Sexual Preference Definition Roy Model, Homosexuals Sample

	College	Employment		Income	
	Means	Means	Std.Dev.	Means	Std.Dev.
SI					
1. Model Without Endogenous Education Choice					
Actual		0.722	0.448	187.037	153.482
Model		0.705	0.456	183.454	154.725
2. Model With Endogenous Education Choice					
Actual	0.739				
Model	0.719				
No College					
Actual		0.771	0.421	197.709	153.842
Model		0.731	0.430	188.752	159.243
College					
Actual		0.707	0.456	184.355	157.720
Model		0.694	0.460	177.723	157.386
SP					
1. Model Without Endogenous Education Choice					
Actual		0.740	0.439	188.186	148.691
Model		0.723	0.447	184.378	150.918
2. Model With Endogenous Education Choice					
Actual	0.678				
Model	0.662				
No College					
Actual		0.788	0.410	204.260	148.560
Model		0.745	0.431	196.365	157.397
College					
Actual		0.720	0.450	181.901	154.018
Model		0.694	0.458	167.424*	154.405

Note: *** p<0.01, ** p<0.05, * p<0.1 indicate the probability of rejecting the null hypothesis of the model predictions being different to the actual moments provided by the data. The model predictions are the result of 40,000 simulations of the estimated models. *Source*: Own calculations.

D Goodness-of-Fit of Models with Homosexuality as a Factor

Table D.1: Goodness of Fit - Annual Income by Schooling level
Overall Sample

	College	**Employment**		**Income**	
	Means	Means	Std.Dev.	Means	Std.Dev.
Employed					
1. Model Without Endogenous Education Choice					
Actual		0.804	0.397	223.187	156.443
Model		0.802	0.398	222.466	156.761
2. Model With Endogenous Education Choice					
Actual	0.688				
Model	0.676				
No College					
Actual		0.840	0.367	244.936	145.460
Model		0.840	0.366	244.512	145.625
College					
Actual		0.771	0.420	223.312	161.473
Model		0.770	0.421	223.250	162.155
Full Time					
1. Model Without Endogenous Education Choice					
Actual		0.608	0.488	181.083	174.761
Model		0.609	0.488	180.793	174.368
2. Model With Endogenous Education Choice					
Actual	0.682				
Model	0.671				
No College					
Actual		0.641	0.480	200.978	174.080
Model		0.645	0.478	202.051	174.308
College					
Actual		0.573	0.495	176.562	177.097
Model		0.571	0.495	175.004	176.686

Note: *** p<0.01, ** p<0.05, * p<0.1 indicate the probability of rejecting the null hypothesis of the model predictions being different to the actual moments provided by the data. The model predictions are the result of 40,000 simulations of the estimated models. *Source*: Own calculations.

Table D.2: Goodness of Fit - Annual Income Gender Specific Models
Males

	College	Employment		Income	
	Means	Means	Std.Dev.	Means	Std.Dev.
Employed					
1. Model Without Endogenous Education Choice					
Actual		0.827	0.379	251.367	167.840
Model		0.823	0.381	249.887	168.638
2. Model With Endogenous Education Choice					
Actual	0.607				
Model	0.600				
No College					
Actual		0.882	0.323	287.180	149.636
Model		0.874	0.331	284.946	152.562
College					
Actual		0.778	0.416	243.243	177.536
Model		0.767	0.422	237.917	178.456
Full Time					
1. Model Without Endogenous Education Choice					
Actual		0.752	0.432	239.183	180.509
Model		0.750	0.433	238.542	181.420
2. Model With Endogenous Education Choice					
Actual	0.601				
Model	0.600				
No College					
Actual		0.831	0.375	278.003	164.301
Model		0.828	0.377	276.680	166.016
College					
Actual		0.684	0.465	225.199	189.382
Model		0.682	0.465	224.043	189.293

Note: *** p<0.01, ** p<0.05, * p<0.1 indicate the probability of rejecting the null hypothesis of the model predictions being different to the actual moments provided by the data. The model predictions are the result of 40,000 simulations of the estimated models. *Source*: Own calculations.

Table D.3: Goodness of Fit - Annual Income Gender Specific Models
Females

	College	Employment		Income	
	Means	Means	Std.Dev.	Means	Std.Dev.
Employed					
1. Model Without Endogenous Education Choice					
Actual		0.787	0.410	200.971	143.040
Model		0.783	0.412	200.329	143.820
2. Model With Endogenous Education Choice					
Actual	0.736				
Model	0.733				
No College					
Actual		0.794	0.405	196.027	122.846
Model		0.791	0.406	195.460	123.727
College					
Actual		0.769	0.421	211.830	149.295
Model		0.766	0.423	211.018	149.794
Full Time					
1. Model Without Endogenous Education Choice					
Actual		0.498	0.500	136.583	156.306
Model		0.499	0.500	135.705	155.606
2. Model With Endogenous Education Choice					
Actual	0.725				
Model	0.721				
No College					
Actual		0.438	0.497	118.913	143.839
Model		0.442	0.496	118.492	142.733
College					
Actual		0.504	0.500	145.991	162.094
Model		0.504	0.500	145.257	161.768

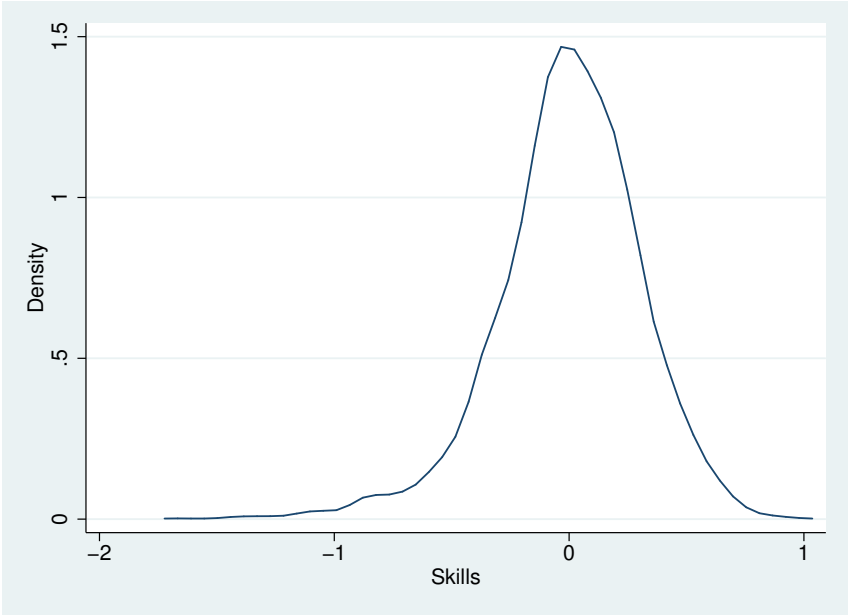
Note: *** p<0.01, ** p<0.05, * p<0.1 indicate the probability of rejecting the null hypothesis of the model predictions being different to the actual moments provided by the data. The model predictions are the result of 40,000 simulations of the estimated models. *Source*: Own calculations.

E Estimates of Skill Distributions and Loadings

This appendix presents the details of the results of estimating model (3) to identify the skill factors in different subsamples. Namely, the whole sample and homosexual and heterosexual subsamples according to the SI and the SP definitions. The estimations on the whole sample are the ones that allow the results presented in Section 5.1. The estimations on the sexual-preference-specific subsamples according to each definition relate to the results presented in Sections 5.2 and 5.3.

E.1 Whole Sample

Figure E.1: Latent Skills Distribution (Whole Sample)



Note: Estimated from measurement systems presented in Table E.1. Estimations use the mixing of two normals. Distributional parameter are the following: $\mu_1 = 0.555$, $\sigma_1 = 0.393$, $\mu_2 = -3.264$, $\sigma_2 = 0.030$, and the mixing probability is 0.058. Author's calculations.

Table E.1: Skills Measurement System Estimation (Whole Sample)

	Soc. Accept.	Sympathetic	Self-esteem	Leadership	Grades	Scholastic
Female	0.007	0.309***	-0.267***	-0.066***	0.339***	-0.136***
	(0.027)	(0.028)	(0.028)	(0.022)	(0.069)	(0.026)
Age	0.039***	0.032***	0.005	0.033***	0.178***	-0.027***
	(0.008)	(0.008)	(0.008)	(0.006)	(0.019)	(0.007)
Father: Univ	0.048	0.047	0.083*	0.107***	0.793***	0.216***
	(0.045)	(0.045)	(0.045)	(0.036)	(0.113)	(0.042)
Father: 3yrColl	0.029	0.071	0.017	0.063	0.922***	0.227***
	(0.048)	(0.049)	(0.049)	(0.039)	(0.123)	(0.045)
Father: Vocat	0.023	0.063	-0.044	0.100***	0.129	0.025
	(0.040)	(0.041)	(0.041)	(0.033)	(0.102)	(0.038)
Mother: Univ	0.036	0.040	0.017	0.035	0.296**	0.094*
	(0.059)	(0.059)	(0.059)	(0.048)	(0.148)	(0.055)
Num. Siblings	-0.014	-0.012	-0.006	-0.024**	-0.015	-0.020*
	(0.013)	(0.013)	(0.013)	(0.010)	(0.032)	(0.012)
LivesBothParents	0.081**	-0.012	0.107***	-0.028	0.413***	0.109***
	(0.035)	(0.034)	(0.034)	(0.027)	(0.085)	(0.031)
Father: HighSES	0.001	-0.019	0.032	0.053*	0.512***	0.090***
	(0.034)	(0.034)	(0.034)	(0.027)	(0.085)	(0.031)
Mother: HighSES	0.097*	0.117**	0.060	0.107**	0.079	0.119**
	(0.057)	(0.057)	(0.057)	(0.046)	(0.142)	(0.052)
Constant	-0.659***	-0.657***	-0.021	-0.453***	-3.454***	0.336***
	(0.128)	(0.126)	(0.127)	(0.101)	(0.312)	(0.116)
Skills	1.865***	1.367***	1.419***	0.742***	0.774***	1
	(0.113)	(0.084)	(0.075)	(0.050)	(0.131)	.

Note: *Univ* (*universitetet*) includes program of four or more years. *3yrColl* corresponds to the *høyskole*. *High SES* describes parents who have a high administrative or academic job. *Soc. Accept.* (social acceptance), *Sympathetic* (capable of building close friendships), *Self-esteem*, *Leadership* and *Scholastic Competence* are measures that come from SPPA scales (Harter, 1988). *Grades* correspond to a demeaned aggregation of school grades (Math, Norwegian and English). Observations: 2,595. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. *Source*: Own calculations.

E.2 By Sexual Preference

Table E.2: Skills Measurement System Estimation (Homosexual SI)

	Soc. Accept.	Sympathetic	Self-esteem	Leadership	Grades	Scholastic
Female	0.119**	0.230***	-0.156**	-0.108*	0.244	-0.171***
	(0.050)	(0.065)	(0.068)	(0.056)	(0.163)	(0.062)
Age	0.005	0.015	-0.018	0.020	0.149***	-0.035**
	(0.009)	(0.015)	(0.016)	(0.013)	(0.038)	(0.015)
Father: Univ	0.009	-0.013	0.066	0.187***	0.634***	0.270***
	(0.061)	(0.084)	(0.088)	(0.072)	(0.212)	(0.081)
Father: 3yrColl	0.095*	0.131	0.078	0.047	0.786***	0.170*
	(0.054)	(0.088)	(0.093)	(0.077)	(0.228)	(0.087)
Father: Vocat	0.119*	0.157*	-0.122	0.206***	0.017	-0.022
	(0.069)	(0.083)	(0.085)	(0.070)	(0.202)	(0.078)
Mother: Univ	-0.018	-0.110	-0.005	0.178**	0.241	0.023
	(0.052)	(0.101)	(0.109)	(0.090)	(0.268)	(0.102)
Num. Siblings	-0.036***	-0.045*	-0.006	-0.024	-0.032	-0.016
	(0.014)	(0.023)	(0.024)	(0.020)	(0.060)	(0.023)
LivesBothParents	-0.095**	-0.178***	0.019	-0.148***	0.658***	0.106*
	(0.037)	(0.061)	(0.065)	(0.054)	(0.160)	(0.061)
Father: HighSES	0.024	0.069	0.074	-0.015	0.366**	0.083
	(0.043)	(0.064)	(0.068)	(0.056)	(0.165)	(0.063)
Mother: HighSES	0.013	0.098	0.074	-0.048	0.189	0.086
	(0.061)	(0.098)	(0.103)	(0.086)	(0.253)	(0.096)
Constant	-0.098	-0.207	0.248	-0.111	-2.902***	0.532**
	(0.140)	(0.236)	(0.252)	(0.209)	(0.617)	(0.235)
Skills	4.541***	2.549***	1.729***	1.036***	-0.243	1
	(0.824)	(0.494)	(0.364)	(0.244)	(0.481)	.

Note: *Univ* (*universitetet*) includes program of four or more years. *3yrColl* corresponds to the *høyskole*. *High SES* describes parents who have a high administrative or academic job. *Soc. Accept.* (social acceptance), *Sympathetic* (capable of building close friendships), *Self-esteem*, *Leadership* and *Scholastic Competence* are measures that come from SPPA scales (Harter, 1988). *Grades* correspond to a demeaned aggregation of school grades (Math, Norwegian and English). Observations: 568. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. *Source*: Own calculations.

Table E.3: Skills Measurement System Estimation (Heterosexual SI)

	Soc. Accept.	Sympathetic	Self-esteem	Leadership	Grades	Scholastic
Female	-0.006	0.324***	-0.274***	-0.066***	0.322***	-0.144***
	(0.031)	(0.031)	(0.031)	(0.025)	(0.080)	(0.029)
Age	0.046***	0.036***	0.011	0.038***	0.191***	-0.024***
	(0.009)	(0.009)	(0.009)	(0.007)	(0.023)	(0.008)
Father: Univ	0.057	0.049	0.100*	0.082*	0.825***	0.197***
	(0.052)	(0.052)	(0.052)	(0.042)	(0.134)	(0.048)
Father: 3yrColl	0.047	0.081	0.024	0.076*	0.978***	0.271***
	(0.057)	(0.057)	(0.057)	(0.046)	(0.147)	(0.053)
Father: Vocat	0.009	0.037	-0.010	0.064*	0.159	0.044
	(0.046)	(0.046)	(0.046)	(0.037)	(0.119)	(0.043)
Mother: Univ	0.055	0.102	0.015	-0.013	0.316*	0.106*
	(0.069)	(0.069)	(0.069)	(0.055)	(0.177)	(0.064)
Num. Siblings	-0.011	-0.004	-0.007	-0.023*	-0.007	-0.026*
	(0.015)	(0.015)	(0.015)	(0.012)	(0.038)	(0.014)
LivesBothParents	0.118***	0.026	0.121***	0.015	0.332***	0.102***
	(0.040)	(0.040)	(0.040)	(0.032)	(0.101)	(0.037)
Father: HighSES	-0.004	-0.030	0.017	0.073**	0.577***	0.095***
	(0.039)	(0.039)	(0.039)	(0.031)	(0.100)	(0.036)
Mother: HighSES	0.118*	0.110*	0.060	0.145***	0.024	0.129**
	(0.067)	(0.067)	(0.067)	(0.054)	(0.171)	(0.062)
Constant	-0.781***	-0.750***	-0.101	-0.575***	-3.651***	0.303**
	(0.146)	(0.144)	(0.145)	(0.115)	(0.365)	(0.133)
Skills	1.667***	1.238***	1.373***	0.686***	0.902***	1
	(0.099)	(0.078)	(0.074)	(0.049)	(0.136)	.

Note: *Univ* (*universitetet*) includes program of four or more years. *3yrColl* corresponds to the *høyskole*. *High SES* describes parents who have a high administrative or academic job. *Soc. Accept.* (social acceptance), *Sympathetic* (capable of building close friendships), *Self-esteem*, *Leadership* and *Scholastic Competence* are measures that come from SPPA scales (Harter, 1988). *Grades* correspond to a demeaned aggregation of school grades (Math, Norwegian and English). Observations: 2,001. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. *Source*: Own calculations.

Table E.4: Skills Measurement System Estimation (Homosexual SP)

	Soc. Accept.	Sympathetic	Self-esteem	Leadership	Grades	Scholastic
Female	0.132*	0.353***	-0.099	-0.053	0.126	-0.144**
	(0.072)	(0.071)	(0.069)	(0.059)	(0.164)	(0.065)
Age	0.009	-0.003	-0.050***	0.005	0.162***	-0.048***
	(0.019)	(0.019)	(0.018)	(0.016)	(0.043)	(0.017)
Father: Univ	0.025	0.011	0.169	0.266***	0.323	0.358***
	(0.112)	(0.109)	(0.106)	(0.090)	(0.250)	(0.099)
Father: 3yrColl	0.040	0.094	0.053	0.131	0.656**	0.144
	(0.116)	(0.113)	(0.111)	(0.095)	(0.265)	(0.104)
Father: Vocat	0.160	0.211**	0.036	0.222***	0.027	0.016
	(0.104)	(0.101)	(0.097)	(0.082)	(0.225)	(0.089)
Mother: Univ	0.084	-0.064	0.147	0.125	0.477	0.038
	(0.126)	(0.125)	(0.123)	(0.106)	(0.295)	(0.116)
Num. Siblings	0.009	-0.022	0.026	-0.035	-0.005	0.003
	(0.025)	(0.025)	(0.025)	(0.021)	(0.060)	(0.023)
LivesBothParents	-0.006	-0.076	0.047	-0.139**	0.803***	0.267***
	(0.072)	(0.071)	(0.069)	(0.060)	(0.167)	(0.065)
Father: HighSES	-0.010	0.039	-0.080	-0.042	0.450**	0.024
	(0.090)	(0.087)	(0.084)	(0.071)	(0.195)	(0.077)
Mother: HighSES	0.239**	0.187	0.133	0.062	0.256	0.082
	(0.120)	(0.117)	(0.114)	(0.097)	(0.269)	(0.106)
Constant	-0.377	-0.207	0.583**	0.020	-3.430***	0.459*
	(0.299)	(0.291)	(0.284)	(0.244)	(0.677)	(0.266)
Skills	2.777***	2.198***	1.762***	0.890***	0.448	1
	(0.449)	(0.359)	(0.281)	(0.173)	(0.373)	.

Note: *Univ* (*universitetet*) includes program of four or more years. *3yrColl* corresponds to the *høyskole*. *High SES* describes parents who have a high administrative or academic job. *Soc. Accept.* (social acceptance), *Sympathetic* (capable of building close friendships), *Self-esteem*, *Leadership* and *Scholastic Competence* are measures that come from SPPA scales (Harter, 1988). *Grades* correspond to a demeaned aggregation of school grades (Math, Norwegian and English). Observations: 507. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. *Source*: Own calculations.

Table E.5: Skills Measurement System Estimation (Heterosexual SP)

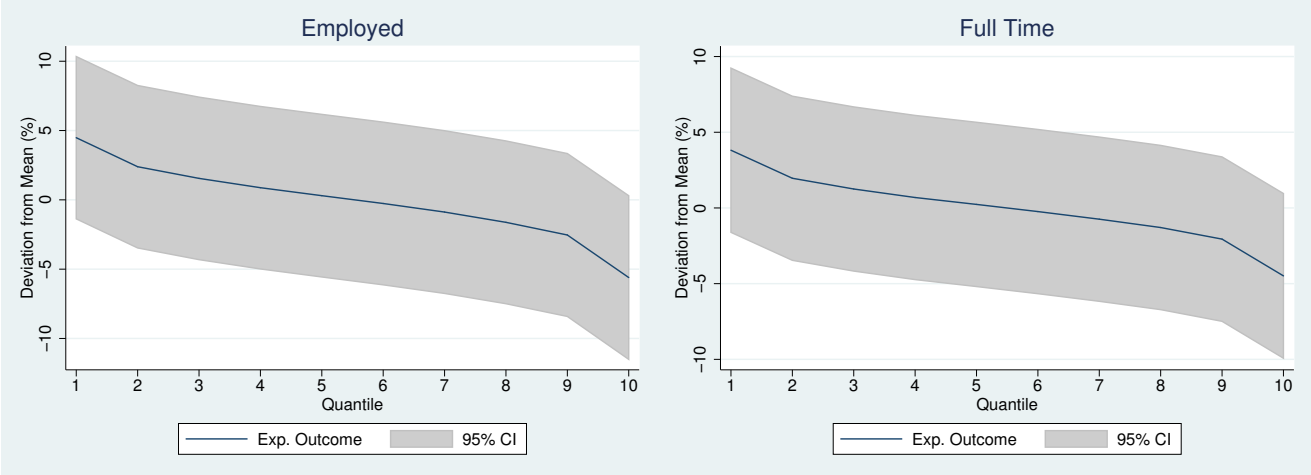
	Soc. Accept.	Sympathetic	Self-esteem	Leadership	Grades	Scholastic
Female	0.000	0.311***	-0.286***	-0.067***	0.409***	-0.129***
	(0.030)	(0.030)	(0.031)	(0.024)	(0.078)	(0.028)
Age	0.045***	0.039***	0.018**	0.039***	0.178***	-0.022***
	(0.008)	(0.009)	(0.009)	(0.007)	(0.022)	(0.008)
Father: Univ	0.064	0.047	0.081	0.078**	0.890***	0.192***
	(0.049)	(0.050)	(0.050)	(0.040)	(0.127)	(0.046)
Father: 3yrColl	0.040	0.069	0.023	0.049	0.986***	0.266***
	(0.052)	(0.054)	(0.054)	(0.043)	(0.138)	(0.050)
Father: Vocat	0.003	0.034	-0.054	0.071**	0.153	0.043
	(0.044)	(0.045)	(0.045)	(0.036)	(0.114)	(0.041)
Mother: Univ	0.029	0.086	-0.014	0.011	0.270	0.104*
	(0.065)	(0.066)	(0.067)	(0.053)	(0.170)	(0.062)
Num. Siblings	-0.023	-0.008	-0.020	-0.021*	-0.013	-0.031**
	(0.014)	(0.015)	(0.015)	(0.012)	(0.038)	(0.014)
LivesBothParents	0.112***	0.009	0.127***	0.010	0.290***	0.060*
	(0.038)	(0.039)	(0.039)	(0.031)	(0.098)	(0.036)
Father: HighSES	-0.007	-0.027	0.045	0.067**	0.528***	0.103***
	(0.037)	(0.037)	(0.038)	(0.030)	(0.095)	(0.035)
Mother: HighSES	0.087	0.118*	0.073	0.126**	0.020	0.143**
	(0.063)	(0.065)	(0.065)	(0.052)	(0.165)	(0.060)
Constant	-0.732***	-0.759***	-0.187	-0.579***	-3.380***	0.331**
	(0.138)	(0.139)	(0.141)	(0.111)	(0.352)	(0.129)
Skills	1.688***	1.235***	1.351***	0.713***	0.821***	1
	(0.105)	(0.081)	(0.075)	(0.051)	(0.138)	.

Note: *Univ* (*universitetet*) includes program of four or more years. *3yrColl* corresponds to the *høyskole*. *High SES* describes parents who have a high administrative or academic job. *Soc. Accept.* (social acceptance), *Sympathetic* (capable of building close friendships), *Self-esteem*, *Leadership* and *Scholastic Competence* are measures that come from SPPA scales (Harter, 1988). *Grades* correspond to a demeaned aggregation of school grades (Math, Norwegian and English). Observations: 2,066. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. *Source*: Own calculations.

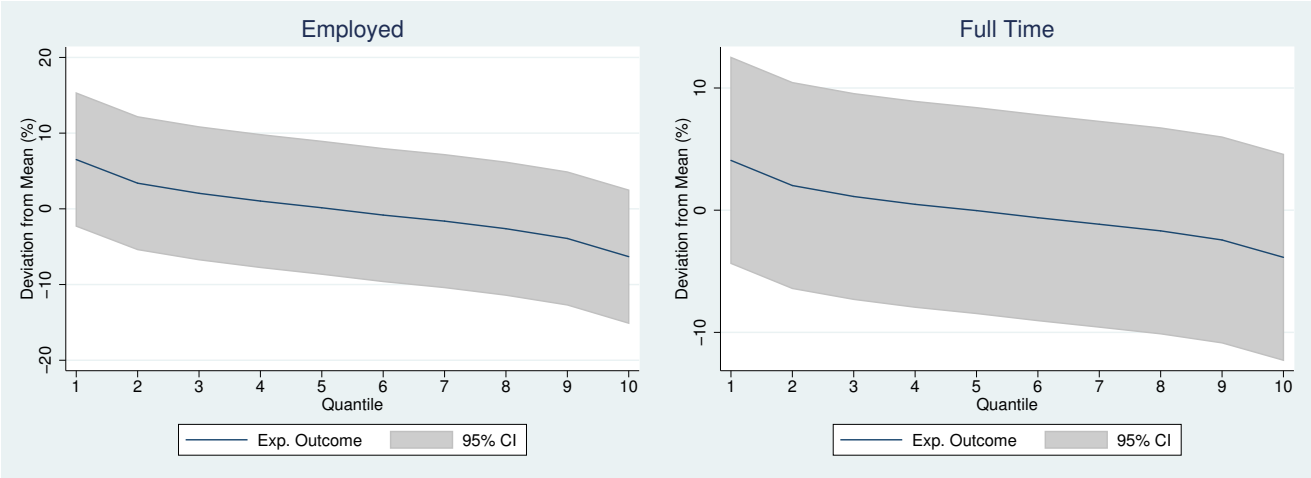
F Additional Simulations of the Models with Homosexuality Factor

Figure F.1: Expected Income (Censored) at Levels of Homosexuality

(a) Complete Sample



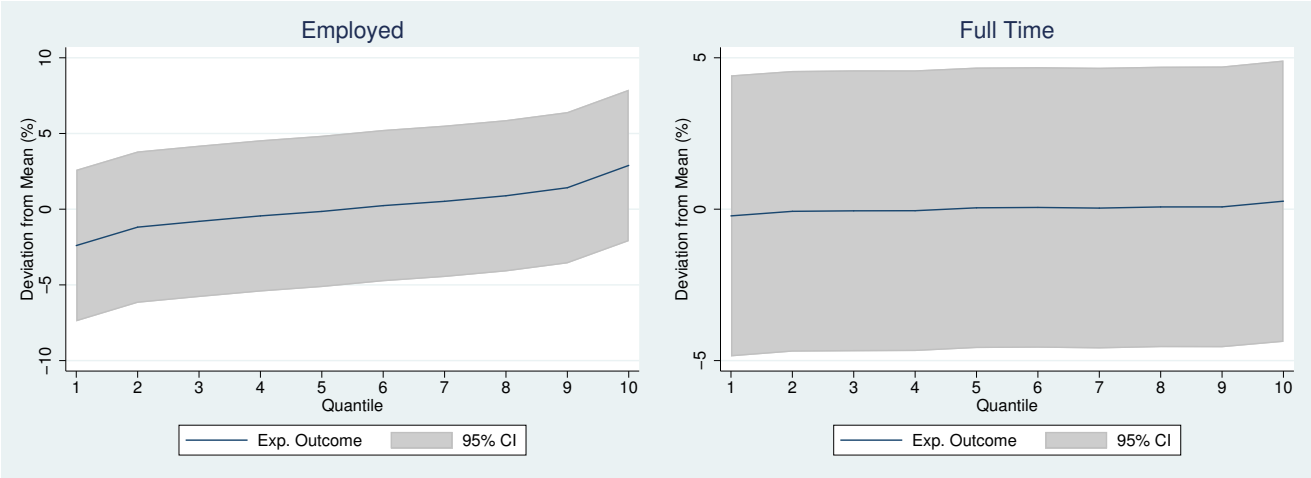
(b) Males



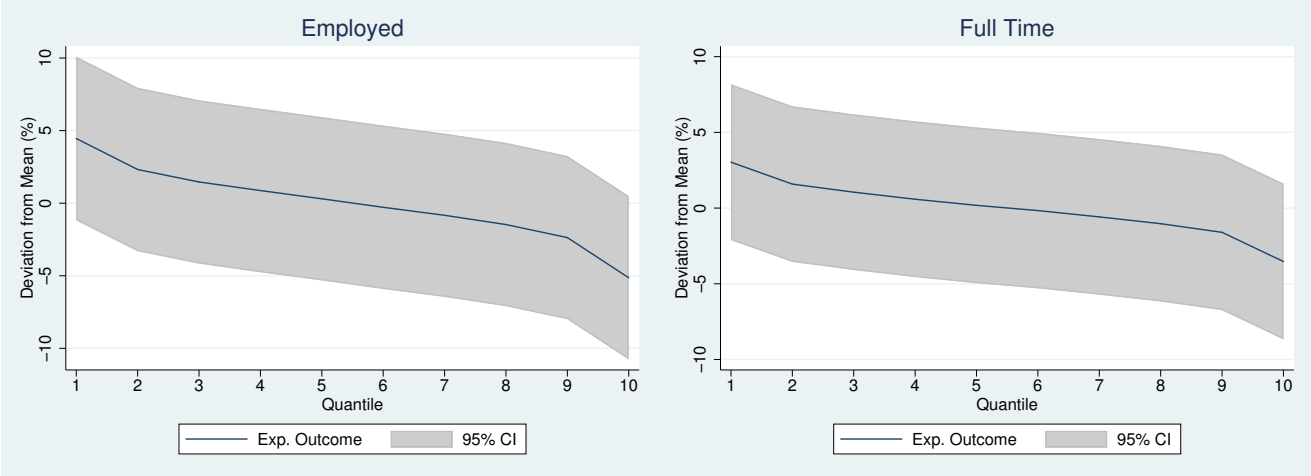
Note: Simulated incomes and employment probabilities using the estimated parameters and 40,000 draws from each dimension of unobserved heterogeneity. *Source*: Own calculations.

Figure F.2: Income (Censored)

(a) Highest Education Level Achieved: No College



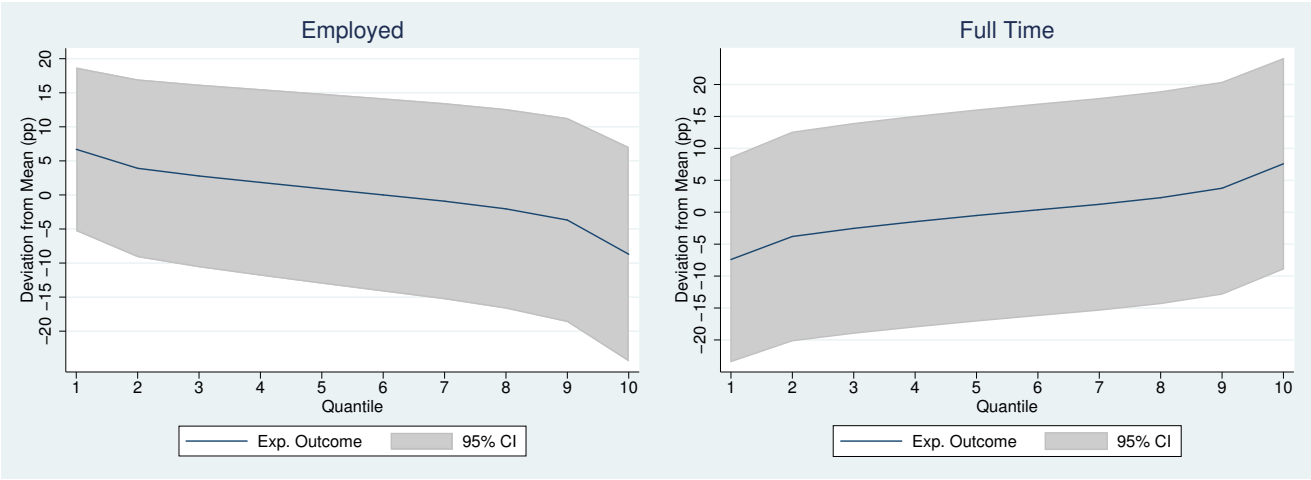
(b) Highest Education Level Achieved: College



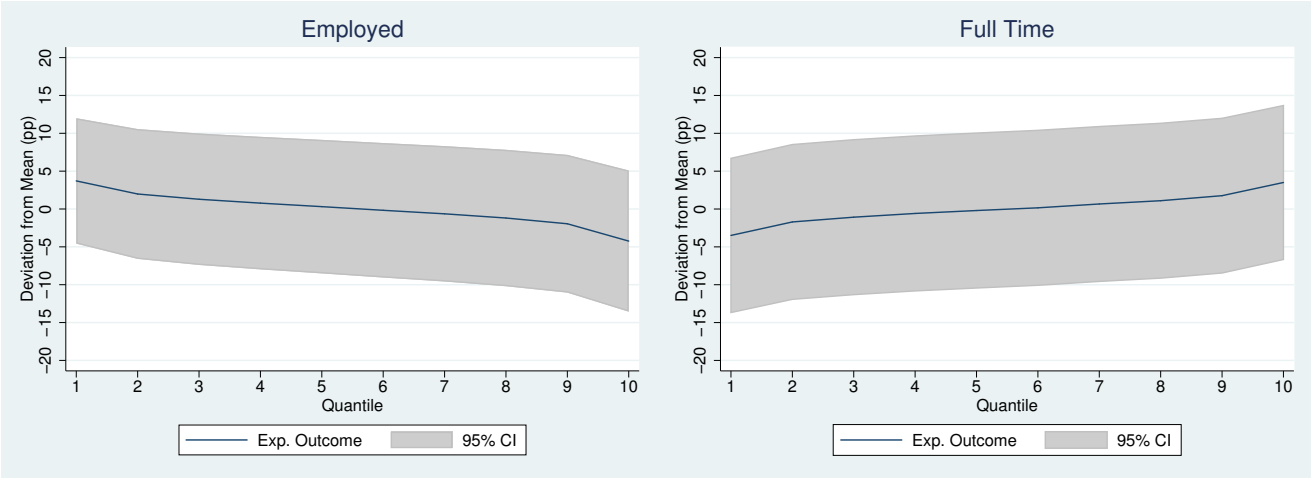
Note: Simulated incomes and employment probabilities using the estimated parameters and 40,000 draws from each dimension of unobserved heterogeneity. *Source*: Own calculations.

Figure F.3: Women: Probability of Being Employed

(a) Highest Education Level Achieved: No College

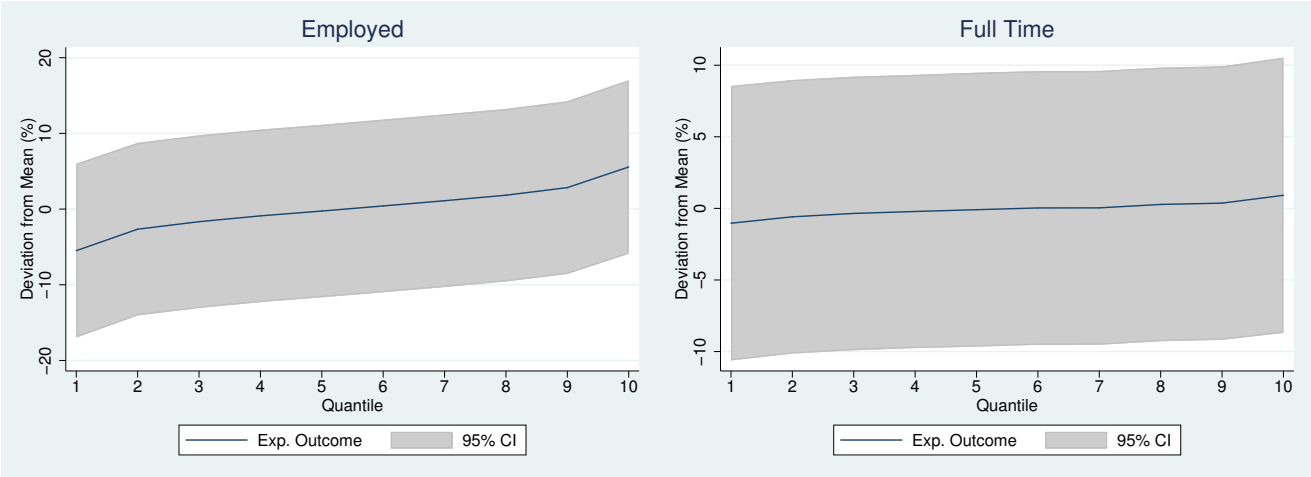


(b) Highest Education Level Achieved: College



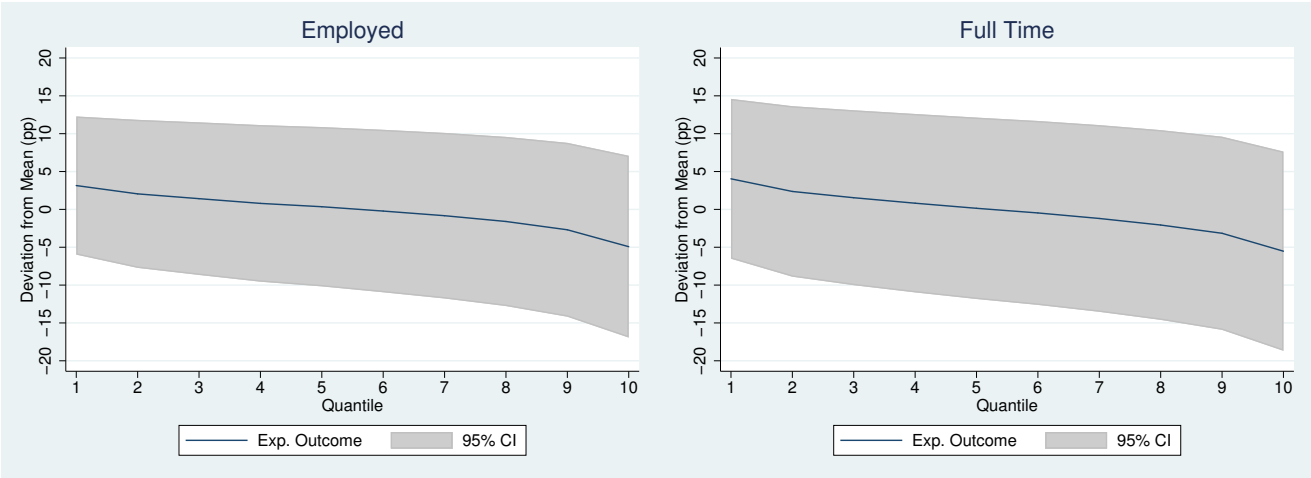
Note: Simulated incomes and employment probabilities using the estimated parameters and 40,000 draws from each dimension of unobserved heterogeneity. *Source*: Own calculations.

Figure F.4: Women: Income (Censored)
Highest Education Level Achieved: No College



Note: Simulated incomes and employment probabilities using the estimated parameters and 40,000 draws from each dimension of unobserved heterogeneity. *Source*: Own calculations.

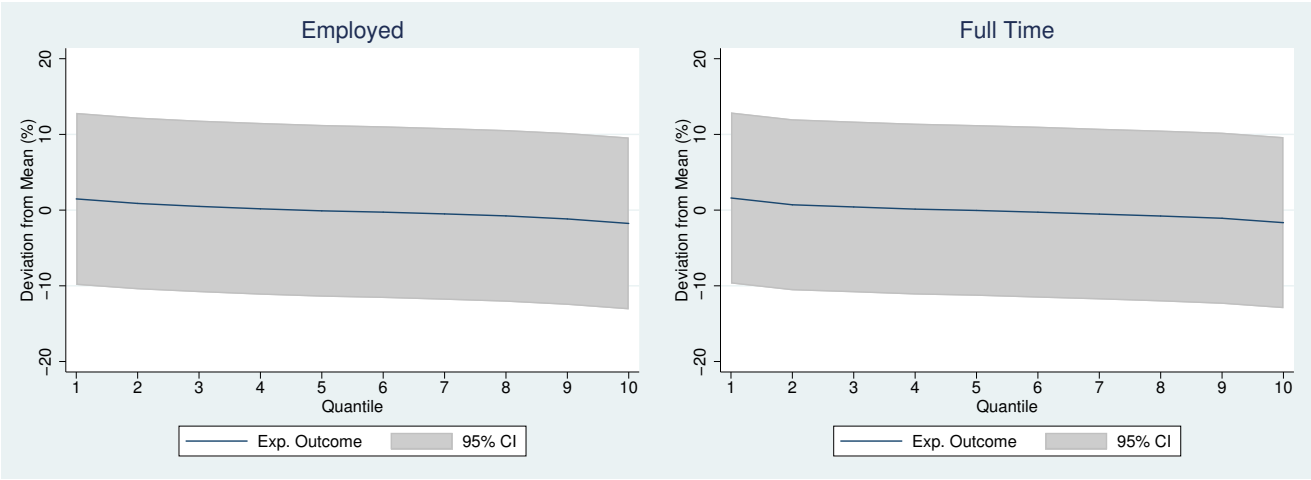
Figure F.5: Men: Probability of Being Employed
Highest Education Level Achieved: No College



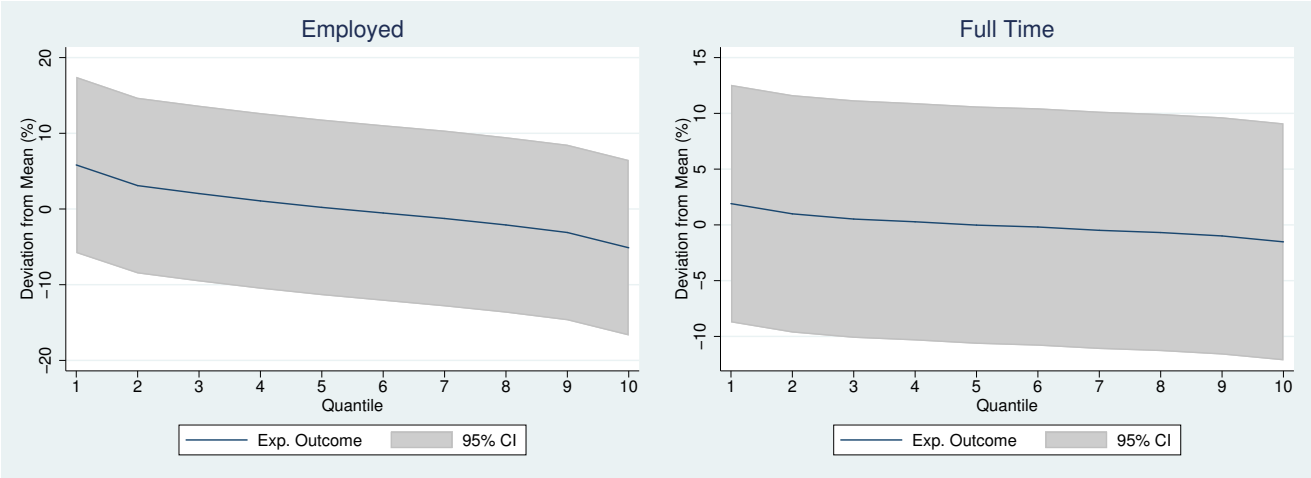
Note: Simulated incomes and employment probabilities using the estimated parameters and 40,000 draws from each dimension of unobserved heterogeneity. *Source*: Own calculations.

Figure F.6: Men: Income (Censored)

(a) Highest Education Level Achieved: No College



(b) Highest Education Level Achieved: College



Note: Simulated incomes and employment probabilities using the estimated parameters and 40,000 draws from each dimension of unobserved heterogeneity. *Source*: Own calculations.

G Additional Tables and Graphs

Table G.1: Gap in College Attendance

	(1)		(2)		(3)		(4)	
Defini.	Coeff.	Std.Err.	Coeff.	Std.Err.	Coeff.	Std.Err.	Coeff.	Std.Err.
SI	0.068***	(0.025)	0.032	(0.025)	0.041	(0.048)	0.024	(0.048)
SI×*female*					-0.013	(0.056)	0.001	(0.056)
SP	-0.008	(0.026)	-0.028	(0.026)	0.039	(0.046)	0.023	(0.046)
SP×*female*					-0.099*	(0.055)	-0.051	(0.055)
SX	-0.016	(0.032)	-0.016	(0.031)	0.067	(0.049)	0.072	(0.049)
SX×*female*					-0.137**	(0.063)	-0.139**	(0.063)
Age & gender			X		X		X	
Test Scores							X	

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The College variable takes the value of 1 when the person has undertaken any kind of tertiary education in colleges (*høyskole*) or universities (*universitetet*). This includes three-year, four-year college studies or studies in the university with the same length. Age enters in a quadratic polynomial. The estimations with test scores include six scores, one related to school grades (Math, Norwegian and English), two of them relate to agreeableness and the ease to make friends, the others relate to positivism, leadership and scholastic competence. All of them collected in the first wave of the survey. Sample comprises the economically active by wave 4 to be comparable to structural model results. *Source*: Own calculations.

Table G.2: Homosexuality, Education and Labor Market Choices

	Active	Employed	Full Time	White Collar	Has ISCO
Complete Sample					
Latent Homosex.	-0.077***	-0.072***	-0.027	-0.011	0.001
	(0.020)	(0.019)	(0.017)	(0.021)	(0.019)
Latent Skills	0.318**	0.427***	0.379***	0.914***	0.063
	(0.140)	(0.131)	(0.119)	(0.142)	(0.125)
Obs.	2417	2417	2417	1900	2687
Males					
Latent Homosex.	-0.079***	-0.068***	-0.084***		
	(0.023)	(0.020)	(0.019)		
Latent Skills	0.141	0.295	0.360**		
	(0.207)	(0.183)	(0.172)		
Obs.	1027	1047	1047		
Females					
Latent Homosex.	-0.043*	-0.046*	0.036*		
	(0.026)	(0.025)	(0.022)		
Latent Skills	0.358**	0.485***	0.343**		
	(0.176)	(0.168)	(0.152)		
Obs.	1370	1370	1370		

Note: *** p<0.01, ** p<0.05, * p<0.1. The controls used in all the equation and not presented in the Table are: age, age squared, gender, dummies for father's education, whether as a child the person lived with one parent, a remarried parent or with no parents. Standard error in parentheses. *Source*: Own calculations.

Table G.3: Difference in Observable Characteristics Between Heterosexuals and Homosexuals

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
			Father's Education			Father's SES			When Child Lived With:		
	Age	Gender	Univers	3YrColl	Vocat.	High	Skilled	Sibling	OnePar	RemPar	NoPar
SI	-0.050	0.281***	0.042**	0.015	-0.010	0.053**	-0.022	-0.032	0.027*	0.024**	0.001
	(0.095)	(0.025)	(0.018)	(0.015)	(0.018)	(0.023)	(0.018)	(0.058)	(0.016)	(0.011)	(0.011)
SP	-0.317***	0.200***	0.014	-0.022	-0.019	-0.021	-0.019	0.078	0.042**	0.023*	0.004
	(0.099)	(0.026)	(0.019)	(0.015)	(0.019)	(0.024)	(0.019)	(0.060)	(0.017)	(0.012)	(0.011)
SX	-0.121	0.071**	0.067***	-0.014	-0.027	0.039	-0.050**	0.031	0.060***	0.027*	0.024*
	(0.121)	(0.032)	(0.023)	(0.019)	(0.023)	(0.029)	(0.023)	(0.073)	(0.021)	(0.014)	(0.014)
SX+	-0.266***	0.165***	0.014	-0.023	-0.029	-0.020	-0.019	0.071	0.057***	0.021*	0.012
	(0.102)	(0.027)	(0.020)	(0.016)	(0.019)	(0.025)	(0.019)	(0.062)	(0.018)	(0.012)	(0.012)

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All estimations were drawn from different regressions with the dependent variable being the homosexuality indicator. *Univers* estimates whether the father went to the university. *3YRColl* estimates whether the father went to a three-year college. *Vocat* estimates whether the father undertook vocational training. *OnePat* estimates if the respondent lived with only one of the two parents. *RemPar* estimates if the respondent lived with one father that remarried. *NoPar* estimates whether the respondent lived without her parents during childhood. *Source*: Own calculations.