Childhood Gender Nonconformity and Gender Gaps in Life Outcomes*

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Abstract

We study the role of childhood gender conformity in determining gender gaps. We present a conceptual framework that uses gender norms to explain why some women make less profitable choices than comparable men. Using unique longitudinal survey and register data, we show that gender-nonconforming girls have substantially better education and labor market outcomes than gender-conforming girls. In contrast, gender-nonconforming boys perform substantially worse at school, sort into lower-paying occupations, earn less, and have a greater incidence of mental health disorders and substance abuse during adulthood than gender-conforming boys. Our analyses suggest that such divergence develops from an early age.

JEL Classification: I21, J15, J16, J24
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1 Introduction

Numerous studies in the social sciences seek to understand why women, despite having surpassed men in terms of school outcomes for the past five decades in most Western countries, make educational and career choices that depress their labor market outcomes (Bertrand, 2011; DiPrete and Buchmann, 2013; Olivetti and Petrongolo, 2016; Bertrand, 2020; Lundberg, 2020). They tend to opt out of math-intensive STEM fields in high school and tertiary education, are underrepresented in the higher-paying STEM occupations (where the gender gap in earnings is relatively small), and bear most of the earnings losses due to childbirth (Goldin, 2014; Kleven et al., 2019). In an effort to solve this puzzle, much recent work on gender economics explores between-gender differences in preferences, and the impact of societal gender norms and sticky stereotypes about what men and women are "good" or "bad" at and what they inherently like or dislike (West and Zimmerman, 1987; Akerlof and Kranton, 2000, 2002; Bertrand, 2011; Zafar, 2013; Wiswall and Zafar, 2014; Bertrand et al., 2015; Nollenberger et al., 2016).[1] Prevailing social norms and gender stereotypes impose certain life choice expectations that differ between the sexes (e.g., women should be modest caretakers, men agentic breadwinners), in turn affecting career decisions, ultimately translating into the observed persistent gender gaps (Bertrand, 2020).

The burgeoning literature that attributes gender gaps to differences in male and female prescriptive stereotypes has thus far employed a binary concept of gender. Such an approach makes sense in that binary sex is a convenient proxy for gender norm identity. Perhaps more importantly, societal prescriptions largely police individuals into one of these two social categories: man or woman (Akerlof and Kranton, 2000). Yet, *within*-gender differences in cognition, traits, and preferences have been shown to be larger than the *between*-gender differences (Hyde, 2014; Hyde et al., 2019). Sizeable within-gender heterogeneity is partly the result of a non-trivial variation in the degree of conformity to societal prescriptions. Closing gender gaps thus necessarily requires a more nuanced understanding of the latter—our paper represents a first step in

[1] In economics, Akerlof and Kranton (2000) was the first to argue that the persistent gender gap in labor market outcomes is in large part due to prevailing social norms. Notions of "prescriptions" and "identity" that had previously been used predominantly in the field of social psychology have since been incorporated into economic models of utility to help explain, for example, why men work in the labor force and women work in the home. Marianne Bertrand's (2011) chapter in the Handbook of Labor Economics explicitly formulates this research agenda, referenced in comprehensive survey articles such as those by Bertrand (2020) and Lundberg (2022).

this direction. We exploit variation in preferences and behaviors during childhood to study how nonconformity to gender norms predicts lifetime outcomes.

The study of gender norms and their impact has become ever more important. Indeed, as Generation Z's formative years draw to a close, an increasing number of young individuals are contesting the prescriptions of binary gender norm identities (Pew Research Center, 2020). Approaches able to capture the heterogeneity in men's and women's outcomes across degrees of conformity to gendered expectations are indubitably needed (Lundberg, 2022). To add to this, gender norms themselves, though shown to be sticky (Alesina et al., 2013), are not set in stone. Research demonstrates that they can change considerably over a generation (Goldin and Katz, 2002; Fernández et al., 2004; Fogli and Veldkamp, 2011; Miho et al., 2019). Generally, gender norms have become more fluid (Diamond, 2020; Hyde et al., 2019) and the categorical notion of gender has been increasingly challenged across disciplines (Hyde et al., 2019; Mittleman, 2022; Yavorsky and Buchmann, 2019; Burn and Martell, 2022).

We begin by presenting a conceptual framework that uses gender norms to explain why some women make less profitable choices than do men with similar preferences. In our framework, men and women have idiosyncratic endowments of skills and "male typicality" and choose how much "masculinity" to reveal (this can differ from the true endowment, at a cost) based on societal incentives. On the one hand, the market rewards masculinity. On the other, society punishes deviations from the stereotypes. Based on this framework, we derive implications for men and women with high and low innate masculinity levels. We show that gender norms lead to a misallocation of time between marketable and domestic activities.

We underpin these arguments using a Swedish longitudinal data set that links a 1966 survey of 10,154 13-year-olds to administrative registers spanning five decades. We measure gender conformity by re-purposing a battery of survey questions on general preferences and choices. While these do not directly ask about gender conformity, they do generate *empirically* gendered answers—especially given that the respondents were growing up in the 1960s. The questions explore preferences in leisure time interests. As these interests are measured in childhood, many are rather toy and play preferences (e.g., playing with trains, fixing bikes and baking) which literature has documented to be gendered (Adelson, 2012; Davis and Hines, 2020). They relate however to home production, market skills, and action-oriented activities.[2] We also include information on gender homophily and preferred subjects in school. We identify the variation common across all measures to create a one-dimensional continuous index of gender typicality. Our metric does not discriminate between girls and boys. Rather, it reveals gender-typical and atypical behaviors and preferences for both genders. We define children with gender-atypical behaviors and preferences as "nonconformers" and document how childhood gender nonconformity (as opposed to conformity with gender-typical preferences associated with one's own gender) relates to later life outcomes. We cover early education outcomes and choices and then follow these individuals throughout life, observing their occupational and fertility decisions, health indicators, labor market success, and lifetime earnings.

Our results indicate that childhood gender nonconformity is strongly associated with life outcomes. Consistent with the implications of our conceptual framework, we observe asymmetric consequences for men and women. In general, childhood gender nonconformity is associated with better life outcomes for women and worse life outcomes for men. Gender-nonconforming women perform better at school, are more likely to continue into higher education, and to choose a STEM track in upper secondary school than are their gender-conforming female peers. Compared to gender-typical women, gender-nonconforming women are furthermore substantially more likely to work full time, sort into STEM occupations, postpone fertility, and earn more, especially if they go into male-dominated fields. Conversely, relative to gender-typical men, male nonconformers perform worse at school, are less likely to choose a STEM track in upper secondary or sort into STEM occupations, and earn roughly 10% less during their working career. To analyze earnings gaps in the context of endogenous occupational choices, we implement a Roy model of self-selection into occupations and counterfactual earnings. We confirm our reduced-form findings indicating that STEM occupations significantly reward gender-nonconformity in women. Gender-nonconforming

[2] The areas of interest map nicely onto two fundamental dimensions of Social Role Theory regarding how gender-typical behavior results from the imposition of different social expectations on men and women: *communion* and *agency*. Men are generally perceived as oriented towards agentic (motivated to master, receive recognition) goals and women towards communal (selfless and concerned with others) goals (Eagly and Steffen, 1984). Further, being good at sports is associated with high social status at school for adolescent boys, while it is less of a status marker for girls (Coleman, 1961b). Preferences for interests is one area in which Hyde's (2005) gender similarity hypothesis is rejected by empirical research (Su et al., 2009). As Hyde (2014) notes, these differences are cultural artifacts that are not immutable.

women in STEM occupations earn 49% more than they do in non-STEM ones. When exploring possible mechanisms, we find that school experiences differ significantly for gender-nonconforming boys and girls. While gender-nonconforming girls enjoy school and befriend smarter peers, gender-nonconforming boys feel unsafe, have little interest in schoolwork and experience isolation. The latter translates to a higher incidence of behavioral problems, mental health issues, and substance abuse during adolescence. Our results are robust to potentially important confounding factors such as cognitive ability, parental socioeconomic status (SES), and having opposite-sex siblings.

Our study advances the understanding of gender gaps by linking them to heterogeneous degrees of conformity to prevailing social norms and behavioral prescriptions. The results highlight the matter that average gender gaps mask significant variation, and that the progress made towards achieving gender equality has not benefited all women uniformly. A subgroup of women, namely those who challenged gender norms early in life, face significantly smaller gender gaps compared to other women. Even in domains like student performance, where average gaps are in favor of women, it is the gender-nonconforming women who account for this advantage, while the average gender-typical woman fares worse than the average gender-typical man. We conceptualize a novel data-driven way of measuring gendered childhood behaviors and preferences for which prescriptions of social gender categories provide salient guidance. In particular, ones that are grounded in Economics and Psychology literature as being associated with feminine and masculine prescriptions (Eagly and Steffen, 1984; Su et al., 2009; Ceci et al., 2014).

The remainder of this article is structured as follows. Section 2 introduces a conceptual framework that rationalizes our empirical findings based on gender norms. Section 3 describes the data and the construction of our measure of gender conformity. Section 4 presents our regression analysis and the main results. Section 5 explores earnings gender gaps under the prism of endogenous occupational choices. Section 6 discusses potential mechanisms underlying our findings, and Section 7 concludes.

2 Framework

To fix ideas, we begin by presenting a simple model inspired by Akerlof and Kranton (2002) where gender conformity is salient. As in Bertrand (2011), we use gender-based differences in traits, preferences, and social norms, to rationalize why gender nonconformity should be associated with life outcomes. Unlike Akerlof and Kranton (2002), our simple framework does not explore identity choices. Rather, it describes how gender-(non)conforming traits and tastes influence later outcomes. In our model, individual i belongs to one of two categories $\mathbf{C} = \{F, M\}$, men and women, which are fixed. But following Akerlof and Kranton (2002), society holds prescriptions $\mathbf{P}$ for each category. That is, $\mathbf{P}$ collects social norms or, as Bertrand (2020) puts it, prescriptive stereotypes that dictate the expected behaviors for each category.[3] In our model, those norms prescribe that men's (women's) actions and choices should reveal high (low) levels of masculinity. Individuals reveal their level of masculinity through behaviors that society considers to be gender-specific. For instance, that boys (girls) should play with other boys (girls) and spend more time in athletic (domestic) activities.

Each person has two exogenously given traits: ability, n_i, and masculinity m_i. Ability and masculinity are both independently distributed bounded between $[0, 1]$. In particular, people with m_i close to one will find it easier to comply with the societal norms imposed on men. Conversely, people with m_i close to zero will find it easier to comply with the societal norms imposed on women. m_i's distribution could be bimodal, where members of each gender tend to cluster around a different level of m_i. More women's m_i are closer to zero and more men's m_i are closer to one. That is, $\mathbb{E}[m_i|c_i = M] > \mathbb{E}[m_i|c_i = F]$.

Agents split their time endowment T into the production of marketable and domestic goods.[4] Let $\alpha(m_i)$ be the fraction of time agent i devotes to marketable activities $e_i = \alpha(m_i)T$. Then, $1 - \alpha(m_i)$ is the fraction of the time endowment devoted to domestic production, $h_i = (1 - \alpha(m_i))T$. We assume $\alpha'_{\hat{m}} > 0$ to reflect that time allocation, to a significant degree, is the product of societal norms: women are expected to spend more time in domestic activities, men are expected to devote more of their

[3] Just like most of the literature on gender gaps, we assume that the social norms are exogenous to the individual and in this sense, we abstract from any general equilibrium effects. Endogenous social norms are widely studied in the literature on linear social interaction models (see, e.g., Blume et al., 2015; Boucher and Fortin, 2016; Ushchev and Zenou, 2020). In that context, the models capture conformist behavior or peer pressure on outcomes such as studying effort and smoking initiation.

[4] To keep interpretation simple, we consider as marketable any activity that is conducive to a public societal reward (e.g., spending time working in the labor market, or investing time in preparing for an exam). We also include indirect activities, e.g., playing with tools during childhood.

time in marketable ones (Eagly, 1987).[5] Society considers time allocation as a signal of the agent's masculinity endowment and it enforces the prescriptive stereotypes **P** by punishing deviations from its ideal of masculine men ($\hat{m}_i = 1$) and feminine women ($\hat{m}_j = 0$) (Moss-Racusin et al., 2010; Bertrand, 2020).[6] We materialize the enforcement mechanism through society levying a punishment $t > 0$ proportional to the deviations from the ideal time allocation dictated by social norms for men and women (Fortin, 2005; Booth and Van Ours, 2009). That is $t(1 - \alpha(\hat{m}))$ for men and $t\alpha(\hat{m})$ for women, where $\hat{m}_i$ refers to the level of masculinity agent i decides to *reveal*—our model's choice variable.

People derive utility from three payoffs. The first one, $w(c_i, m_i)n_i e_i$, is an age-specific payoff from their marketable activities (e.g., higher grades at school while adolescents, earnings when adult), which is increasing in ability n_i and the time devoted to it e_i. The age-specific payoffs rely on an outcome-specific societal reward function, $w(c_i, m_i)$, that varies by gender—includes gender based discrimination—and values masculinity (i.e., $w(M, \bar{m}) > w(F, \bar{m})$ and $w'_m > 0$). The latter characteristic could reflect the differences in traits that have been shown to contribute to gender productivity gaps in favor of men (Bertrand, 2011). For instance, risk aversion, willingness to compete, and time preferences are traits that have been shown to differ on average between men and women.[7] These are potentially important determinants of the payoffs obtained from marketable activities holding skills and effort constant (Buser et al., 2014; Blau and Kahn, 2017; Shurchkov and Eckel, 2018; Cortes et al., 2021). These trait-related regularities are not limited to the labor market. Evidence on test taking behavior, for instance, shows that women tend to follow strategies that are less risky but lead them to misplace effort in questions that have lower marginal reward (Borges et al., 2022), and that women tend to score less than what they should in high-stakes exams (Ors et al., 2013). In adult outcomes like the labor market,

[5] Becker (1985), Albanesi and Olivetti (2009), and others leverage those societal norms to explain gender occupational and wage gaps.

[6] This closely relates to the concept of *Backlash effect* in social psychology that recognizes that people pay a social cost when they show gender atypical behaviors (Rudman, 1998; Rudman and Phelan, 2008; Babcock et al., 2017).

[7] Surveys and experiments in the lab and on the field suggest that women are on average less patient and more risk averse than men and that men choose gambles with higher expected payoffs (Croson and Gneezy, 2009; Eckel and Grossman, 2008; Dohmen et al., 2010, 2011). In the same way, an extensive literature has established that relative to men, women on average dislike competition, especially against men (Gneezy et al., 2003; Niederle and Vesterlund, 2007). Additionally, men are overconfident relative to women (Niederle and Vesterlund, 2007).

$w'_m > 0$ can also reflect the evidence showing that incumbent men prefer a masculine environment in their work place and like to interact with, schmooze, and promote other men instead of women (Cullen and Perez-Truglia, 2021).[8] We assume these masculine traits are more easily deployed by people with high masculinity endowment. That is, although the reward function values revealed masculinity, the reward decreases as the revealed masculinity deviates from the true endowment. Therefore, $w(c_i, \hat{m}_i; \mathbf{P}, m_i) = w(c_i, \hat{m}_i - \frac{\gamma}{2}(\hat{m}_i - m_i)^2)$, where $\gamma > 0$.

The second payoff from which people derive utility is the consumption of a domestic good $G(h_i)$ that is produced devoting time to domestic activities and $G'_h > 0$. The third payoff comes from being true to oneself. That is, choosing to reveal a masculinity level different from the true masculinity endowments is personally costly.[9]

By normalizing $T = 1$, we can write the utility functions for people belonging to each of the two gender categories as:[10]

$$U_i(M; m_i, n_i, \mathbf{P}) = w(M, \hat{m}_i; m_i) n_i \alpha(\hat{m}_i) + \theta G(1 - \alpha(\hat{m}_i)) - \frac{(\hat{m}_i - m_i)^2}{2} - t(1 - \alpha(\hat{m}_i))$$
$$U_j(F; m_j, n_j, \mathbf{P}) = w(F, \hat{m}_j; m_j) n_j \alpha(\hat{m}_j) + \theta G(1 - \alpha(\hat{m}_j)) - \frac{(\hat{m}_j - m_j)^2}{2} - t\alpha(\hat{m}_j)$$

To maximize utility, people choose how much masculinity to reveal. The first order condition with respect to revealed masculinity can be written as:

[8] For instance, in the case of adults $w(M, m_i) n_i e_i$ would entail a gender-specific wage rate that rewards more male dominated occupations than female dominated ones. People with greater abilities and those who spend more time in marketable activities will earn more, given a wage rate. For the case of adolescents, consider for instance STEM enrollment as outcome. Then, the payoff entails a reward function that embeds a behavior that the society tends to attach to men (i.e., men are engineers, women are caregivers) (Bertrand, 2020), more skilled children and those who spend more time in STEM-related activities are more likely to enroll in STEM fields.

[9] This is a recurring argument for replacing the gender binary with a more complex conception of gender that stresses diversity. Maintaining the binary is associated with a number of negative consequences of gender stereotyping (Hyde et al., 2019). Further, stereotyping (in this case, gender-typing) may be particularly costly for those not fitting in as they cause belief distortions towards the individuals most representative to the group (gender) (Bordalo et al., 2016). Genicot (2022) incorporates a similar concept of adopting an identity that differs from one's own inherent identity into individual utility and fittingly calls it *compromising*.

[10] As in Albanesi and Olivetti (2009), we could add a term collecting the disutility of producing marketable and domestic goods $V(h, e)$. But as in this case, the individual will always exhaust her time endowment T, disutility $V(h, e)$ will only reflect the benefits of specialization. To see this, consider for instance, $V(h, e) = he$, which we can write as $V(\hat{m}) = (1 - \alpha(\hat{m}))\alpha(\hat{m})T^2$. Thus, the disutility will be maximum if $\alpha(\hat{m}) = 1/2$. That is, when the person splits her time in the production of domestic and marketable good equally. Adding that term does not change the model's predictions.

$$\hat{m}_i = m_i + \frac{n_i \left[\alpha(\hat{m}_i) w'_{\hat{m}}(c_i) + \alpha'_{\hat{m}} w(c_i)\right] + \alpha'_{\hat{m}} \left\{[t - \mathbf{1}(c_i = F)2t] - \theta G'_h\right\}}{1 + \gamma n_i \alpha(\hat{m}_i) w'_{\hat{m}}(c_i)} \tag{1}$$

where $\mathbf{1}[c_i = F]$ takes on value 1 if i is female and zero otherwise. Equation (1) indicates that optimal revealed masculinity depends positively on true masculinity, but that, as indicated in the social psychology literature, society's normative stereotypes become self-fulfilling as they push people to disclose a masculinity level away from their true endowment and closer to what is expected from their gender category (Bertrand, 2020). First, the societal punishment for deviating from the norms pushes revealed masculinity up for men and down for women. Second, the optimal deviation from true masculinity is mediated by how transferable "faked" masculinity is into the reward function. Low transferability implies a high γ, making the bias smaller by discounting the forces that incentivize the inflation and deflation of the revealed masculinity relative to the true one. Third, optimal revealed masculinity also depends positively on the marginal benefit of increased masculinity in the age-specific payoffs on the marketable activities, which materializes in two ways. The marginal increase in the societal reward function (the more the "market" rewards masculinity, the greater the incentive to reveal a higher masculinity endowment) and the marginal increase in the fraction of time devoted to the marketable activities. Note that $w'_{\hat{m}}(M, \hat{m})$ need not be equal to $w'_{\hat{m}}(F, \hat{m})$. In fact, a very plausible scenario is one in which $w'_{\hat{m}}(M, \hat{m}) > w'_{\hat{m}}(F, \hat{m})$, where masculinity is valued more in the production of the marketable good among men than among women. Thus, how societies reward masculinity in marketable activities can affect the reported masculinity differently by gender. Finally, optimal revealed masculinity will be lower if there is a higher marginal value of the domestic good.

Equation (1) also shows an important attribute of the model: $\alpha'_{\hat{m}}$, the extent to which society infers masculinity from a marginal increase in e_i, is critical in determining $\hat{m}_i$. A large $\alpha'_{\hat{m}}$ means that large changes in e_i imply small changes in masculinity. Thus, larger $\alpha'_{\hat{m}}$ in equation (1) implies that an agent who wants to inflate their masculinity by a given amount needs to increase the time spent at the marketable activity by more.

The first order condition shows that gender norms produce an interesting asymmetry across genders in the difference between the true and the revealed masculinity. We summarize this asymmetry in Implication 1.

Implication 1 (*Asymmetry*) *If $t > 0$ then $\hat{m}_i \geq m_i$ for $c_i = M$ and $\hat{m}_i \lesseqgtr m_i$ for $c_i = F$.*
Given a sizable enough societal punishment for deviating from the gender norm, men will have an incentive to inflate their masculinity, while women can reveal more or less masculinity than their true endowment depending on the size of the marginal ability-mediated gains relative to the marginal utility produced by the domestic good.

It is easy to see that men with high m_i have a strong incentive to reveal a high $\hat{m}_i$ and enjoy the benefits of higher payoffs, while not paying the cost of deviating from societal norms for men. Men with low m_i face a trade-off. The benefit of being true to their traits (disclose a low $\hat{m}_i$) is countered by the societal punishment t and the losses in the age-specific payoffs on the marketable activities. The higher the societal punishment t and the premium for masculinity are, the higher the disclosed masculinity will be, despite having a low true m_i. In fact, all men will inflate their masculinity unless they have a marginal utility of the domestic good that exceeds the marginal increases in the age-specific payoffs from their marketable activities plus the societal punishment from deviating. This formalizes the notion held in social psychology that men need to project more masculinity than what they really have because the societal normative prescriptions for men relate highly with status (Moss-Racusin et al., 2010).

For women, the direction of the bias $\hat{m}_j - m_j$ could go either way. Even though they face the possibility of greater rewards in the marketable activity if they choose an $\hat{m}_j > m_j$, the societal punishment for deviating from social norms and the gains to low masculinity through the increased consumption of domestic good push $\hat{m}_j$ to be less than m_j. Women with high m_j are incentivized to reveal their true high masculinity by facing higher rewards from marketable activities, especially if they are high-skilled. At the same time, they are disincentivized to reveal their high m_j by society's punishment for not complying with gender norms and the value given to the domestic good. An example of this type of behavior is documented by Bursztyn et al. (2017) who find that unmarried female MBA students under-report professional ambition when they are aware male peers will see their responses. Another example is Exley and Kessler (2022), who find that women are less likely to self-promote themselves when it comes to male-typical tasks than their equally performing male counterparts. When it comes to stereotypically female tasks, the gender gap in self promotion disappears.

Implication 2 (*The role of discrimination*) *Gender discrimination (i.e., $w(M, \bar{m}) > w(F, \bar{m})$) leads to men choosing a higher revealed masculinity than women, even if they both have the same true masculinity endowment.*

Gender discrimination makes women's payment from the marketable activity more easily offset by the societal punishment and the payoff from the domestic good, which relate negatively with $\hat{m}$. As social norms incentivize people to reveal a masculinity level that is different from their true endowment, they also have an incidence on the misallocation of time in marketable *versus* domestic activities—relative to the time allocation we would observe in the absence of gender norms and punishments for deviations (Ashraf et al., 2022). We summarize this concept in Implication 3.

Implication 3 (*Misallocation*) *Time misallocation between marketable and domestic activities is increasing in the size of the societal punishment t.*

Communities with greater societal punishment t will have more outcome (e.g., occupation) sorting along gender lines as men (women) are pushed to inflate (deflate) their revealed masculinity further away from their true endowment. As t increases, the average true masculinity among men who sort into gender-conforming roles falls, and only those whose true masculinity is very low sort into gender-nonconforming roles. Thus there is an over-provision of marketable time and under-provision of domestic time among men. Conversely, for women, increasing t implies that the average true masculinity among those who sort into gender-conforming roles increases. Thus, there is an under-provision of time in marketable activities and an over-provision of domestic time among women. There is ample evidence attesting to that. More sexist societies (in the sense that more people hold anti-egalitarian views of the role of women) have lower female employment and labor force participation rates (Fortin, 2005; Bertrand, 2020). Placing people in roles they would not have chosen in the absence of gender norms is costly for themselves and for the society as a whole (Hsieh et al., 2019; Jiang, 2021).

The asymmetry described in Implications 1-3 uncovers how heterogeneity in revealed masculinity $\hat{m}_i$ links to variation in life outcomes that, in turn, are heavily influenced by gender norms. On the one hand, gender-nonconforming men are those who choose a relatively low $\hat{m}_i$ even after being unequivocally incentivized to inflate it. Thus, they are men with low m_i who do not anticipate the net gains from further inflation to be worth it, due to, for instance, low productivity of 'faked' masculinity relative to true masculinity, γ, or high returns to home production.[11] We therefore expect to find a negative empirical relationship between the outcomes of marketable activities and gender nonconformity among men. On the other hand, the incentives to inflate $\hat{m}_i$ are ambiguous for women. In particular, holding all other parameters constant, gender-nonconforming women will be those with high m_i who find that the benefits in the marketable activity of relatively high $\hat{m}_i$ exceed the societal punishment of not deflating it and the payoff provided by domestic activities. Hence, we expect a positive empirical relationship between the outcomes of marketable activities and gender nonconformity among women.

3 Data

3.1 The Stockholm Birth Cohort

We use data from the Stockholm Birth Cohort Study (SBC) which follows the cohort of children born in 1953 who were living in the Stockholm metropolitan area in November 1963. This cohort study links individuals across two longitudinal data sets. The first is the Stockholm Metropolitan Study 1953–85, which consists of birth records, Census data and a comprehensive in-class school survey for the complete cohort of children born in 1953 who were still living in the Stockholm metropolitan ten years later. The second is The Swedish Work and Mortality Database, an administrative data set which follows up individuals' education, earnings, employment history and mortality through 2009 for all cohort members still living in Sweden by

[11] In this sense, revealed masculinity has a biological basis in our model through m_i. Sex differences are documented at multiple levels of brain organization (Halpern et al., 2007), and there is evidence of neuroanatomic differences between gender-typical and gender-atypical individuals (Bussey and Bandura, 1999; Folkierska-Zukowska et al., 2020). While acknowledging this biological basis, the development of a child's cognitive understanding of gender—for example, whether competitiveness and self confidence can be feminine, or whether empathic, nurturing activities can be masculine—is still deeply rooted in societal norms (West and Zimmerman, 1987; Eagly, 1987).

1980 or 1990.[12]

The SBC study includes an in-class school survey that was conducted in 1966 when the cohort members were in sixth grade (age 13). During one school day, all sixth graders in the county of Stockholm filled out two questionnaires, including cognitive tests (verbal, numeric and spatial), friendship nominations of three best friends, questions on whether they hang out with mixed- or single-sex reference groups, favorite school subject and preferences for leisure interests (e.g., domestic, mechanical and sports). Importantly, the survey took place at school which gave it a mandatory character. As a result, the non-response rate is only 9% (the percentage of pupils absent on that particular school day). The school survey was combined to data backwards in time, such as delivery records and Census data and forward in time to data on the cohort members' subsequent schooling careers, occupational choices, earnings over three decades, life events and demographic outcomes. Table 1 provides descriptive statistics on the individuals in the study. See Appendix A and Appendix C for additional summary statistics and variable definitions.

3.2 The Gender Conformity Index

To study the association between revealed masculinity $\hat{m}_i$ and life outcomes, we set out to construct a context-specific measure of revealed masculinity in childhood. Based on it, we consider men with low $\hat{m}_i$ and women with high $\hat{m}_i$ to be childhood gender nonconformers. Unlike the contributions of the personality trait-based approach to gender identity that impose prespecified scales of "femininity" to "masculinity" that are thought to distinguish men from women (Bem, 1974; Spence et al., 1975; Magliozzi et al., 2016; Brenøe et al., 2022), we develop a measure of childhood gender nonconformity based on seemingly innocuous reports on interests and choices during childhood. We use reports on preferences for leisure interests, subject at school and peer group preferences because, as we will show below, those preferences and choices *empirically* differ across genders at that time (late 1960s) and age (i.e., 13 year-olds). By not imposing any gendered structure on the data, we take a data-driven approach in which we simply collect the common latent variation shifting the

[12] The two data sets were matched based on variables which are available in both data sets. For 96% of the original cohort, data were matched. See (Stenberg and Vågerö, 2006) for a description of the data set and the matching procedure. Codebooks are available online at: https://www.stockholmbirthcohort.su.se.

Table 1: Descriptive Statistics Split by Student's Sex

	Obs.	All	Male	Female	Difference	
Sociodemographic Background						
Older brother	10,154	0.351	0.341	0.36	-0.018*	0.009
Older sister	10,154	0.331	0.326	0.335	-0.009	0.009
Younger brother	10,154	0.339	0.336	0.343	-0.007	0.009
Younger sister	10,154	0.32	0.313	0.326	-0.013	0.009
Professional mother	10,154	0.04	0.041	0.038	0.003	0.004
Working mother	10,154	0.187	0.187	0.186	0.001	0.008
Female head of house	10,154	0.074	0.07	0.079	-0.009*	0.005
Mother any college	10,154	0.018	0.019	0.017	0.002	0.003
Father any college	10,154	0.089	0.093	0.085	0.008	0.006
Home-ownership	10,154	0.184	0.186	0.182	0.004	0.008
Month of Birth	10,154	6.226	6.133	6.315	-0.182***	0.065
Educational Outcomes						
GPA in grade 9*100 (scale 1-5)	9,701	321.96	320.01	323.84	-3.832**	1.545
Upper secondary dropout	9,396	0.423	0.416	0.43	-0.014	0.010
Any post secondary	9,396	0.429	0.408	0.448	-0.040***	0.010
STEM secondary track	6,843	0.383	0.593	0.18	0.413***	0.011
Any college	9,396	0.244	0.245	0.243	0.002	0.009
Labor Market Outcomes						
Log earnings age 37	9,596	1.626	1.847	1.413	0.434***	0.013
Log average earnings age 37-47	9,638	1.757	1.921	1.598	0.323***	0.012
Work Full time in 1980	9,763	0.657	0.797	0.522	0.275***	0.009
Work Part time in 1980	9,763	0.176	0.085	0.264	-0.179***	0.007
Professional	7,789	0.118	0.152	0.082	0.070***	0.007
Legal or business	10,085	0.18	0.174	0.185	-0.012	0.008
STEM Occupation	10,085	0.1	0.148	0.053	0.095***	0.006
Blue collar	10,085	0.244	0.392	0.101	0.291***	0.008
Clerical support	10,085	0.122	0.047	0.195	-0.148***	0.006
Teacher-other health	10,085	0.15	0.072	0.225	-0.153***	0.007
Service and sales	10,085	0.118	0.092	0.142	-0.050***	0.006
Did not work	10,085	0.086	0.074	0.098	-0.024***	0.006
Marriage, Fertility, and Mental Health Outcomes						
Married by 1980	9,816	0.344	0.252	0.433	-0.180***	0.009
Divorced by 1980	9,816	0.032	0.019	0.044	-0.025***	0.004
Total fertility	5,171			1.675		
Teenage childbearing	5,171			0.023		
Age at first birth	2,749			23.87		
Mental health disorders	9,817	0.079	0.088	0.071	0.016***	0.005
Substance abuse	9,817	0.039	0.053	0.025	0.028***	0.004
Leadership ability	3,612		0.000			
Ability to function under stress	4,492		0.000			

Note: Statistics are shown for the full sample and for the male and female subsamples. Variables Leadership ability and Ability to function under stress are only available for men and were standardized to have mean zero and standard deviation one. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Additional descriptive statistics can be found in Appendix A

manifest responses on preferences and choices and generate a one-dimensional continuous measure that abstracts completely from gender categories. It is only *ex-post* that we plot the gender-specific distributions of the resulting continuous measure and confirm that it contains relevant information about childhood gender conformity as it clearly discriminates between most boys and girls.

By selecting existing survey questions that elicit information on typically masculine (agentic) and feminine (communal) preferences, without any *ex ante* notion of how they should map on a feminine-masculine scale, our measure is capturing the relevant social context such as ingrained preferences and societal expectations. Like other measures, ours is based on psychology's "big two" dimensions of agentic and communal behaviors. However, unlike trait-based measures of gender identity, such as the Sex Role Inventory (Bem, 1974) and Personal Attributes Questionnaire (Spence et al., 1975), we do not impose prespecified scales to map personal traits into masculinity scores. Our measure is closer in spirit to the interest-based gender diagnosticity approach. Existing approaches predict individuals' gender typicality using survey items on hobbies or occupational preferences that discriminate men from women based on clearly defined statistical significance criteria (Lippa and Connelly, 1990; Fleming et al., 2017; Yavorsky and Buchmann, 2019; Burn and Martell, 2022), or automated learning algorithms (Mittleman, 2022). Ours shares the advantage with the gender diagnosticity approach of generating a social- and culture-specific measure of gender identity, but unlike the gender diagnosticity approach we do not rely on the binary categorization of gender.[13] Instead, we collect the common variation from our selected variables for every individual in the data, men and women pooled.[14]

3.2.1 Observed Measures as Inputs for the GCI

We use the following variables to construct our gender conformity index. See further details in Appendix B.

[13]Our approach is not the first or only indirect way of inferring gender identity. The best known indirect measure, the Implicit Association Test, assesses the strength of people's cognitive associations between themselves and gender-typical traits through reaction times (Greenwald et al., 2009).

[14]Lippa and Connelly (1990) argue that " 'masculinity' and 'femininity' are not necessarily universal across cultures, but rather are, to some degree, defined by behaviors that vary across cultures and subcultures....[they] are not necessarily equivalent to instrumental or expressive personality traits, or to wearing pants or skirts. Rather, they are defined by behaviors that discriminate men from women in a particular population in a particular society during a particular historical era."

Gender homophily. We use the survey question "with whom do you spend most of your time?" Extensive literature in Psychology and Sociology documents the important role that gender homophily plays in building friendship links, especially for school-aged children (Maccoby, 1998; McPherson et al., 2001; Stehlé et al., 2013). Appendix Figure B.1 shows that students in our sample tend to spend most of their time with other same-sex students.

Favorite school subject. We find a clear difference between boys and girls on their preferred school subject. Boys more frequently reported subjects like history and math, while girls preferred subjects like home-economics, foreign languages, Swedish language arts, music and religion (see Appendix Figure B.2). This difference in class preferences that we find along gender lines has been established by earlier research in psychology, education and economics (Henderson et al., 1999; Jones et al., 2000; Lupart et al., 2004; Fryer Jr and Levitt, 2010; Buccheri et al., 2011; Buser et al., 2014; Joensen and Nielsen, 2016; Justman and Méndez, 2016).

Preferences for leisure time interests. The school survey in sixth grade included a battery of scrambled items on preferences for the three following areas of leisure interests that map onto the dimensions of communal and agentic behavior (Wood and Eagly, 2015), and towards which boys and girls on average tend to have different preferences: domestic interests, mechanical interests, and sports (Lippa and Connelly, 1990; Lippa, 2005). Even though the items were scrambled in the questionnaire, the areas were sets of ten items each and the students rated their interest preferences for each individual item using a 4-step scale that ranged from "would be very much fun" to "would be very boring" practicing the mentioned interest. In this sense, the battery of items inquires about hypothetical scenarios. Thus, it does not inform about the child's proficiency in each particular interests.[15]

Domestic interests include items such as making clothes, cooking foreign dishes and interior decoration. Mechanical interests include items such as playing with model railways, repairing a bike or reading about space ships. Finally, the area of interests that deal with sports includes items such as bike racing, playing basketball for a

[15]These responses translate to corresponding numerical values of 5, 4, 2, or 1 points and only the sum of scores for each set of interests made it to the coded data set (not the scores on the single items). Specifically, a score of 10 means the student would find practicing the area of interests (e.g., mechanical interests) very boring whereas a score of 50 instead means that the student thinks it would be very much fun.

club, high jump and coaching athletes.[16] Appendix Figure B.3 shows that the preferences collected by these three areas of interests differ greatly along gender lines. Appendix Figures B.3(a) and B.3(b) show that boys had a higher average preference for sports, while girls have higher preference for domestic activities—have in mind that all children in the sample were born in 1953. Finally, Appendix Figure B.3(c) shows that most boys have a preference for mechanical interests, while most girls find them unappealing.

The differences in preferences between boys and girls are well established in social psychology and education literatures (Ashmore et al., 1986; Gibbons et al., 1997; Aros et al., 1998; Lippa, 2010). When allowed to choose, boys are more likely to select conventionally masculine toys (e.g., cars, trains), whereas girls are more likely to choose conventionally feminine toys (e.g., jewelry, cooking and nurturing games) (Adelson, 2012). Further, as was mentioned before, sports achievements are higher valued among boys than among girls (Coleman, 1961b). Displaying gender-atypicality on many of our measured behaviors and preferences (e.g., opposite-sex toy and friend preferences) belong to the most common manifestations of childhood gender nonconformity (Adelson, 2012).

3.2.2 The Construction of the Index

For our main empirical approach, we collect the common variation across the measures described above using principal component analysis (PCA).[17] We keep the variation in the first component—which amounts to 42% of the total variation in the manifest measures—to build our measure of interest. We normalize the values of the factor produced by that first component to the $[0, 1]$ interval. Figure 1(a) shows the distribution of component scores for boys and girls separately. This figure can be interpreted as a *revealed* masculinity scale since girls are clustered near zero and boys are clustered near one. Therefore, we can think of the boys who are near one and the girls who are near zero as expressing more gender-typical behaviors. To keep boys and girls in the same scale, we create a gender conformity index (GCI) by reversing

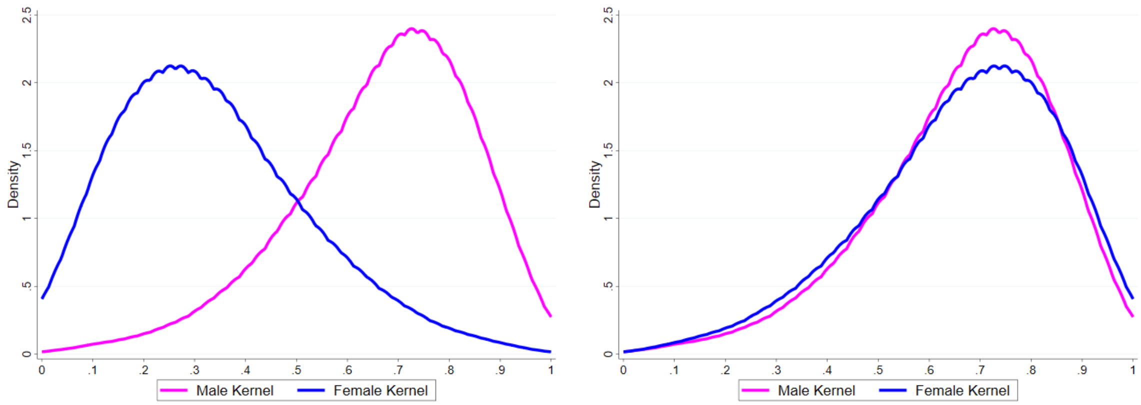
[16] See Appendix Table B.1 for all the individual items.

[17] The school subject input variable is categorical. To use it in the PCA, we coded it to reflect if they are female dominated (-1), male dominated (1), or neither (0).

Figure 1: Gender Conformity Index

(a) Gender Typicality by Gender

(b) Gender Conformity Index



Note: As in Figure 1(a), the score for girls was subtracted from one in order to flip the girls' distribution, so that the bulk of the girls' data was clustered near one in Figure 1(b). This allows us to make the assumption that the boys and girls near zero are gender-nonconforming since they are different than the norm set by their peers. To create this figure an in-built kernel density command was used on the modified first component variable while also splitting the data by gender. Data from Stockholm Birth Cohort.

the gender-typical masculine factor for girls. By doing so, we have all of the girls who reveal feminine characteristics and the boys who reveal masculine characteristics near one, and the boys who reveal feminine characteristics and the girls who reveal masculine characteristics near zero. Put another way, the children who are near one would be considered "extremely gender-conforming," and the children who are near zero are considered "extremely gender-nonconforming" regardless of their gender. Figure 1(b) shows the distribution of the gender conformity index by gender.

We define the gender-nonconforming individuals in relation to their gender's typical individuals. To operationalize childhood gender nonconformity (CGN), we set the threshold for conformity at the twentieth percentile of the GCI distribution. Thus, we define a binary variable that takes on value one for the bottom 20% of the GCI distribution and zero otherwise. We test the robustness of our results to the use of other thresholds, and we also provide results using the continuous GCI index.

3.2.3 Proof of Concept

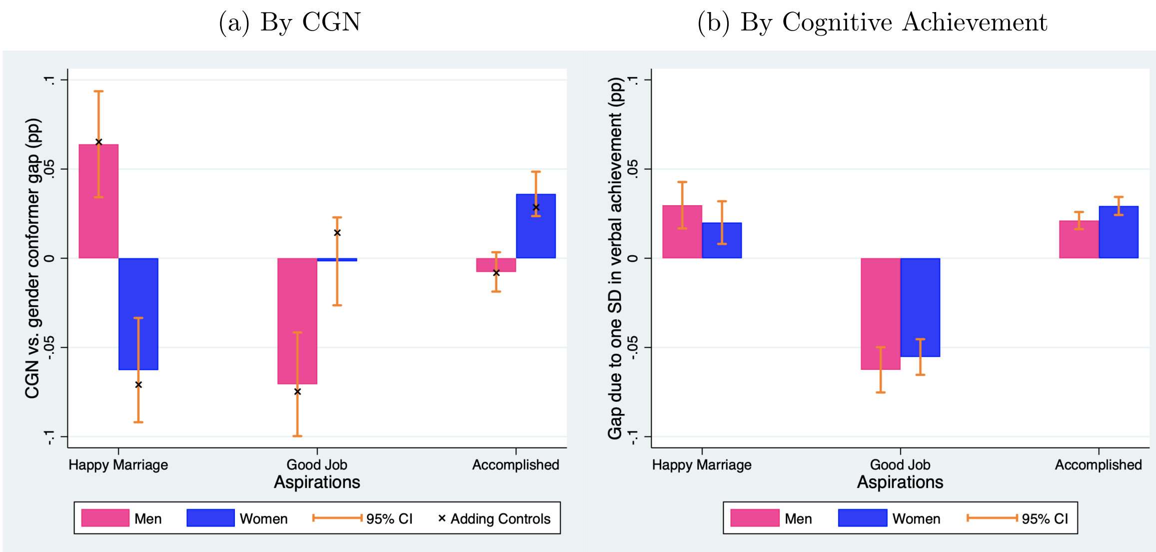
In this subsection, we test the internal validity of our novel metric of gender nonconformity by providing evidence that it captures intrinsic preferences as opposed to parental influences in our analytic sample. We also test its external validity by replicating our metric in contemporary school surveys for three different European countries: Sweden, Germany, and the United Kingdom. We document the same bimodal GCI distributions in all three auxiliary surveys. We further repeat the internal validity test in each of these three surveys. We confirm that our metric is not sensitive to a) our choice of country; and b) our choice of cohort.

We first validate our measure using data on the marriage and career aspirations of the cohort members in sixth grade. As mentioned, heavily influenced by gender norms, life goals is an area where men and women display vast differences from an early age (Lippa and Connelly, 1990). In Figure 2(a), we relate our CGN measure to self-reported marriage (communal) and career (agentic) aspirations ascertained in the same school survey as all questions underlying our CGN measure.[18] We exclude marriage and career aspirations from the nonconformity index as they might capture *ex ante* beliefs teenagers have on their future outcomes. It would nevertheless be reassuring to find strong and asymmetric correlations between our CGN measure and life goals. In congruence with the framework we presented in Section 2, our working hypothesis is that gender-nonconforming women (men) are more career-oriented (family-oriented) than their gender-typical counterparts.

Our results reassuringly show that female (male) gender nonconformers are less (more) likely to believe that having a "happy marriage" will be the most important factor determining their happiness during adulthood than their gender-typical counterparts. In addition, gender-nonconforming men value less getting a "good job" as a grown up as compared to their gender-conforming male peers, while female gender nonconformers aspire more for "accomplishing things in life" than female gender-conformers. Taken together, these associations suggest that the gender nonconformers in our data have clearly different life goals than their gender-conforming counterparts, and go against the gendered life goals postulated by the Social Role Theory (Eagly, 1987). The relationships between CGN and life goals remain unaltered, and even become stronger, when we control for cognitive achievement (both measured in the same survey). This result is relevant for two important reasons. First, cognitive achievement and life goals are correlated even after controlling for school fixed-effects to deal with neighborhood sorting, as we do throughout out the paper (Figure 2(b)). Second, cognitive

[18] According to Alice Eagly's (1987) Social Role Theory shared gender stereotypes develop from the gender division of labor and lead to differentiated skills and life goals.

Figure 2: Which will be the strongest driver of your happiness and life satisfaction as a grown up?



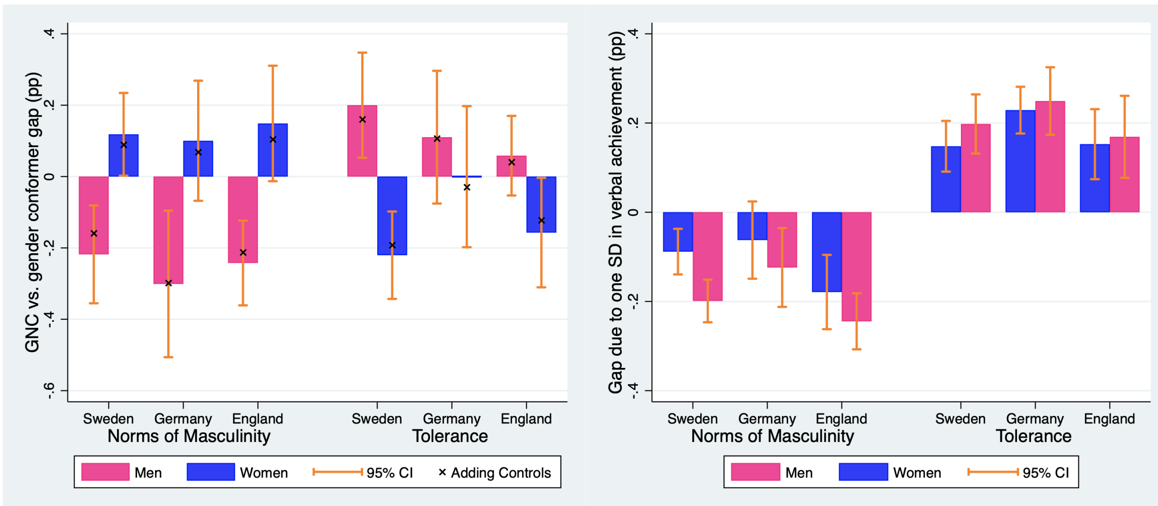
Note: Data from Stockholm Birth Cohort. The question inquires about which aspect of life the child believes will be most important for her happiness as a grown up. Ninety-five percent of the students chose one of the following (exclusive) four categories: i.) to be happily married (51.4%), ii.) to have a good job (31.1%), iii.) to accomplish things (4%), and iv.) to have good friends (7.8%). The bars represent the coefficients of a regression of each aspiration on a gender-nonconformity dummy separately for men and women. We control for observable sociodemographic characteristics like household composition, parental education and home-ownership. We also include school fixed-effects. Black x symbols in Figure 2(a) indicate the value of the coefficient when the list of controls is expanded to include cognitive achievement. The variable in the vertical axis in 2(b) measures verbal achievement at age 13.

achievement tests—especially ones gauging verbal and numeric achievement—are, to a great extent, the product of parental practices and investments (Agostinelli and Wiswall, 2016; Agostinelli et al., 2020). The answers to the questions we use to construct our GCI might also reflect parental practices and investments. Thus, if our GCI did collect information mainly inherent to differential parental investments, the estimates in Figure 2(a) would mirror those that present the relationship between aspirations and cognitive achievement in Figure 2(b) and would significantly change once one controls for cognitive achievement. Reassuringly, this is not the case. These results lead us to confirm that the GCI we construct captures intrinsic preferences.

In order to test the external validity of our proposed metric of gender nonconformity, we use the longitudinal Youth in Europe Study (YES!) for three European countries representing school systems with different degrees of selectivity and extent of tracking: Germany (high selectivity), Sweden (moderate) and England (low) (Dollmann, 2021; Kalter et al., 2016). The study collects nationally representative data on 8^{th} graders

Figure 3: GNC and Gender Norms in Contemporary School Surveys

(a) By CGN (b) By Cognitive Achievement



Note: Data from YES! (Kalter et al., 2016). Samples exclude migrant children. Masculine norms collects information on how much the respondent agrees with men having to use violence in different contexts. Tolerance collects information on how much the respondent is at ease with a couple cohabiting without being married, divorce, homosexuality and abortion. For symmetry across Figures 2(a) and 3(a), the y-axis displays the percentage point difference between gender nonconformers (bottom 20 percent of the GCI by gender) and gender conformers. We include school fixed-effects. Black x symbols in Figure 3(a) indicate the value of the coefficient when the list of controls is expanded to include cognitive achievement. The variable in the vertical axis in 3(b) measures verbal achievement at age 13.

in 2010. The survey collects information covering student performance, achievement, school environment, attitudes towards school, friendship and classmate networks, attitudes and norms and leisure time activities (see detailed descriptions of the data and instruments in Appendix B.1).

Using the same inputs as we did in our primary study sample (i.e., gender homophily, favorite subject at school and leisure time activities), we calculate our gender conformity index in the contemporaneous data sets.[19] Reassuringly, Appendix Figure B.7 shows that the gender-specific distributions of the GCI in the three auxiliary surveys present similar gender-skewed patterns to the ones obtained from our primary data in Sub-figure 1(a). We then correlate the auxiliary surveys' GCI with the students' level of agreement to statements indicating that *men* should use violence in particular situations ("Norms of Masculinity"), and the students' level of agreement with cohabitation, divorce, abortion and homosexuality ("Tolerance"). A clear pattern emerges

[19]Appendix B.1 describes the survey design and variables used as inputs for the gender nonconformity index. All codebooks and technical reports are available online at https://www.cils4.eu/.

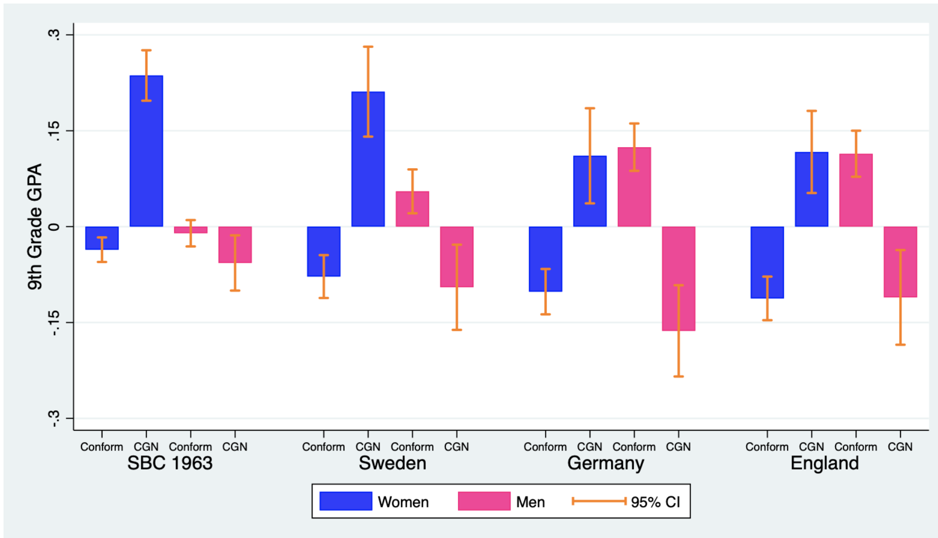
from Figure 3(a) across all three countries: female (male) gender-nonconformers are more (less) likely to sympathize with the statements gauging norms of masculinity than their gender-conforming counterparts. When it comes to tolerance, male (female) gender-nonconformers are more (less) tolerant than their gender-conforming counterparts. As all survey respondents in our auxiliary data were tested for verbal achievement we can contrast the correlations presented in Figure 3(a) with correlations of verbal achievement and norms of masculinity as well as tolerance (Figure 3(b)). As expected, both *a priori* and based on the results in our primary data (Figure 2), the latter correlations are symmetric for both genders, the higher the verbal achievement score at age 14, the less prone one is to sympathize with the norms of masculinity and the more tolerant one tends to be.[20] Thus, these patters serve as proof of concept and give us grounds to believe that our novel theory-based metric of gender nonconformity captures intrinsic preferences in multiple settings and cohorts.

3.3 Gender Nonconformity & Gaps in Student Performance

We conclude this section by documenting a novel descriptive pattern of gender gaps in student performance. There is ample evidence indicating that, on average, girls outperform boys in school (DiPrete and Buchmann, 2013)—which might suggest that masculinity is somehow at odds with school success. However, when we split the data by gender conformity, we find that the exceptional performance of gender-nonconforming girls drives the average performance gap. As indicated in Figure 4, we observe this regularity in our primary data and among contemporaneous students in other European countries. In Sweden, gender-nonconforming girls widely outperformed any other group in the 1960s and the 2010s. In England and Germany, gender-nonconforming girls perform better than their conforming counterparts and gender-nonconforming boys while being on par with conforming (masculine) boys. To our knowledge, we are the first to document this more complex picture than the one produced by computing the difference between the two conditional means for binary gender categories, as is commonly seen in the literature on gender gaps in student performance. Furthermore, these results provide a basis for the divergent life paths

[20] Appendix Figure B.8 confirms that the results remain qualitatively identical for the same validation exercise when using the continuous GCI instead of the derived binary metric of childhood gender nonconformity (CGN).

Figure 4: GNC and School Performance



Note: Data from SBC and YES!. Samples in YES! exclude migrant children. The bars represent the average 9^{th} grade GPA by gender and nonconformity relative to each country's mean.

we document in the next section.[21]

4 Regression Analysis

This section presents our main empirical analyses. Given that our aim is to explore the relationship between gender nonconformity and life outcomes, we regress the outcome y_{is} of student i in school s (e.g., education, career choices, labor market outcomes, marital status, mental health, and fertility outcomes) against a CGN_{is} dummy variable that takes the value of one if an individual was categorized as being a gender-nonconforming according to our metric (i.e., belonging to the bottom 20% of our gender conformity index), and zero otherwise. The reference group are thus the same-sex individuals who conform to the gender norms. We estimate the following equation:

$$\mathrm{y}_{is} = \alpha_0 + \omega_s + \mathrm{CGN}_{is}\beta + \mathbf{x}_{is}\alpha_1 + \epsilon_{is}, \tag{2}$$

[21] Other studies have compared student performance beyond the gender binary. Aksoy et al. (2022) find that high school students who identify themselves as something other than male or female (n=173) in their data (n=10,637) perform better than women and as good as men in math and science tests. However, most gender-nonconforming children identify as cisgender (Adelson, 2012). Thus, ours is the first to study student performance across different degrees of gender conformity within genders.

for each gender separately, where $\mathbf{x}_{is}$ includes the following sociodemographic background covariates: single-parenthood, parental level of education, home-ownership status, whether the mother worked or had a professional position (Olivetti et al., 2018), and the number of younger and older siblings (Brenøe, 2021). The regressions also include ω_s, a school-level fixed effect that captures potential neighborhood-level confounders like those driving income and socioeconomic segregation. Thus, all our results refer to differences across students *within* the same school. These socio-economic controls capture predetermined factors that are known to determine parental investments—which can correlate with GCI—and later life outcomes (OECD, 2014). Recent literature has shown that parental investments respond to the child characteristics (Attanasio et al., 2020; Agostinelli et al., 2020). Given that the child's CGN status can be one of those characteristics, we do not include in $\mathbf{x}_{is}$ controls that are not predetermined. For instance, $\mathbf{x}_{is}$ should not include cognitive achievement scores because they inevitably capture acquired knowledge, personality and educational opportunity up until the time of taking the test (Borghans et al., 2016). All of which can be the direct or indirect—through parental investment—result of the child's CGN status.[22]

Finally, to aid interpretation, we use the binary variable for whether a child is gender-nonconforming. In Section 4.5, we test the robustness of our results to using the continuous nonconformity metric (GCI) and alternative GCI metrics.

4.1 Student Performance and Career Choice

We start by examining the link between gender nonconformity and student performance, education choices and career outcomes. To conserve space we only present estimates for our main variable of interest. The first panel in Table 2 reveals that gender-nonconformity is positively associated to student performance for girls while negatively so for boys. The magnitude of the coefficients are sizable and confirms the descriptive fact presented in Section 3.3 on gender-nonconforming girls' exceptional

[22]Section 5 takes a semi-structural approach and estimates the relation between life outcomes (i.e., earnings and occupation choices) and latent factors of gender nonconformity and cognitive ability. The latter identified from the common variation in achievement scores. This allows us to analyze the association between each factor and life outcomes independently of each other.

Table 2: Gender Nonconformity and Student Performance and Career Choices

	Explanatory variable: *Gender nonconformity*					
	Sample: Boys/Men			Sample: Girls/Women		
Outcome:	Coeff.	S.E.	Obs.	Coeff.	S.E.	Obs.
Student performance						
GPA in grade 9 (in hundredths)	-6.104**	(2.701)	4,746	21.328***	(2.542)	4,955
Upper secondary dropout	0.036**	(0.018)	4,588	-0.077***	(0.017)	4,808
Educational choice						
Any post secondary	-0.008	(0.017)	4,588	0.074***	(0.017)	4,808
STEM secondary track	-0.213***	(0.021)	3,374	0.170***	(0.016)	3,469
Any college	0.014	(0.015)	4,588	0.085***	(0.015)	4,808
Occupational choice†						
Legal or business	0.018	(0.013)	4,947	-0.001	(0.014)	5,138
STEM	-0.090***	(0.015)	4,947	0.023***	(0.007)	5,138
Blue collar	-0.011	(0.017)	4,947	-0.004	(0.011)	5,138
Clerical support	0.026***	(0.007)	4,947	-0.016	(0.014)	5,138
Teacher-other health	0.012	(0.009)	4,947	0.026*	(0.014)	5,138
Service and sales	0.027***	(0.010)	4,947	-0.024*	(0.013)	5,138
Did not work	0.018**	(0.009)	4,947	-0.004	(0.010)	5,138

Note: The entries in the top-two panels of the table represent the coefficient β from separate regressions of student performance and career choice on our binary variable for gender nonconformity as in equation (2). All regressions control for school fixed effects and sociodemographic background covariates such as parents' presence in the household, parents' level of education, a dummy for family living in an owner-occupied home, having older and younger brothers and sisters, and whether the mother worked or had a professional position. See Appendix C.2 for a definition for all the included covariates. The sample has 189 schools and 543 classrooms. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. † Marginal effects from a multinomial logit reported in the bottom panel. Multinomial logit's coefficient estimates provided in Appendix D.

student performance. Here, when controlling for a number of potential confounders, our regression results show that CGN girls' academic GPA in 9^{th} grade is 0.21 points greater than gender-conforming girls. In contrast, we find that CGN boys' academic 9^{th} grade GPA is 0.06 points *lower* than their gender-conforming male peers. Table 2 also shows that CGN girls are less likely to drop out from school before completing upper secondary than gender-conforming girls. A CGN girl is 7.7 percentage points (14% in relative terms) less likely to drop out of school after completion of compulsory school in 9^{th} grade than gender-conforming girls. We find the opposite for CGN boys. They are 3.6 percentage points (6.2%) *more* likely to drop out of school after completion of compulsory school as compared to gender-conforming boys.

After documenting that the link between gender nonconformity and student performance holds after controlling for potential confounders, and importantly, that opposite patterns for men and women remain robust, we assess its relation with educational and occupational choices in the bottom two panels of Table 2. We focus on educational track choices for upper secondary education, a pivotal junction that determines which prerequisites for tertiary education the student will acquire. We further explore occupational choices by age 27, which is late enough in life for most individuals to have completed their education and to be several years into their labor market history. Gender nonconformity is strongly associated with educational and occupational choices. We find that CGN girls were 7.4 percentage points (16.5%) more likely to take any post-secondary study and 17.0 percentage points (94.4%) more likely to apply to a STEM track than their gender-conforming female peers. The last gap is remarkable given that women have historically been vastly under-represented in STEM fields (Carrell et al., 2010; Kahn and Ginther, 2018; Bertrand, 2020). In contrast, CGN boys were 21.3 percentage points (35.9%) less likely to opt into the STEM track than their gender-conforming counterparts. However, even though CGN boys are less likely to choose STEM tracks, we do not find statistically significant evidence that CGN boys are less likely to reach post-secondary education than their gender-typical counterparts.

We find notable differences in occupational choices across gender conformity types. While women who were gender nonconformers during childhood (henceforth, CGN women) tend to sort into STEM occupations, CGN men tend to sort away from them and into female-dominated occupations like clerical support and services and sales. Given the general backdrop of women's underrepresentation in STEM occupations, which are on average high-paying and with relatively small gender gaps,[23] these occupational differences by CGN type must not be taken lightly. The differences are remarkable. While CGN women are 49% (2.3 percentage points relative to a 4.66% mean) more likely to work in a STEM occupation than gender-conforming women, CGN men are 55% less likely to sort into a STEM occupation than their gender-conforming male peers. Instead, CGN men are 63% and 31% *more* likely to choose clerical or service and sales occupations than comparable gender-conforming men.

[23] See, for instance, Goldin (2014); Blau and Kahn (2017); Cortes and Pan (2018); Bertrand (2020). In fact, in our data, STEM occupations pay on average 30% more, and the gender gap within them is 40% smaller than in the rest of the occupations.

Table 3: Gender Nonconformity and Labor Market Outcomes

	Explanatory variable: *Gender nonconformity*					
	Sample: Men			Sample: Women		
Outcome:	Coeff.	S.E.	Obs.	Coeff.	S.E.	Obs.
Employment						
Full time in 1980	-0.036**	(0.015)	4,803	0.028	(0.018)	4,960
Part time in 1980	0.015	(0.010)	4,803	-0.030*	(0.016)	4,960
Not employed in 1980	0.021*	(0.012)	4,803	0.001	(0.015)	4,960
Professional	-0.014	(0.014)	4,090	0.032***	(0.011)	3,699
Earnings						
Log earnings age 37	-0.094***	(0.023)	4,716	0.031	(0.022)	4,880
Log average earnings age 37-47	-0.096***	(0.024)	4,735	0.028	(0.019)	4,903
Log av. earnings 37-47 in STEM$^{\gamma}$	0.000	(0.062)	733	0.112*	(0.068)	272

Note: The entries in the table represent the coefficient β from separate regressions of labor market outcomes on our binary variable for gender nonconformity as in equation (2). See Table 2's note for the details of the sociodemographic controls included. All regressions include school fixed effects. The sample has 189 schools and 543 classrooms. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. $^{\gamma}$ Refers to earnings of those working in STEM occupations, estimates do not include school fixed effects due to the small number of observations.

4.2 Employment and Earnings

Thus far, we have documented a consistent pattern of female gender nonconformers outperforming gender-conforming women (and men, for that matter) at school and making career choices that should narrow the gender gap on the labor market even in terms of earnings. The next question to ask is thus, did gender-nonconforming women capitalize on those choices in terms of better labor market outcomes and higher financial reward. Similarly, we ask whether gender-nonconforming men earn less due to making career choices that resemble those of gender-conforming women more than gender-conforming men. We report the results in Table 3.

We find that CGN men are 17.8% less likely to be employed and 4.5% less likely to have a full time job than gender typical men by age 27. Meanwhile, CGN women participate in the labor force as much as gender typical women, but they are more likely (5.4%) to hold a full time job as opposed to a part time one. Importantly, that job is 39% more likely to be a professional post.

Given this divergence in labor market participation, full-time employment, and occupational choices along gender typicality lines, we inquire if they have any bearing on earnings in the bottom panel of Table 3. We find that CGN men earn about 10% less than gender-conforming men during their prime labor market years (37-47). This gap contrasts with the result that, during the same years, CGN women earn about 3% more than gender-conforming women—albeit not statistically significant at standard levels. This asymmetry in the way the labor market rewards male typicality goes in line with the predictions of our framework in Section 2, as it seems to matter whether *masculine* traits are displayed by a man or a woman and what type of occupation they are displayed in (Pan, 2015). While CGN men who work in STEM occupations see no earnings *punishment*, CGN women in STEM see their childhood gender atypicality rewarded in adulthood. They earn 11% more than their gender-conforming female classmates who sort into STEM. Of course, the latter estimates may be biased due to sample selection. Namely, as we showed in Table 2, sorting into STEM occupations is itself influenced by childhood gender nonconformity. For this reason, in Section 5, we revisit the occupation-specific associations between earning and gender nonconformity using a Roy model in which we allow for endogenous occupational choices. The results remain: STEM occupations reward childhood gender nonconformity among women about four times more.

4.3 Marriage, Fertility, and Behavior

Lastly, we look at demographic and health outcomes in Table 4. Our results show that CGN girls were not less likely to get married but were nevertheless 33.7% more likely to get divorced by age 27 than their gender-conforming peers. These findings align with our framework in Section 2. Female gender atypicality would imply a lower production of the domestic good and increased production of the market good. Increased labor force participation and income would provide gender atypical women an outside option to staying in an unhappy marriage and increase their potential for divorce. These results are consistent with recent research stating that gender norms make marriages in which women are high earners less stable (Bertrand et al., 2015; Folke and Rickne, 2020). Furthermore, CGN women are 39.1% less likely to become mothers as teenagers and overall postpone childbearing relative to gender-conforming girls.[24] These results together with their outperformance on education and occupational choices reported in Section 4.1 suggest that the gender-nonconforming, in

[24] Here, it warrants mention that our sample comprises "baby boomers", the generation that started postponing childbirth and age at marriage. In Sweden, the median age at first birth was roughly 24.5 years for the 1953 cohort and rose to age 28 by the 1960 cohort (Hoem, 1990).

this cohort, are the most career-oriented women. When we consider the subsample of female individuals in this study who pursued professional career paths, the differences in marriage outcomes are considerably more dramatic. CGN women who end up in a professional career are 56.5% less likely to marry and roughly two times more likely to divorce by the age of 27 relative to gender-conforming women with equivalent career outcomes. However, we see no difference in total fertility between CGN women and their gender-conforming counterparts—neither overall nor within the professional subsample. This lack of a difference in total fertility may help explain why the magnitude of the gain in earnings for CGN women is smaller than that of the loss for CGN men. It seems as if, just like their gender-conforming counterparts, CGN women end up paying the "child penalty", which research has shown to persist throughout a woman's career (Angelov et al., 2016; Doepke and Kindermann, 2019; Kleven et al., 2019). Taken together, these results suggest that CGN women, despite attaining higher and more profitable degrees and demonstrating similar preferences to the typical man, are yet penalized in the labor market for childbearing. This relates to the stats put forth by Goldin (2004, 2021) that show that only around 15% of college educated female 'baby boomers' in the US managed to combine career after marriage *and* childbearing.

Regarding mental health outcomes, we find that CGN boys are more likely to have mental health conditions and suffer from addiction during adulthood than gender-conforming boys. According to inpatient records, CGN men were 24% more likely to be hospitalized for mental health disorders during their life up until age 56 than gender-conforming men. Similarly, CGN men were 43.5% more likely to be hospitalized for substance abuse than gender-conforming men. As our framework describes, these adult outcomes can result from not fitting into the prescriptive stereotypes society imposes. They could be the long-term manifestation of i.) the emotional cost society puts on deviants from the norm in the form of social rejection (Landolt et al., 2004; Lippa, 2008; MacMullin et al., 2021; Sarzosa and Urzúa, 2021), or ii.) the personal cost of having to fit into a masculine role (i.e., $\hat{m}_i > m_i$). Social psychology literature has established that even though gender norms have clear advantages for men, the pressure to conform to them may be harmful (Moss-Racusin et al., 2010). Failing to be as agentic, self-reliant, and stoic as society expects can undermine a person's self-worth (Carver et al., 2003; Yunger et al., 2004; Lippa, 2008; DiFulvio,

Table 4: Gender Nonconformity and Demographic, Health & Socio-Emotional Outcomes

	Explanatory variable: *Gender nonconformity*					
	Sample: Men			Sample: Women		
Outcome:	Coeff.	S.E.	Obs.	Coeff.	S.E.	Obs.
Marriage & fertility						
Married by 1980	-0.021	(0.016)	4,825	-0.022	(0.018)	4,991
Divorced by 1980	0.004	(0.005)	4,825	0.015**	(0.007)	4,991
Total fertility				-0.019	(0.019)	5,171
Teenage childbearing				-0.009*	(0.005)	5,171
Age at first birth				0.301**	(0.130)	2,749
Mental health						
Mental health disorders	0.021**	(0.010)	4,826	0.002	(0.009)	4,991
Substance abuse	0.023***	(0.008)	4,826	0.011*	(0.006)	4,991
Socio-emotional						
Leadership ability	-0.195***	(0.042)	3,612			
Ability to function under stress	-0.167***	(0.037)	4,492			

Note: The entries in the table represent the coefficient β from separate regressions of marriage, fertility, mental health and socioemotional outcomes on our binary variable for gender nonconformity as in equation (2). See Table 2 for the details of the sociodemographic controls included. All regressions include school fixed effects. The sample has 189 schools and 543 classrooms. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

2011). Table 4 provides some evidence on that matter. The last panel uses detailed military psychological evaluations of men at the time of conscription (end of high school), assessing leadership abilities and ability to function under stress, qualities related to agency. The results show that CGN men had a fifth of a standard deviation lower leadership ability and a sixth of a standard deviation less capacity to perform under stress than gender-conforming men in their cohort.

4.4 Male Typicality and Gender Gaps

Thus far, our results show that gender conformity is strongly associated with men's and women's choices and outcomes. Rewards to displayed male typicality—except for marriage stability—generates an asymmetric relationship between gender nonconformity and life outcomes across genders. Thus, our results *suggest* that gender gaps vary depending on the degree of gender conformity. Given that our gender conformity index does not discriminate between genders, we can compare outcomes of men and women while holding our gender conformity index constant. The thought experiment is: Will the gender gap close when comparing equally masculine (or feminine) individuals? In Appendix Table E.2, we show how the gender gaps change when we compare outcomes of men and women with the same degree of male typicality.[25]

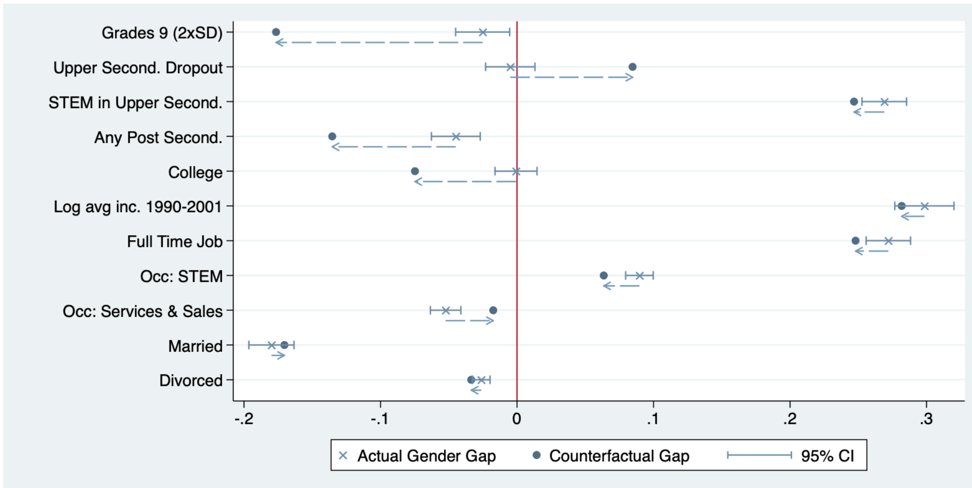
When we compare men and women with the same level of 'male typicality,' we find that the gender gap for 9^{th} grade GPA in favor of women more than triples the overall gender gap (0.18 *versus* 0.05 points). Moreover, women's returns to 'male typicality' in terms of grades are greater than those of men. Similarly, we see that while there is no gap in the incidence of dropping out from upper secondary between the average male and female students, women drop out 3.8 percentage points (9% in relative terms) *less* than men with the same level of 'male typicality.' In addition, the post-secondary enrollment gap in favor of women almost doubles from 4.6 to 8.3 percentage points if we compare men and women with the same level of 'male typicality.'

Consistent with the existing literature (Carrell et al., 2010; Jiang, 2021), our data indicate that relative to the average man, the average woman is 41.2 percentage points (69% in relative terms) less likely to pursue a STEM major. However, when we compare men and women with identical 'male typicality,' the gap shrinks by more than 40%. Still, even when comparing men and women with the same 'male typicality,' we see that women are 4 percentage points less likely to work in a STEM occupation. This gap speaks to the high barriers (i.e., hostile work environments, discrimination, and harassment) women face at entering male-dominated fields (Ahlqvist et al., 2013; Dresden et al., 2018; Funk and Parker, 2018; Folke and Rickne, 2022). Even those women with similar tastes and behaviors as, and better grades than, men stay out of STEM fields. Finally, the results in Appendix Table E.2 show that the earnings gender gap between men and women with the same level of 'male typicality' is 6.4 percentage points (12.9% *versus* 16.3%) smaller than the existing gap between the average man and woman.

Another way to further conceptualize these relations is to create some simple counterfactual exercises where we quantify the gender gaps that would arise if women had the tastes and preferences the typical man has (i.e., as women become increasingly gender nonconforming). That is, we predict women's individual outcomes based on a version of equation (2) in which we regress outcomes on the gender nonconformity

[25] As conforming to the male gender norm is what pays off on the labor market, we operationalize our exercise in terms of male typicality instead of female typicality.

Figure 5: Female Outcomes at the Average Male Typicality of Men



Note: The figure plots how much the outcomes of the average woman would change if she had the male typicality of the average man. 9^{th} grade GPA is plotted in terms of two standard deviations so as to keep the scale common to other outcomes. Data from Stockholm Birth Cohort.

index. We then impute the gender nonconformity with that one of the average male. We collect the results in Figure 5.

Figure 5 compares the gaps we observe with the counterfactual gaps we would obtain if women had men's gender typicality. We see that 9^{th} grade grades gender gap would be much more in favor of women. Women would drop out less and achieve more years of schooling. The earnings gap and other labor market gaps that are vastly in favor of men would shrink. Finally, more women would end up divorced.

4.5 Summary of Robustness Checks

This sub-section summarizes our robustness checks, which are described in detail in Appendix D. To support the validity of our results we run four variants of our main regressions. First, we replace our binary CGN variable with the underlying continuous gender conformity index as the independent variable of interest. We perform this analysis to confirm that our results are not influenced by our binary definition of gender nonconformity versus conformity. We report the results of this exercise in Table D.1. Second, in order not to conflate our nonconformity with general apathy towards leisure interests, we run our original analyses with a restricted sample. The restricted sample excludes individuals in the bottom fifth percentile of reported interest in domestic interests, mechanical interests, and sports. The results for this exercise is reported in Table D.2. Third, we add month of birth as a control variable in order to partial out possible confounding variation stemming from the assumption that those born earlier in the year might be physically stronger than the peers born later. As strength is often associated with masculinity, age variation (within the year) can affect gender conformity reporting. We present the results in Table D.3. Fourth, we recalculate our GCI, excluding information on students' favorite subjects, as there is a concern that its variation might be skewing the GCI to pick up STEM orientation rather than more general gendered preferences. Table D.4 presents the results.

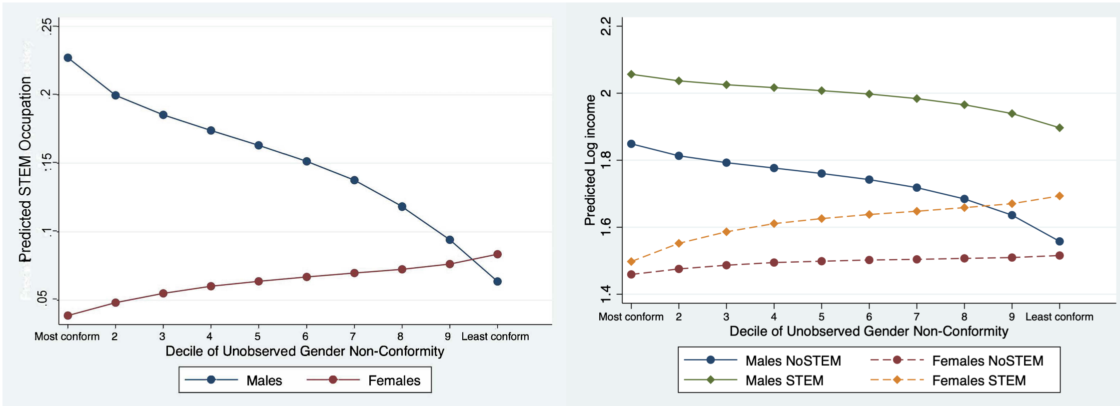
Overall, our results remain robust to these alternative specifications. CGN boys earn lower grades, drop out more often and enroll less in STEM fields. They also earn significantly less than their gender-conforming male peers, work less full-time, and forgo STEM occupations for clerical, service, and sales jobs. Furthermore, CGN girls earn higher grades, go on to enroll in STEM fields, and further their education more than their gender-conforming female peers. We find that CGN girls are more likely to pursue professional career paths, work in STEM, divorce, postpone childbirth and seek help for substance abuse more than their gender-typical counterparts.

5 Endogenous Occupational Choice & Earnings Gaps

The earnings gap is arguably the most studied gender gap in economics. Works like Bertrand (2020) and Goldin (2021) show the importance of analysing it in the context of a sequence of career choices that end up defining the feasible set of monetary rewards for a given worker. In this study, we have already shown that the gender atypical individuals opt for substantially different careers relative to their gender-typical counterparts. The *raw* earnings gaps we report in Table 3 embed the different career choices made up until that point in life. Here, to inquire about the counterfactual earnings had the individual chosen a male-dominated occupation as opposed to a female-dominated one (or vice versa), we present and estimate an extended Roy Model of potential outcomes (Heckman and Honoré, 1990). Specifically, we explore this counterfactual contrast across the entire distribution of gender conformity. Our Roy model endogenizes occupational selection while allowing earnings to be a function of observable and unobservable characteristics that depends on the occupational

Figure 6: Gender Nonconformity and Career Outcomes

(a) Occupational Choices (b) Log earnings by Occupational choice



Note: Figure 6(a) presents the $E[\text{STEM}|\theta^{CGN}]$ in the vertical axis product of 20,000 simulations based on the findings of the choice equation (in array (5)) of the Roy model presented in Section G.1. Figure 6(b) presents $E[y_0|\theta^{CGN}] = E[\mathbf{x}\beta_0]+\alpha^{Y_0,G}\theta^{CGN}$ and $E[y_1|\theta^{CGN}] = E[\mathbf{x}\beta_1]+\alpha^{Y_1,G}\theta^{CGN}$ as estimated by the outcome equations of the Roy model (again, in array (5)) and simulated using 20,000 simulations. The horizontal axes in all panels displays the deciles of the gender-nonconforming factor. Data from Stockholm Birth Cohort.

category (Heckman et al., 2006). In this section, we present the results of the model and refer the reader to Appendix G for the underlying model and the assumptions required for identification.

Figure 6 presents the results. Figure 6(a) shows that CGN men are more likely to sort into (out of) lower (higher) paying occupations. Twenty-three percent of the most gender-conforming men work in a STEM occupation, while only 6.4% of the least gender-conforming do. That is a relative difference of about 73%. Although the relation between occupation choice and gender-conformity is not as steep among women as it is in men, we do find some interesting differences. Figure 6(a) indicates that virtually none of the gender-conforming women choose a STEM occupation, while about 8.3% of the least gender-conforming women do. Thus, CGN women are more likely to sort into STEM occupations than CGN men. That is remarkable given the vast under-representation of women in STEM occupations.[26]

[26] In Appendix Figure G.1 we show the opposite regarding the take-up of lower paying occupations like service and sales. CGN men are twice more likely to sort into service and sales (12.9%) than into STEM (6.4%) occupations. On the contrary, gender-conforming men are about three times *more* likely to sort into STEM occupations (23%) than into service and sales (8%). In contrast, CGN women are 4 percentage points (18%) *less* likely to sort into a services or sales occupation

Figure 6(b) presents the estimates of the outcome equations. It shows that gender nonconformity is punished among men regardless of the occupation. The punishment is larger in non-STEM occupations than in STEM ones. Relative to the most gender-typical men, CGN men in STEM occupations earn 15% less. The tantamount differential is 29% in non-STEM occupations. CGN women experience the opposite. While gender-typical women earn on average roughly the same in STEM occupations as outside of STEM occupations, CGN women in STEM occupations earn 49% more than CGN women in non-STEM fields. Thus, gender nonconformity pays off for women in terms of earnings as long as they sort into high-paying male-dominated occupations like the ones in STEM fields.[27]

6 Gender Norms and Divergent Youth Paths

In Sections 3.3 and 4.1, we show that, on average, CGN boys do poorly in school while CGN girls do exceptionally well. We then show that these gaps persist in many respects into adulthood. But what are the underlying mechanisms opening up these performance gaps at school? This section shows evidence attributing these divergent school paths to a combination of preferences (e.g., taste for school) and social interactions, all fueled by gender norms.[28] Using self-reported attitudes towards school and measures of social capital based on characteristics of their social network in sixth grade (age 13), and administrative data on engagement risky behaviors recorded by the Child Protection and Social Welfare Services for the high school years (ages

than gender-conforming women.

[27]In Appendix G.4, we present evidence of strong gender conformity gradients of outcomes that go beyond the labor market. They all go in line with our regression results presented in Section 4.

[28]The literature has, of course, presented alternative explanations as to why grades might reward masculine traits more than feminine ones. For instance, STEM teachers could be biased against feminine traits (Riegle-Crumb and Humphries, 2012), or girls' math performance drops when their teachers hold strong implicit stereotypes (Carlana, 2019). The literature is inconclusive on this point though, Mittleman (2022) shows contradicting evidence of gender atypicality (i.e., femininity for boys and masculinity for girls) being symmetrically a risk factor for discrimination of boys and girls at school. Also, greater fear of failure leads women to become more risk averse when taking exams, which can make them misallocate effort by over-investing time and energy in lower yielding questions (Borges et al., 2022). Therefore, risk-taking and confidence—traits associated with masculinity (Eckel and Grossman, 2008)—produce higher scores. Thus, gender-nonconforming girls' success might be partly explained by them displaying more masculine traits than their gender-conforming counterparts. Although we lack data to explore these potential reasons, all of them fit into our framework and can potentially contribute to explaining our results.

14-18), we explore the mechanisms underlying the asymmetric outcomes of gender nonconformers among men and women.

CGN girls thrive at school. Table 5 shows that CGN girls are 27% of a standard deviation *more* interested in school than gender typical girls that go *to the same school.* Likewise, CGN girls feel much safer in school than their gender-conforming female peers. In addition, CGN girls' social networks at school have different characteristics. CGN girls tend to befriend substantially smarter peers relative to gender typical girls in the same school. Relative the to friends of gender typical girls, the average friend of CGN girls score 16%, 12% and 10% of a standard deviation higher on verbal, numeric and spacial cognitive tests, respectively. Those gaps are sizeable, and as the extensive literature on peer effects has shown, they are very likely to create positive spillovers that boost scholastic performance of the CGN girls (Sacerdote, 2011; List et al., 2020; Opper, 2019). Although, they report having a similar number of close friends as their gender-conforming classmates, Table F.1 of Appendix F shows that CGN girls increase the social capital of the classroom by linking female and male networks together. A higher share of CGN girls in the classroom reduces its clustering (i.e., the degree to which students in the network tend to group in cliques) and diameter (i.e., the shortest distance between the two most distant nodes in the network), both standard measures of social cohesion. That is, CGN girls connect social cliques that otherwise would not be connected. Recent literature highlights the importance social capital has in determining life outcomes ranging from education to intergenerational mobility (Chetty et al., 2022).

What about boys? Much of the literature on gender gaps in student performance attributes at least part of the male underperformance at school to school cultures or toxic masculinity that may adversely affect educational investments (Coleman, 1961a; Akerlof and Kranton, 2002; Goldin et al., 2006; Bursztyn and Jensen, 2017; Bursztyn et al., 2018). Our results challenge the hypothesis of gender nonconformity leading to greater human capital accumulation for adolescent boys through shielding them from male-typical risky behaviors (Yavorsky and Buchmann, 2019; Mittleman, 2022). Using data from the Child Protection and Social Welfare Services for the high school years (ages 14-18), we observe the incidence of risky behavior during adolescence. Panel C of Table 5 shows that, on average, adolescent CGN men are *not* less likely than gender typical boys to be involved in delinquent or violent behaviors. They are

Table 5: Gender Nonconformity and Social Interactions, Attitudes and Behaviors

	Explanatory variable: *Gender nonconformity*					
	Sample: Boys/Men			Sample: Girls/Women		
Outcome:	Coeff.	S.E.	Obs.	Coeff.	S.E.	Obs.
Panel A: Social Network Characteristics						
Nominating only one friend	0.016*	(0.009)	4,776	-0.003	(0.008)	4,985
At least one friends is CGN	0.099***	(0.017)	4,983	0.145***	(0.016)	5,171
Average verbal score of friends	-0.013	(0.025)	4,765	0.162***	(0.026)	4,968
Average numeric score of friends	0.011	(0.025)	4,765	0.126***	(0.024)	4,967
Average spatial score of friends	-0.037	(0.026)	4,765	0.098***	(0.023)	4,968
Panel B: Attitude toward school						
Student's feeling safe at school	-0.159**	(0.080)	4,961	0.349***	(0.080)	5,152
Student's interest in school work	-0.267***	(0.034)	4,967	0.272***	(0.034)	5,139
Panel C: Risky behavior at age 14-18						
Misbehavior	0.013**	(0.006)	4,983	0.006	(0.006)	5,171
Stealing	0.012	(0.012)	4,983	0.002	(0.006)	5,171
Crimes of violence	0.011	(0.008)	4,983	-0.002	(0.003)	5,171
Abuse of alcohol and narcotics	0.017***	(0.006)	4,983	-0.001	(0.005)	5,171
Drunkenness and abuse of solvents	0.021**	(0.008)	4,983	-0.004	(0.004)	5,171

Note: The entries in the table represent the coefficient β from separate regressions of measures of social interaction, attitudes and behaviors on our binary variable for gender nonconformity as in equation (2). See Table 2 for the details of the sociodemographic controls included. See Appendix C.2 for a definition for all outcomes and included controls. All regressions include school fixed effects. The sample has 189 schools and 543 classrooms. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

roughly 50% *more* likely to misbehave as reported by either the school teachers or parents, and 31% more likely to have problems with substance abuse. Thus, we reject the 'toxic male school culture' hypothesis, at least for Sweden in the late 1960s.

Rather, our framework and results indicate that deviating from the norm can be harmful for CGN boys. Discomfort and anxiety of being forced to participate in gender-typical activities and fear of social rejection may predispose CGN adolescent boys to high-risk behavior and substance abuse (Adelson, 2012). According to Panel A of Table 5, CGN boys tend to be less socially connected than their gender-conforming peers. Relative to their gender-conforming peers are 27% more likely to have only one close friend, and the classmates that they do befriend are 28% more likely to be CGNs themselves.[29] Thus, unlike CGN girls, CGN boys face greater risk of social

[29]The relative changes come from the following calculations. Overall, 5.7% of gender typical boys report having only one close friend. Thus, 0.016/0.057 yields the 27% increase in the probability of a CGN boy reporting having only one close friend relative to gender typical boys. Likewise, 35.4% of gender typical boys report befriending at least one CGN peer. CGN boys are 9.9% more likely to do so. Thus the relative change amounts to 28%.

rejection, which is known to have negative effects on grades (Eriksen et al., 2014), skill accumulation (Sarzosa, 2022), and adult outcomes (Sarzosa and Urzúa, 2021). In fact, CGN boys are 15.7% of a standard deviation less likely to feel safe at school than their gender typical male classmates. In line with the literature showing that social rejection in the classroom increases the distaste for school (NAS, 2016; Sarzosa and Urzúa, 2021), CGN boys are 27% of a standard deviation less interested in schoolwork than gender typical boys.[30]

Taken together, these results indicate that the consequences of gender nonconformity differ greatly along gender lines even early in life. There is a reward for CGN girls and a steep cost for CGN boys. The social interactions seem to play an important role in mediating those rewards and costs. While CGN girls thrive at school and make more and smarter friends, CGN boys feel isolated and unsafe, which in turn may contribute to the observed behavioral problems. These differences enroute CGN boys and girls in the divergent paths that we document throughout the paper.

7 Conclusions

Our study provides new insight on the relationship between childhood gender nonconformity and life outcomes. We use a novel approach to measure the former, facilitated by the availability of unique data on preferences in early adolescence and outcomes throughout individuals' professional careers. Among women, gender nonconformers fare better compared to their gender-conforming peers, while among men, the opposite is true. Female gender nonconformers outperform other women at school and are more likely to choose a STEM track and sort into higher-paying STEM jobs. They also delay fertility and earn more throughout their lives. Male gender nonconformers, on the contrary, do worse at school, achieve lower levels of education, sort into less well paid occupations, and have substantially lower earnings than comparable gender-conforming men. Furthermore, male gender nonconformers present a higher incidence of troubling behaviors and mental health issues.

[30] Sarzosa (2022) shows that children who are uncommon (i.e., have rare traits relative to classroom peers, as CGNs do) are more likely to be victimized. Our results also go in line with earlier research documenting that gender-nonconforming boys in particular may be upset by not feeling sufficiently masculine, especially in contexts in which gender norms are highly valued (Friedman, 1988).

Our study does not evaluate a specific policy, nor do our results provide direct policy implications. They, however, highlight the role of gender norms and their rewards to male typicality in determining individuals' career pathways and drive gender gaps. Our findings are in line with the recent literature in economics showing that gender norms and gender gaps in preferences hinder progress towards achieving equality in career choices and the labor market. We observe that gender gaps are narrower for girls who challenge gender norms as early as adolescence. In particular, when it comes to student performance gender gaps, our results suggest that the current state of the literature paints a vexingly incomplete picture. In fact, in all school surveys used in our analysis, representing two different time periods spaced more than 40 years apart and different school systems across Europe, the entire student performance gap in favor of girls is driven by the gender-nonconforming girls. From a simplified static perspective, if they were absent from the classroom, girls would not be outperforming boys. Our results also support the idea that society rewards masculine traits more so than feminine ones, and that men who do not display the former pay a significant cost. Furthermore, that such men display a greater incidence of troubling behaviors and mental health issues suggests that the pressure to conform to the agentic male ideal during adolescence can translate into profound emotional harm for boys who go against the grain.

To our knowledge, this is the first study in the Economics literature to explore the role that societal prescriptions play in perpetuating gender gaps by analyzing *within*-gender complexity. Our evidence on drastic within-gender differences in life outcomes across the distribution of conformity to stereotypical gender norms and preferences shows just how critical it is to consider more complex gender norm identities. In this, we respond to Hyde et al.'s (2019) multidisciplinary call to move "beyond" a simple male-female gender binary and to develop new, pioneering research methods that allow to study the complexity of gender norm identity (Lundberg, 2022). Hopefully, increased availability of data about the complex notions of gender will spur more economics research on the emergence of gender gaps from early school years on.

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Appendix For Online Publication

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A Descriptive statistics

Table A.1: Descriptive Statistics: Sociodemographic Background & IQ Components

	Male				Female			
	CGN	GC	Diff	S.E.	CGN	GC	Diff	S.E.
Household characteristics								
Older brother	0.39	0.33	0.07***	0.02	0.33	0.37	-0.04**	0.02
Older sister	0.33	0.32	0.01	0.02	0.35	0.33	0.02	0.02
Younger brother	0.34	0.33	0.01	0.02	0.34	0.34	0.00	0.02
Younger sister	0.31	0.31	-0.00	0.02	0.33	0.33	0.00	0.02
Professional mother	0.05	0.04	0.01	0.01	0.05	0.03	0.02***	0.01
Working mother	0.19	0.19	0.01	0.01	0.18	0.19	-0.01	0.01
Female head of house	0.07	0.07	0.00	0.01	0.08	0.08	-0.00	0.01
Mother less than HS	0.93	0.93	-0.00	0.01	0.91	0.94	-0.03***	0.01
Mother any college	0.02	0.02	0.00	0.00	0.02	0.01	0.01**	0.00
Father less than HS	0.71	0.74	-0.02	0.02	0.68	0.76	-0.07***	0.02
Father any college	0.11	0.09	0.02**	0.01	0.12	0.08	0.04***	0.01
Single father	0.01	0.01	0.00	0.00	0.02	0.01	0.00	0.00
Single mother	0.06	0.05	0.00	0.01	0.05	0.06	-0.00	0.01
Home-ownership	0.20	0.18	0.01	0.01	0.21	0.17	0.04***	0.01
1953 Month of Birth								
Month of birth	6.01	6.16	-0.16	0.12	6.41	6.29	0.12	0.11
Cognitive test at age 13								
Numeric score	22.99	22.50	0.49	0.27	22.60	20.46	2.14***	0.25
Verbal score	25.81	25.82	-0.02	0.21	27.10	25.08	2.03***	0.22
Spatial score	22.28	24.63	-2.35***	0.24	24.08	22.11	1.97***	0.23
Observations	1,001	3,982			1,042	4,129		

Note: The table provides statistics by sex and gender conformity. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

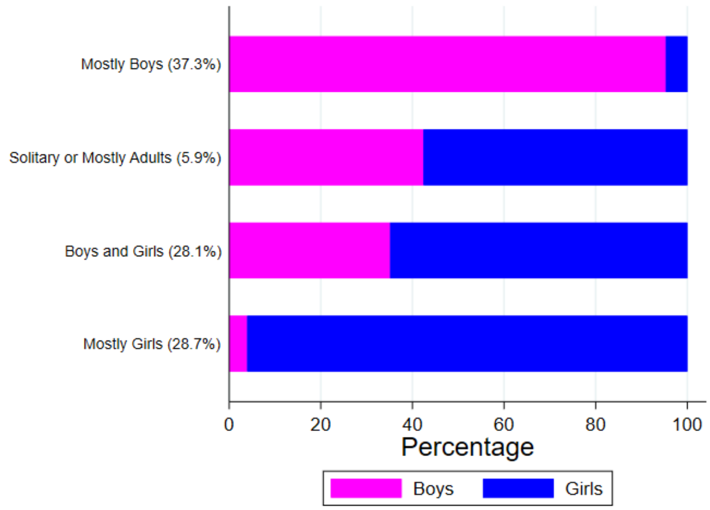
Table A.2: Descriptive Statistics: Life Outcomes

	Male				Female			
	CGN	GC	Diff	S.E.	CGN	GC	Diff	S.E.
Life Outcomes								
GPA in grade 9	316.28	320.93	-4.65	2.83	345.61	318.35	27.26***	2.61
Upper secondary dropout	0.44	0.41	0.02	0.02	0.33	0.45	-0.12***	0.02
Any post secondary	0.41	0.41	0.01	0.02	0.54	0.43	0.11***	0.02
STEM secondary track	0.44	0.63	-0.19***	0.02	0.32	0.14	0.18***	0.02
Any college	0.27	0.24	0.03*	0.02	0.33	0.22	0.11***	0.02
Log earnings age 37	1.78	1.86	-0.08***	0.02	1.44	1.41	0.03	0.02
Log average earnings age 37-47	1.86	1.94	-0.08***	0.02	1.63	1.59	0.04**	0.02
Full time in 1980	0.77	0.80	-0.03**	0.01	0.55	0.51	0.03*	0.02
Part time in 1980	0.09	0.08	0.01	0.01	0.24	0.27	-0.03**	0.02
Not employed in 1980	0.14	0.11	0.02*	0.01	0.21	0.21	-0.00	0.01
Professional	0.14	0.15	-0.01	0.01	0.12	0.07	0.05***	0.01
Legal or business	0.19	0.17	0.02	0.01	0.18	0.19	-0.00	0.01
STEM	0.09	0.16	-0.08***	0.01	0.08	0.05	0.03***	0.01
Blue collar	0.37	0.40	-0.02	0.02	0.09	0.10	-0.01	0.01
Clerical support	0.07	0.04	0.03***	0.01	0.17	0.20	-0.03*	0.01
Teacher-other health	0.08	0.07	0.01	0.01	0.25	0.22	0.04**	0.01
Service and sales	0.11	0.09	0.03***	0.01	0.12	0.15	-0.03***	0.01
Did not work	0.09	0.07	0.02**	0.01	0.10	0.10	0.00	0.01
Married by 1980	0.24	0.26	-0.02	0.02	0.41	0.44	-0.03	0.02
Divorced by 1980	0.02	0.02	0.00	0.00	0.05	0.04	0.01*	0.01
Total fertility					1.65	1.68	-0.04	0.04
Teenage childbearing					0.01	0.03	-0.01**	0.01
Age at first birth					24.25	23.79	0.46***	0.13
Mental health disorders	0.10	0.08	0.02**	0.01	0.07	0.07	-0.00	0.01
Substance abuse	0.07	0.05	0.02***	0.01	0.03	0.02	0.01	0.01
Leadership ability	-0.12	0.04	-0.16***	0.04				
Ability to function under stress	-0.09	0.07	-0.17***	0.04				
Student and family attitudes toward school								
Feeling safe at school	6.66	6.83	-0.17*	0.08	6.41	5.95	0.46***	0.08
Interest in school work	4.29	5.00	-0.71***	0.09	5.68	4.94	0.73***	0.09
Family's attitude toward ed	6.20	6.32	-0.13	0.08	6.58	5.83	0.75***	0.08
Adolescent risky behavior (age 14-18)								
Stealing	0.14	0.12	0.02	0.01	0.03	0.03	-0.00	0.01
Crimes of violence	0.06	0.05	0.01	0.01	0.00	0.01	-0.00	0.00
Abuse of alcohol & narcotics	0.04	0.03	0.02***	0.01	0.01	0.02	-0.00	0.00
Drunkenness & abuse of solvents	0.07	0.05	0.02**	0.01	0.01	0.02	-0.01*	0.00
Acting out	0.04	0.03	0.01**	0.01	0.03	0.03	0.00	0.01
Observations	1,001	3,982			1,042	4,129		

Note: The table provides statistics based on individual sex and gender conformity. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

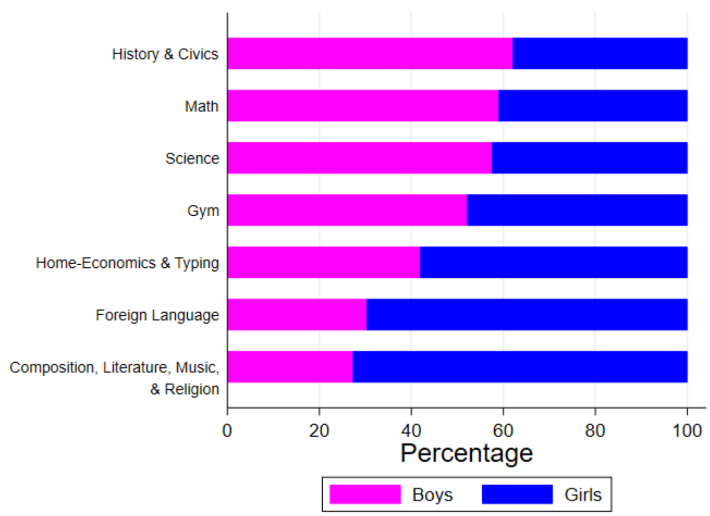
B Construction of the GCI

Figure B.1: Distribution of Gender Homophily



Note: Students report with whom they spend their time. We present their responses in this figure by the respondents own gender.

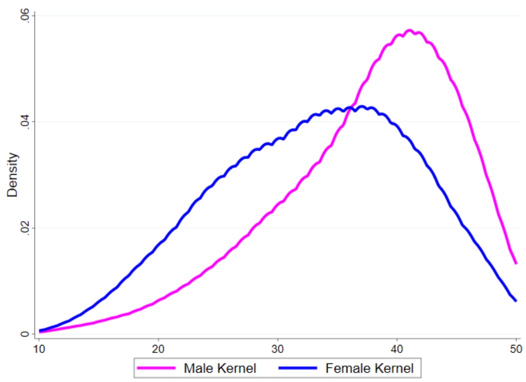
Figure B.2: Gender Distribution of the Preferred School Subject



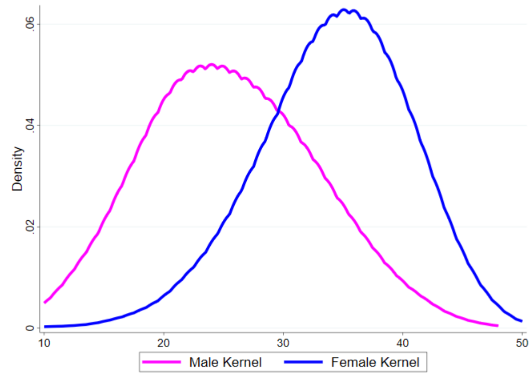
Note: Students report their favorite subject of study in school. We present their responses in this figure by sex of the individual in the study. The favorite school subject input variable is categorical. To use it in the PCA, we coded it to reflect whether it is female dominated (-1), male dominated (1), or neither (0). Data from Stockholm Birth Cohort.

Figure B.3: Interests in Leisure Activities by Gender

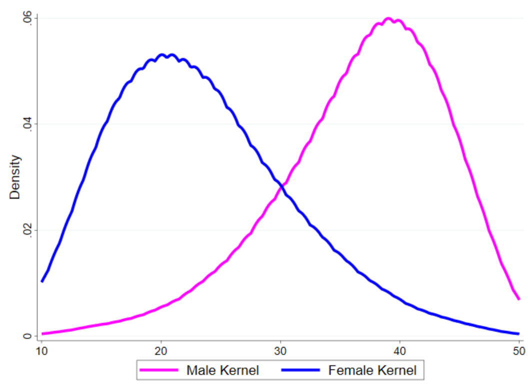
(a) Interest in Sports



(b) Interest in Domestic Activities



(c) Interest in Mechanical Activities



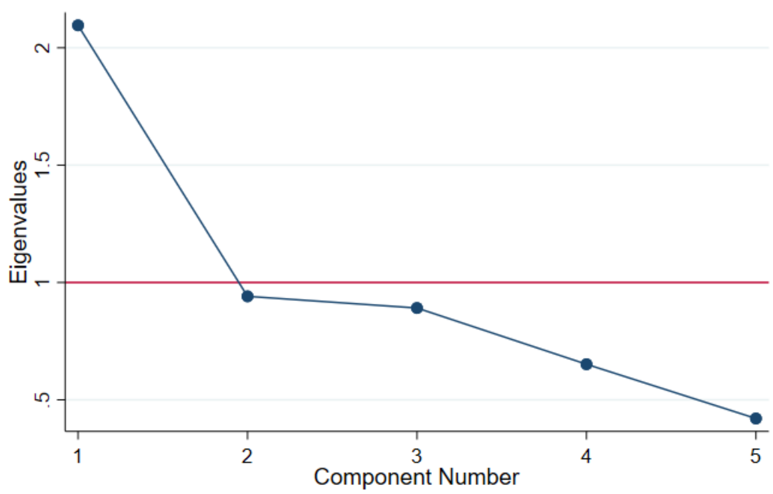
Note: The given three variables in the data each provide a numerical score from 10 to 50, where 10 indicates that the study person finds the area of activities "very boring" and 50 indicates that the study person finds the area of activities "very much fun". Each figure was constructed using an in-built kernel density command while also splitting the data by gender. Data from Stockholm Birth Cohort.

Table B.1: Preferences for Leisure Time Interests

Domestic interests	**Mechanical interests**	**Sports**
Making clothes	Playing with model railways	Practicing gymnastics
Interior decoration	Visiting a museum of technology	Bike racing
Visiting an furniture exhibition	Repairing bikes	Practicing high jumping
Baking bread	Figuring out how a washing machine works	Practicing winter sports
Using a washing machine	Building a radio set	Coaching athletes
Using kitchen appliances	Mending mechanical toys	Playing basketball for a club
Working as a chef in a hotel	Assisting with the construction of a television	Cross-country running
Prepare a sausage dish for guests	Reading about space ships	Sailing
Cooking foreign dishes	Building models	Participating in an athletics event
Cooking a school meal	Constructing high-jump hurdles	Attending an athletics event

Note: The school survey questionnaire presented a list of items on preferences for leisure time interests. For each interest the student rated their preferences using a 4-step scale that ranged from "would be very much fun" to "would be very boring" to practice it. All items were scrambled in the questionnaire in order to elicit the true preference for each particular interest.

Figure B.4: Eigenvalues after PCA



Note: To create this figure, an in-built scree plot command was used after running principal component analysis. Data from Stockholm Birth Cohort.

Table B.2: PCA Input Variable Loadings

	Loadings
Domestic interests	0.4276
Mechanical interests	0.5454
Sports	0.3669
Who do you spend time with?	0.5538
Favorite school subject	0.2801

Note: The table provides loadings for each of the input variables of the principal component analysis.

B.1 Auxiliary data: Youth in Europe Study, 2010-2012

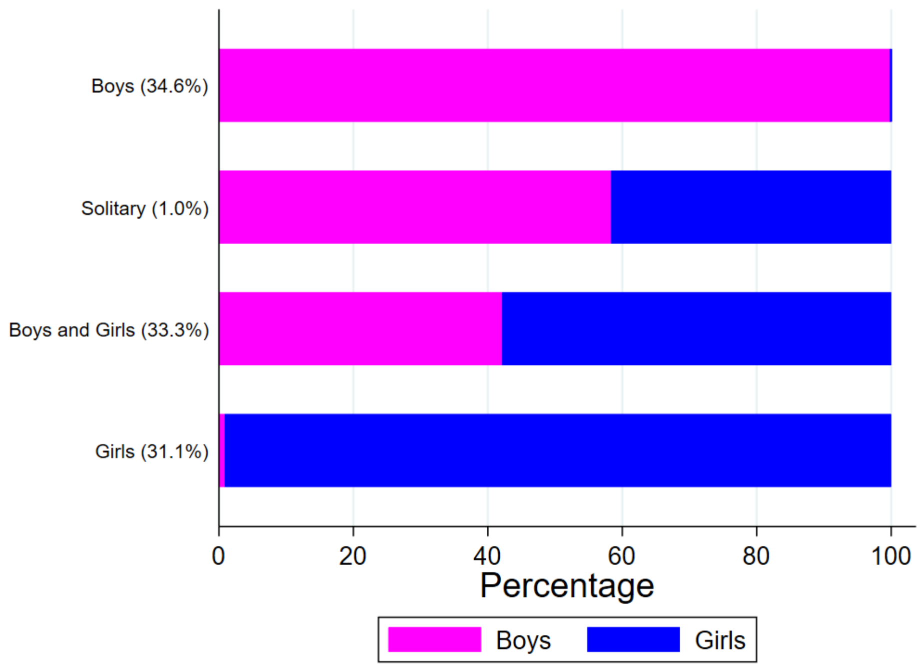
This longitidinal in-class school survey was conducted in three waves beginning with the cohort of 14-year-old students in 2010. The sampling of schools was stratified at three levels (school, classroom and student), to guarantee a sufficient representation of immigrants. Two complete classrooms were then drawn at random in each school within relevant grades. The school interviews consisted of a 45 minute self-completion questionnaire (including questions on friendship and classmate networks (6 nominations each) as well as a 30 minute written test in basic cognitive and language achievement. Table B.3 below describes the sampling frame and the number of YES! survey participants in wave 1, 2 and 3. Table B.5 and Figures B.4 and B.6 describe the inputs of the principal component analysis that was conducted as described in Section 3.2.3.

Table B.3: Youth in Europe Study: Study samples of the three selected countries

	Schools	Classrooms	Students		
			Wave 1	Wave 2	Wave 3
England	107	214	4,315	3,389	2,284
Germany	144	271	5,013	4,256	3,427
Sweden	129	251	5,025	4,531	2,768
Total	380	736	14,353	12,176	8,479

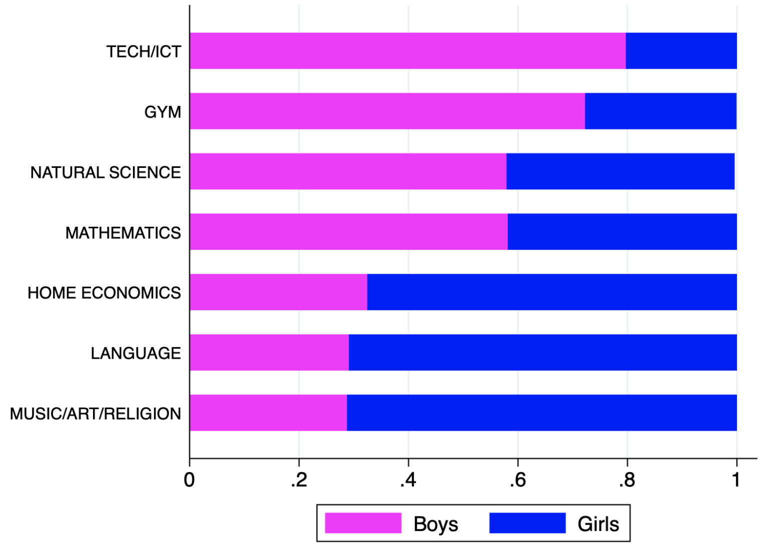
Note: The numbers refer to the absolute numbers for schools, classrooms, and students respectively. Our own analysis samples exclude all immigrants based on country of birth. The surveys of wave one and two were conducted in-class whereas for the third wave survey, the students were contacted through postal and web questionnaires or phone interviews when necessary. In the third wave the students were age 16 and some had already left school while others had transitioned to upper secondary school.

Figure B.5: Youth in Europe Study: Distribution of Gender Homophily



Note: Data from YES! (Kalter et al., 2016). Here, to describe the data, we show results for the Swedish survey (results for England and Germany are available from the authors). Students nominate their five best friends with whom they spend their time within or outside of school and the gender of each, respectively. We coded groups of five best friends including both boys and girls as mixed gender reference groups. We required all five friends to be of opposite gender for opposite-gender reference groups. "Solitary" was categorized based on answer (yes/no) to the statement "Í do not have any friends".

Figure B.6: Youth in Europe Study: Gender Distribution of the Favorite School Subject



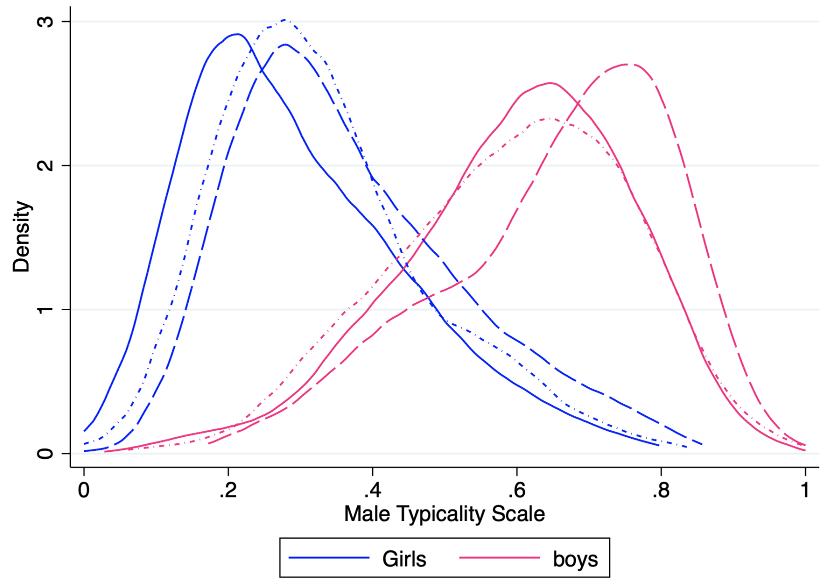
Note: Data from YES! (Kalter et al., 2016). For presentation purposes, we aggregate data from Sweden, Germany and the UK. Students report their favorite subject of study in school. We present their responses in this figure by gender. The favorite school subject input variable is categorical. To use it in the PCA, we coded it to reflect whether it is female dominated (-1), male dominated (1), or neither (0).

Table B.4: Youth in Europe Study: Preferences for Leisure Time Activities and Attitudes Towards Domestic Activities

Leisure time activities				Domestic activities	
Feminine	t-value	Masculine	t-value	Feminine	t-value
Reading	14.4	Video games, alone	36.75	Child care	10.9
Chatting	4.74	Video games,		Cooking	10.5
Homework	6.33	with others	38.1	Cleaning	12.68

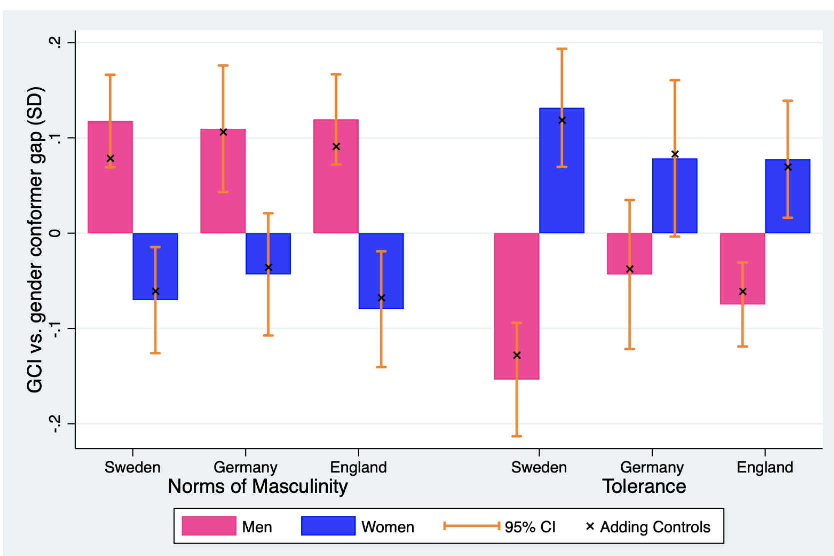
Note: Data from YES! (Kalter et al., 2016). Here, to describe the data, we show results for the Swedish survey (results for England and Germany are available from the authors). Leisure time activities inquire on a 5-step scale about the time spent on practicing the particular activity ranging from “No time at all” to “More than two hours a day”. Domestic activities inquire about the attitudes towards whether the man or the woman in a household should do the domestic activities, the 3-step scale ranging from “Mostly the man” to “Mostly the woman”. The t-value reports the statistic of the t-test of whether the activities are female-typed or male-typed among both genders pooled.

Figure B.7: Gender Typicality by Gender in England, Germany and Sweden in 2010



Note: Data from YES! (Kalter et al., 2016). The gender typicality distributions for England (solid), Germany (dashed) and Sweden (dashed and dotted) are based on the normalized first factor of the principal component analysis equivalent to the one presented for our primary sample in Section 3.2.2.

Figure B.8: GCI and Gender Norms in Contemporary School Surveys



Note: Data from YES! (Kalter et al., 2016). Samples exclude migrant children. Vertical axis measures the gap in the average norms due to a change of a standard deviation in GCI across genders and countries. Masculine norms collects information on how much the respondent agrees with men having to use violence in different contexts. Tolerance collects information on how much the respondent is at ease with a couple cohabiting without being married, divorce, homosexuality and abortion. We include school fixed-effects. Black x symbols indicate the value of the coefficient when the list of controls is expanded to include cognitive achievement.

C Construction of Variables

C.1 Outcome Variables

Educational variables.

- GPA in grade 9 - This is a continuous variable from 100 (lowest) to 500 (highest) indicating the individual's "average marks in spring term of 9th form of elementary school."
- Upper secondary dropout - This binary variable indicates if an individual in this study dropped out of school before completing at a minimum a two-year upper secondary education program. The data contains information on the individual's educational attainment by 2000. If the individual is listed as having completed less than 11 years of schooling, then they are classified as having dropped out of upper secondary school.
- STEM secondary track - This binary variable indicates whether an individual listed a male dominated upper secondary school or vocational program as this first choice of study after having completed compulsory school. An individual who chose a STEM program is assigned as having a "STEM secondary track" choice of study.
- Any post secondary - This binary variable indicates whether an individual attended any form of post secondary education as of 1983. The data provides information on the level of education that the individual had completed or was attending as of 1983. If the individual is listed as any outcome besides "no post-upper secondary school course or program registered," then we assigned the individual as having "any post secondary" education.
- Any college - This binary variable indicates whether an individual had completed an at least three-year long college education by year 2000. of completed any form of post secondary education as of 1983.

Earnings variables. Annual labour income (i.e., earnings, as measured in thousands of SEK) comes originally from registers based on employers' compulsory reports to the tax authorities.

- Log earnings at age 37 (in 1990) - Natural logarithm of annual earnings. Includes sickness benefits, parental benefits and income from self employment and farming activity but excludes capital income, pensions, unemployment benefits and social assistance.
- Log average earnings 37-47 - Natural logarithm of average annual earnings of the individual between 1990-2000. This measure thus captures earnings at a time when the study subjects are established in their careers and close to the most representative years of individuals' lifetime earnings (Böhlmark and Lindquist, 2006; Haider and Solon, 2006).

Career variables.

- Full time in 1980 - The SBC data had 1980 census data on the amount of hours that an individual in the study worked per week in 1980. Full time in 1980 takes on one if an individual worked 35 hours or more per week, otherwise zero.
- Part time in 1980 - Part time in 1980 takes on one if an individual worked less than 35 hours per week in 1980, otherwise zero.
- Not employed in 1980 - This binary variable indicates if the individual was not employed in 1980 based on the 1980 census.
- Professional - Variable that takes the value of one if the socioeconomic index listed the individual as "professional or other higher non-manual posts" or "self-employed professionals," in the 1980 census, otherwise zero.

Occupation. Occupation is based on the 3-digit occupation code in the Censuses 1970, 1975 and 1980. The classification by occupation is based on the Nordic Classification of Occupations, worked out by the Labour Market Boards in the Nordic countries. The classification has been adapted to the International Standard Classification of Occupations (ISCO) developed by the International Labour Office in 1958 (Population and Housing Census 1970 (SOS), 1973).

- Legal or business - This binary variable indicates whether an individual was reported to work in a legal or business sector (1) or not (0).
- STEM - This binary variable indicates whether an individual was reported to work in a STEM sector.
- Blue collar - This binary variable indicates whether an individual was reported to work in a blue collar sector.
- Clerical support - This binary variable indicates whether an individual was reported to work in a clerical support sector.
- Teacher-other health - This binary variable indicates whether an individual was reported to work in a educational or non-medical doctor health related position.
- Service and sales - This binary variable indicates whether an individual was reported to work in a service and sales sector.
- Did not work - This binary variable indicates whether an individual did not work.

Marriage variables.

- Married by 1980 - This binary variable indicates whether an individual in the study was reporter to be married by 1980 according to the 1980 census.
- Divorced by 1980 - This binary variable indicates whether an individual in the study was divorced by 1980 according to the 1980 census.

Mental health variables.

- Mental health disorders - This binary variable indicates whether the person was hospitalized for any mental health disorders between 1981-2008. The data come from the universe of Swedish inpatient records.
- Substance abuse - This binary variable indicates whether an individual in the study was hospitalized for any alcohol and/or drug related abuse between 1981-2008. The data come from the universe of Swedish inpatient records.

Socio-emotional variables. All the men in our data had their psychological profiles evaluated during enlistment in years 1971-1973 according to a procedure that remained unchanged from 1969 through 1995. Conscripts were interviewed by a certified psychologist for about 25 minutes. The interview is semi-structured in the sense that the psychologist has to follow a manual that states certain topics to be discussed, though specific questions are not decided beforehand. The objective of the interview is to assess the conscript's ability to cope with the psychological requirements of the military service and, in the extreme case, war. The psychologists assign each conscript's military aptitude a Stanine score from 1 to 9, a high score meaning high aptitude. This score is in turn based on four different subscores which range from 1 to 5. The subscores work only as a guide to the psychologists—two conscripts with the same sequence of subscores could still get different final scores. In addition to ability to cope with stress, leadership skills are evaluated for those that high enough cognitive scores to become considered for leadership training. The scale of leadership capacity follows the same Stanine distribution, ranging from 1 to 9, as the more general "ability to function under stress" variable. See Lindqvist and Vestman (2011) for a detailed account of the military enlistment's psychological test procedure. We normalize both variables to have mean zero and variance one.

Cognitive tests. We use the three components of ability collected by the school survey in 1966 (at age 13): numeric, verbal, and spatial ability. The tests were constructed at the Swedish Institute for Educational Research in the early 1960s and have served to this date as the default cognitive tests in elementary school (Svensson, 1964).

The verbal and numeric tests are weighted more toward crystallized intelligence (Cattell, 1971). Scores on crystallized intelligence tests are in part determined by innate ability but also by acquired skills and knowledge and are thus depending on educational opportunity and motivation (Borghans et al., 2008, 2016). Some researchers suggest that the numeric and verbal ability tests might therefore more appropriately be called achievement tests than intelligence test (Almlund et al., 2011). The spatial ability test is weighted more towards fluid intelligence (Cattell, 1971), which is often considered the more innate of the two measures of intelligence (Svensson, 1971).

- Numeric ability - The test of numeric ability posed 40 numerical sequences of six numbers, each of which follows a logical pattern based on elementary arithmetic concepts. The students were asked to predict the next two numbers following the same pattern in the sequence. Our measure reports the test score.
- Verbal ability - The verbal ability test presented the student with 40 words, for which the student had to find antonyms among four options.
- Spatial ability - The spatial ability test consisted of 40 unfolded figures that needed to be folded mentally.

Network graphs. The classroom survey conducted for sixth graders (age 13) asked students were asked to nominate their three best classroom friends (the nominations only concerned friends within the same classroom). Of all students in our data who participated in the school survey and completed the friendship nomination component (n=11,854) , 7,497 nominated three friends (63.2%), 3,211 nominated two friends (27.1%), 766 nominated only one friend (6.5%), and 380 did not nominate any friends (3.2%). In our analytic sample (n=10,154), 6,586 students nominated three friends (65.4%), 2,610 students nominated two friends (25.9%), 558 students nominated only one friend (5.5%), and 324 students did not nominate any friends (3.2%).

- Nominating only one friend - This binary variable states whether the student only nominated one friend in their classroom given they had the option to nominate more.

- At least one friend is CGN - This binary variable states whether the student nominated one or more friends who were gender-nonconforming.

- Average verbal/numeric/spatial score of friends - This continuous variable gives the average verbal/numeric/spatial score of the student's nominated friends.

- Clustering - The degree to which students in the network tend to group in cliques. See Section Measuring social capital in Chetty et al. (2022) for an illustrative description.

- Diameter - The shortest distance in terms of number of edges between the two most distant nodes in the network.

Attitude toward school. The school survey in 1966 (at age 13) was a classroom survey that collected information on students' feelings toward school. These variables are the sum of ten questions. Each of the ten questions was a "yes" or "no" question. Answers were assigned 0 or 1 points and tallied to create a final variable.

- Student's feeling safe at school - This variable states how safe/secure the student felt at school. The variable is from 0 (very unsafe/insecure) to 10 (very safe/secure).

- Student's interest in school work - This variable states how interested the student was in school. The variable is from 0 (very uninterested) to 10 (very interested).

Risky behavior at age 14-18. SBC contains the municipal register of dossiers of cases of dependency and Child Welfare Committee cases. The register is cumulative. The register is called the Social Register, which has a different meaning to the Social Registers of American cities. It is not public, but authorities can permit access. In SBC, the records are divided into three periods, ages 0-6, 7-13, and 14-18. We make use of the last period of records for ages 14-18 since we want to see outcomes after the school survey, which was conducted at age 13.

- Misbehavior - This binary variable states whether individuals in this study were investigated by the Child Welfare for any of the following: adjustment problems at home, running away, adjustments at school, truancy, mental illness, or attempted suicide.

- Stealing - This binary variable states whether individuals in this study were investigated by the Child Welfare for stealing.

- Crimes of violence - This binary variable states whether individuals in this study were investigated by the Child Welfare for violent criminal activity.

- Abuse of alcohol and narcotics - This binary variable states whether individuals in this study were investigated by the Child Welfare for abusing alcohol and/or narcotics.

- Drunkenness and abuse of solvents - This binary variable states whether individuals in this study were investigated by the Child Welfare for drinking and/or abuse of solvents.

Birth variables. The data come from the (Swedish) Medical Birth Register of 1984 and contain birth records for the children of all female individuals up until 1983.

- Total births - This variable states the number of children that female individuals in the study had.

- Teenage mother - This binary variable states whether the individual had a child in her teen years. The birth records list the year of birth. Conditional on the individual having at least one child and her age at her first birth being less than 20, then we assigned her as a "teenage mother."

- Age at first birth - This variable provides the age at which a female individual in this study was when she first gave birth conditional on her ever having had a child.

C.2 Sociodemographic characteristics.

- Older (younger) brother - This variable is a binary variable indicating whether the individual had at least one older (younger) brother.
- Older (younger) sister - This variable is a binary variable indicating whether the individual had at least one older (younger) sister.
- Single mother - This variable is a binary variable indicating whether there was a father present in the household. The 1960 census contains information on the "sex of the head of the household" as well as on the "marital status of the head of the household." We assigned the variable as "single mother" if the head of house was female and not married.
- Single father - This variable is a binary variable indicating whether there was a mother present in the household. The 1960 census contains information on the "sex of the head of the household" as well as on the "marital status of the head of the household." We assigned the variable as "single father" if the head of house was male and not married.
- Father less than HS - This variable is a binary variable indicating whether the study person's father did not finish high school.
- Father any college - This variable is a binary variable indicating whether the individual's father acquired any college education.
- Mother less than HS - This variable is a binary variable indicating whether the study person's father did not finish high school.
- Mother any college - This variable is a binary variable indicating whether the individual's father acquired any college education.
- Professional mother - This variable is a binary variable indicating whether the mother worked outside the home in a professional position. We assigned the variable "professional mother" value 1 if the 1960 census variable "Type of occupation of wife of head of household" was coded as "professional" conditioned on her being female, present in the household and being "economically active."

- Working mother - This variable is a binary variable indicating whether the mother worked outside the home. The 1960 census records “economic activity of the wife of the head of household.” We assigned the variable as “working mother” if the wife was reported to be “active”.

- Female head of household - This variable is a binary variable indicating whether the head of the household is female. The 1960 census records “sex of the head of the household”.

D Robustness Checks

Robustness with GCI. Here, to once more confirm that our results in Section 4 are not influenced by our binary definition of gender nonconformity versus conformity, we use the underlying continuous gender conformity index. Equation (3) gives the specification using the gender conformity index:

$$\mathrm{y}_{is} = \alpha_0 + \omega_s + \mathrm{GCI}_{is}\beta + \mathbf{x}_{is}\alpha_1 + \epsilon_{is}. \tag{3}$$

The model is otherwise identical to equation 2 except for the main explanatory variable being the continuous gender conformity index instead of the binary gender-nonconforming variable. The gender conformity index and the binary gender-nonconforming variable are negatively correlated by definition. Hence, we expect the coefficients from equation (2) and equation (3) to hold opposite signs.

Table D.1 presents the results using the continuous gender nonconformity index. It shows that the results hold regardless of the decision to make the distributional cutoff below the twentieth percentile.

Robustness to dropping the apathetic students. Our gender conformity index based on children's responses as to how boring or fun they find particular leisure interests across three domains. potential concern is that boredom towards interests is conflated with general apathy and disinterest. If a student says all of the leisure interests are very dull, then it could be that the individual is generically apathetic to everything rather than gender-nonconforming. This is particularly important for the validity of our index but may also confound our results. General boredom towards life and interests is a common symptom of depression. We could partly be capturing youth depression, which could be biasing our results.

To investigate whether apathy contributes to our results, we restrict the sample to exclude individuals in the bottom fifth percentile of a score in which we aggregate all answers to the questions inquiring about their interests in domestic activities, mechanical activities, and sports. We define them to be the "apathetic" population because in order to have an extremely low score in the aggregated measure, students must consistently report disinterest in all activities. Table D.2 shows that our results do not change in a meaningful way when we drop them.

Robustness to controlling for month of birth. Masculinity may be linked to physical size at young ages. Bigger boys or girls could be deemed stronger, and—given that physical strength is often considered a male trait—masculine. If that size-related variation does not affect the underlying preferences and tastes, we would like to partial it out from our estimates of the relation between gender conformity and outcomes. We do not observe height or weight at the time of the survey (13 years old). However, in this robustness checks we use variation in the month of birth to proxy size with age. The assumption is that children born in earlier months of the year are older and thus more likely to be physically bigger than children born later in the year. Thus, our results in Table D.3 come from estimation that include month of birth fixed-effects. They show that the results do not differ in a meaningful way from the main results we present in the main text.

Robustness to dropping the favorite school subject from the PCA. Favorite subject in school is likely predictive of occupational choices later in life. We drop the favorite school subject from the principle component analysis to probe whether our results are mechanically driven. We report these results in Table D.4. The results do not differ in a meaningful way from the main results presented previously.

Table D.1: Gender Conformity Index Score and Life Outcomes

	Explanatory variable: *Gender conformity*					
	Sample: Men			Sample: Women		
Outcome:	Coeff.	S.E.	Obs.	Coeff.	S.E.	Obs.
Educational outcomes						
GPA in grade 9	19.378***	(6.269)	4,746	-56.031***	(5.483)	4,955
Upper secondary dropout	-0.072*	(0.041)	4,588	0.195***	(0.037)	4,808
Any post secondary	0.022	(0.041)	4,588	-0.201***	(0.037)	4,808
STEM secondary track	0.651***	(0.049)	3,374	-0.413***	(0.034)	3,469
Any college	-0.042	(0.035)	4,588	-0.169***	(0.032)	4,808
Log earnings outcomes						
Log earnings age 37	0.263***	(0.055)	4,716	-0.055	(0.047)	4,880
Log average earnings age 37-47	0.297***	(0.056)	4,735	-0.105**	(0.041)	4,903
Labor market outcomes						
Full time in 1980	0.096***	(0.034)	4,803	-0.064	(0.039)	4,960
Part time in 1980	-0.042*	(0.024)	4,803	0.035	(0.035)	4,960
Not employed in 1980	-0.055**	(0.028)	4,803	0.029	(0.032)	4,960
Professional	0.019	(0.033)	4,090	-0.040	(0.024)	3,699
Occupational outcomes†						
Legal or business	-0.088***	(0.030)	4,947	-0.060**	(0.029)	5,138
STEM	0.243***	(0.031)	4,947	-0.077***	(0.016)	5,138
Blue collar	0.056	(0.039)	4,947	-0.007	(0.023)	5,138
Clerical support	-0.060***	(0.016)	4,947	0.092***	(0.030)	5,138
Teacher-other health	-0.030	(0.020)	4,947	-0.042	(0.031)	5,138
Service and sales	-0.064***	(0.023)	4,947	0.080***	(0.027)	5,138
Did not work	-0.058***	(0.020)	4,947	0.014	(0.022)	5,138
Marriage & fertility outcomes						
Married by 1980	0.077**	(0.037)	4,825	0.015	(0.039)	4,991
Divorced by 1980	-0.010	(0.012)	4,825	-0.032*	(0.016)	4,991
Total fertility				0.022	(0.042)	5,171
Teenage childbearing				0.030***	(0.012)	5,171
Age at first birth				-0.638**	(0.277)	2,749
Social emotional outcomes						
Mental health disorders	-0.093***	(0.024)	4,826	0.025	(0.020)	4,991
Substance abuse	-0.084***	(0.019)	4,826	-0.007	(0.012)	4,991
Leadership ability	0.556***	(0.098)	3,612			
Ability to function under stress	0.516***	(0.087)	4,492			

Note: This table provides the results of the regressions of equation (3) outlined in Appendix Section D in which the continuous gender conformity index as shown in Figure 1(b) is the main explanatory variable. See Table 2 for the details of the sociodemographic covariates included. All regressions include school fixed effects. The sample has 189 schools and 543 classrooms. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

† Results from multinomial logit. Marginal effect reported.

Table D.2: Gender Conformity and Life Outcomes with Restricted Sample

	Explanatory variable: *Gender nonconformity*					
	Sample: Men			Sample: Women		
Outcome:	Coeff.	S.E.	Obs.	Coeff.	S.E.	Obs.
Educational outcomes						
GPA in grade 9	-5.378**	(2.705)	4,730	22.264***	(2.696)	4,454
Upper secondary dropout	0.030*	(0.018)	4,573	-0.081***	(0.018)	4,323
Any post secondary	-0.005	(0.018)	4,573	0.082***	(0.018)	4,323
STEM secondary track	-0.204***	(0.021)	3,364	0.170***	(0.017)	3,139
Any college	0.014	(0.015)	4,573	0.084***	(0.016)	4,323
Log earnings outcomes						
Log earnings age 37	-0.076***	(0.023)	4,701	0.023	(0.023)	4,386
Log average earnings age 37-47	-0.086***	(0.024)	4,720	0.023	(0.020)	4,407
Labor market outcomes						
Full time in 1980	-0.033**	(0.015)	4,787	0.024	(0.019)	4,455
Part time in 1980	0.014	(0.010)	4,787	-0.018	(0.017)	4,455
Not employed in 1980	0.019	(0.012)	4,787	-0.006	(0.016)	4,455
Professional	-0.015	(0.014)	4,080	0.028**	(0.012)	3,320
Occupational outcomes†						
Legal or business	0.014	(0.013)	4,930	0.009	(0.014)	4,615
STEM	-0.088***	(0.015)	4,930	0.027***	(0.007)	4,615
Blue collar	-0.010	(0.017)	4,930	0.002	(0.011)	4,615
Clerical support	0.025***	(0.007)	4,930	-0.022	(0.015)	4,615
Teacher-other health	0.012	(0.009)	4,930	0.024	(0.015)	4,615
Service and sales	0.029***	(0.009)	4,930	-0.037***	(0.014)	4,615
Did not work	0.017**	(0.009)	4,930	-0.003	(0.011)	4,615
Marriage & fertility outcomes						
Married by 1980	-0.021	(0.016)	4,809	-0.027	(0.019)	4,486
Divorced by 1980	0.004	(0.005)	4,809	0.016**	(0.008)	4,486
Total fertility				-0.024	(0.021)	4,646
Teenage childbearing				-0.009*	(0.006)	4,646
Age at first birth				0.285**	(0.138)	2,473
Social emotional outcomes						
Mental health disorders	0.018*	(0.010)	4,810	0.003	(0.010)	4,486
Substance abuse	0.019**	(0.008)	4,810	0.012*	(0.006)	4,486
Leadership ability	-0.187***	(0.042)	3,602			
Ability to function under stress	-0.150***	(0.037)	4,479			

Note: For these results, we drop individuals in the bottom fifth percentile of reported interest in domestic interests, mechanical interests, and sports. We do not want to mistake general disinterest for disliking a given activity. This table provides the results of the regressions of equation (2). See Table 2 for the details of the sociodemographic covariates included. All regressions include school fixed effects. The sample has 189 schools and 543 classrooms. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

† Results from multinomial logit. Marginal effect reported.

Table D.3: Gender Conformity and Life Outcomes Controlling for Month of Birth

	Explanatory variable: *Gender nonconformity*					
	Sample: Men			Sample: Women		
Outcome:	Coeff.	S.E.	Obs.	Coeff.	S.E.	Obs.
Educational outcomes						
GPA in grade 9	-6.109**	(2.702)	4,746	21.326***	(2.543)	4,955
Upper secondary dropout	0.036**	(0.018)	4,588	-0.076***	(0.017)	4,808
Any post secondary	-0.008	(0.017)	4,588	0.074***	(0.017)	4,808
STEM secondary track	-0.213***	(0.021)	3,374	0.170***	(0.016)	3,469
Any college	0.014	(0.015)	4,588	0.085***	(0.015)	4,808
Log earnings outcomes						
Log earnings age 37	-0.094***	(0.023)	4,716	0.031	(0.022)	4,880
Log average earnings age 37-47	-0.096***	(0.024)	4,735	0.028	(0.019)	4,903
Labor market outcomes						
Full time in 1980	-0.036**	(0.015)	4,803	0.028	(0.018)	4,960
Part time in 1980	0.015	(0.010)	4,803	-0.030*	(0.016)	4,960
Not employed in 1980	0.021*	(0.012)	4,803	0.002	(0.015)	4,960
Professional	-0.014	(0.014)	4,090	0.032***	(0.011)	3,699
Occupational outcomes†						
Legal or business	0.018	(0.013)	4,947	-0.002	(0.014)	5,138
STEM	-0.090***	(0.015)	4,947	0.023***	(0.007)	5,138
Blue collar	-0.012	(0.017)	4,947	-0.004	(0.011)	5,138
Clerical support	0.026***	(0.007)	4,947	-0.016	(0.014)	5,138
Teacher-other health	0.013	(0.009)	4,947	0.026*	(0.014)	5,138
Service and sales	0.027***	(0.010)	4,947	-0.023*	(0.013)	5,138
Did not work	0.018**	(0.009)	4,947	-0.004	(0.010)	5,138
Marriage & fertility outcomes						
Married by 1980	-0.021	(0.016)	4,825	-0.021	(0.018)	4,991
Divorced by 1980	0.004	(0.005)	4,825	0.015**	(0.007)	4,991
Total fertility				-0.020	(0.019)	5,171
Teenage childbearing				-0.009*	(0.005)	5,171
Age at first birth				0.301**	(0.130)	2,749
Mental health & Socio-emotional outcomes						
Mental health disorders	0.021**	(0.010)	4,826	0.002	(0.009)	4,991
Substance abuse	0.023***	(0.008)	4,826	0.011*	(0.006)	4,991
Leadership ability	-0.196***	(0.042)	3,612			
Ability to function under stress	-0.168***	(0.037)	4,492			

Note: This table provides the results of the regressions of equation (2). These regressions control for *month of birth* in addition the sociodemographic characteristics described in Table 2. All regressions include school fixed effects. The sample has 189 schools and 543 classrooms. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

† Results from multinomial logit. Marginal effect reported.

Table D.4: Gender Conformity (PCA without Favorite School Subject) and Life Outcomes

	Explanatory variable: *Gender nonconformity*					
	Sample: Men			Sample: Women		
Outcome:	Coeff.	S.E.	Obs.	Coeff.	S.E.	Obs.
Educational outcomes						
GPA in grade 9	-2.965	(2.717)	4,746	17.528***	(2.558)	4,955
Upper secondary dropout	-0.000	(0.018)	4,588	-0.077***	(0.017)	4,808
Any post secondary	0.022	(0.018)	4,588	0.085***	(0.017)	4,808
STEM secondary track	-0.168***	(0.021)	3,374	0.151***	(0.016)	3,469
Any college	0.021	(0.015)	4,588	0.058***	(0.015)	4,808
Log earnings outcomes						
Log income age 37	-0.072***	(0.024)	4,716	0.020	(0.022)	4,880
Log average income age 37-47	-0.081***	(0.024)	4,735	0.041**	(0.019)	4,903
Labor market outcomes						
Full time in 1980	-0.065***	(0.015)	4,803	0.027	(0.018)	4,960
Part time in 1980	0.038***	(0.010)	4,803	-0.012	(0.016)	4,960
Not employed in 1980	0.027**	(0.012)	4,803	-0.015	(0.015)	4,960
Professional	-0.019	(0.014)	4,090	0.014	(0.011)	3,699
Occupational outcomes†						
Legal or business	0.027**	(0.013)	4,947	0.005	(0.014)	5,138
STEM	-0.044***	(0.013)	4,947	0.024***	(0.007)	5,138
Blue collar	-0.045***	(0.017)	4,947	0.010	(0.010)	5,138
Clerical support	0.016**	(0.007)	4,947	-0.051***	(0.015)	5,138
Teacher-other health	0.010	(0.009)	4,947	0.040***	(0.014)	5,138
Service and sales	0.007	(0.009)	4,947	-0.034***	(0.013)	5,138
Did not work	0.028***	(0.008)	4,947	0.006	(0.010)	5,138
Marriage & fertility outcomes						
Married by 1980	-0.025	(0.016)	4,825	-0.002	(0.018)	4,991
Divorced by 1980	0.016***	(0.005)	4,825	0.004	(0.008)	4,991
Total fertility				-0.042**	(0.020)	5,171
Teenage childbearing				-0.003	(0.005)	5,171
Age at first birth				0.181	(0.129)	2,749
Social emotional outcomes						
Mental health disorders	0.028***	(0.010)	4,826	0.006	(0.009)	4,991
Substance abuse	0.024***	(0.008)	4,826	0.011*	(0.006)	4,991
Leadership ability	-0.257***	(0.041)	3,612			
Ability to function under stress	-0.305***	(0.037)	4,492			

Note: For these results, we drop the favorite school subject variable from the principle component analysis in case that is mechanically driving occupational outcomes. This table provides the results of the regressions of equation (2). See Table 2 for the details of the sociodemographic covariates included. All regressions include school fixed effects. The sample has 189 schools and 543 classrooms. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

† Results from multinomial logit. Marginal effect reported.

E Additional Tables

Table E.1: Multinomial Logit Results: Average Marginal Effects

Using Gender Nonconformity Indicator

	Law & Business	STEM	Blue Collar	Clerical	Teacher-Health	Service-sales	Did not work
CGN men	0.018	-0.090***	-0.011	0.026***	0.012	0.027***	0.018**
	(0.013)	(0.015)	(0.017)	(0.007)	(0.009)	(0.010)	(0.009)
CGN women	-0.001	0.023***	-0.004	-0.016	0.026*	-0.024*	-0.004
	(0.014)	(0.007)	(0.011)	(0.014)	(0.014)	(0.013)	(0.010)

	Part time in 1980	Full Time in 1980	Not Employed in 1980
CGN men	0.010	-0.029**	0.019*
	(0.010)	(0.014)	(0.011)
CGN women	-0.028*	0.028	0.001
	(0.016)	(0.018)	(0.015)

	Not Professional	Professional
CGN men	0.012	-0.012
	(0.014)	(0.014)
CGN women	-0.031***	0.031***
	(0.010)	(0.010)

Using Gender Conformity Index

	Law & Business	STEM	Blue Collar	Clerical	Teacher-Health	Service-sales	Did not work
GCI boys	-0.088***	0.243***	0.056	-0.060***	-0.030	-0.064***	-0.058***
	(0.030)	(0.031)	(0.039)	(0.016)	(0.020)	(0.023)	(0.020)
GCI girls	-0.060**	-0.077***	-0.007	0.092***	-0.042	0.080***	0.014
	(0.029)	(0.016)	(0.023)	(0.030)	(0.031)	(0.027)	(0.022)

	Part time in 1980	Full Time in 1980	Not Employed in 1980
GCI boys	-0.031	0.087***	-0.056**
	(0.023)	(0.033)	(0.026)
GCI girls	0.040	-0.067*	0.027
	(0.034)	(0.038)	(0.031)

	Not Professional	Professional
GCI boys	-0.004	0.004
	(0.031)	(0.031)
GCI girls	0.049**	-0.049**
	(0.022)	(0.022)

Note: This table provides the results from multinomial logit analysis. Marginal effects reported. See Table 2 for the details of the sociodemographic covariates included. All regressions include school fixed effects. The sample has 189 schools and 543 classrooms. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table E.2: Male Gender Typicality and Gender Gaps

	Outcome Variables:							
Explanatory Variables:	*GPA in grade 9*$^{\psi}$		*Upper secondary dropout*		*Any post secondary*		*STEM track*	
Female	5.229***	17.526***	0.007	-0.038***	0.046***	0.083***	-0.412***	-0.240***
	(1.471)	(2.017)	(0.010)	(0.013)	(0.010)	(0.013)	(0.011)	(0.014)
Male typicality		4.647***		-0.015		0.005		0.157***
		(1.493)		(0.010)		(0.010)		(0.011)
Female#Male typical.		8.858***		-0.036***		0.047***		-0.054***
		(2.015)		(0.013)		(0.013)		(0.014)
Observations	9,701	9,701	9,396	9,396	9,396	9,396	6,843	6,843
	Occupation: STEM		*Occupation: Service & sales*		*Log av. earnings age 37-47*			
Female	-0.094***	-0.040***	0.052***	0.025***	-0.313***	-0.249***		
	(0.006)	(0.008)	(0.006)	(0.009)	(0.012)	(0.017)		
Male typicality		0.058***		-0.017**		0.069***		
		(0.006)		(0.007)		(0.012)		
Female#Male typical.		-0.037***		-0.006		-0.045***		
		(0.008)		(0.009)		(0.017)		
Observations	10,085	10,085	10,085	10,085	9,638	9,638		

Note: This table provides the results of a linear regressions of the form $y_{is} = \alpha_0 + \omega_s + \text{Female}_{is}\beta_1 + \text{Male Typicality}_{is}\beta_2 + \text{Female} \times \text{Male Typicality}_{is}\beta_3 + \mathbf{x}_{is}\alpha_1 + \epsilon_{is}$ where $\mathbf{x}_{is}$. See Table 2 for the details of the sociodemographic controls included. All regressions include school fixed effects, ω_s. The sample has 189 schools and 543 classrooms. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. $^{\psi}$ coefficient for GPA in grade 9 is given in hundredths of a point.

F CGN Students and the Classroom Network

In this appendix, we explore how the availability of CGN students affect their classmates' social capital as measured by social network cohesion. To do so, we use the sociometric matrices based on the friendship links (three best friends) ascertained through the in-class school survey in 1966. Given that we observe an entire cohort, we are able to characterize complete classroom networks in grade six. We ask specifically whether having more CGN students in the classroom changes its social cohesion. Thus, we regress standard network-cohesion statistics (i.e., clustering and diameter) of classroom c in school s, NC_{cs}, with the fraction of CGN students in the classroom $\mathrm{C\bar{G}N}_{cs}$.[31]

$$\mathrm{NC}_{cs} = \alpha_0 + \mathrm{C\bar{G}N}_{cs}\beta + \omega_s + \epsilon_{cs} \tag{4}$$

We adopt an identification strategy similar to Hoxby (2000), that exploits the within-school across-classroom variation in the share of CGN students in the classroom (all students in our data belong to the same cohort). The school fixed effects, ω_s, in equation (4) controls for sorting of students across schools. Causal identification of β requires random allocation of students into classrooms. Here, we take advantage of the institutional framework that administered student assignments to Swedish primary schools (grades 1 to 6) in the 1960s. In particular, students attended the nearest school in the neighborhood, and tracking based on ability or background was not allowed in the first six grades (Husen, 1961; Paulston, 1966; SOU1961:30, 1961). Further, a homogenous curriculum and a fixed number of weekly hours of instruction resulted in what explicitly was called a primary school system absent of any "organizational differentiation" of students with respect to ability or social background (SOU1961:30, 1961). The only homogenous groupings allowed during the first six grades of Swedish comprehensive school were special education classes for students with special needs (Husen, 1961). Santavirta and Sarzosa (2022) show reassuring evidence of evidence of non-sorting of abused and neglected students in the same context and cohort.

The results in Table F.1 shows that as the fraction of gender-nonconforming students

[31] See C.1 for variable definitions of both network-cohesion statistics. Also, Chetty et al. (2022) provide an illustrative description of the measurement of clusterning.

Table F.1: Effect Share of Gender Nonconformers on Social Cohesion

	Outcomes:			
Explanatory variable	Clustering		Diameter	
Class CGN fraction male	-0.027	-0.020	-0.132	-0.148
	(0.040)	(0.040)	(0.137)	(0.139)
Class CGN fraction female	-0.121***	-0.109***	-0.372***	-0.373***
	(0.040)	(0.040)	(0.137)	(0.136)
Constant	0.494***	0.490***	0.789***	0.792***
	(0.013)	(0.013)	(0.044)	(0.044)
Observations	536	536	536	536
PCA includes homophily?	Yes	No	Yes	No

Note: This table provides the results of the regressions of equation where the fraction of gender-nonconforming men and women are included as explanatory variables (4). These regressions control for school fixed effects. The sample has 185 schools and 536 classrooms. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

in the classroom increases, the classroom networks are significantly less clustered and the relative diameter of the classroom is significantly less. That means that the presence of female CGN students makes classrooms' social networks more cohesive and less fractured. That is, CGN women and not men serve as bridge-builders between social cliques–usually ones defined by gender in this age group. CGN girls help connect students who otherwise would belong to disjoint social networks, despite being in the same classroom. In addition, our results do not change when we exclude homophily from the principle component analysis, which indicates that the results are not mechanically driven by the homophily input variable.

G Extended Roy Model with Factor Structure

G.1 Model of occupational choice and earnings

We consider occupational choices stemming from the perceived monetary rewards and the nonpecuniary benefits (e.g., job flexibility) or costs (e.g., social rejection) that can affect the individual's fit for the occupation. We assume that individuals make their occupation decisions based on a comparison of the expected benefits and costs associated with each alternative. Specifically, if V_o denotes the expected benefit associated with occupation o, then

$$V_o = E\left[\sum_{t=1}^{T} \rho^{t-1} u(Y_o(t), C_o(t)) | \mathcal{I}_0, \mathcal{P}_0\right]$$

where $u(\cdot)$ represents the per period utility function, $Y_o(t)$ represents the total earnings received in period t given occupation o, $C_o(t)$ is a psychic benefit (or cost) associated with occupation o, ρ is the discount factor, $\mathcal{I}_o$ represents the information set available to the agent at $t = 0$, and $\mathcal{P}_o$ represents the gender norms affecting each occupation. We can write earnings and psychic benefits in occupation o as

$$Y_o(t) = \mu^Y_{ot}(X_Y) + \eta_{Y_o t}, \qquad C_o(t) = \mu^C_{ot}(X_C) + \eta_{C_o t}$$

where X_Y and X_C are observable variables, $\eta_{Y_o t}$ and $\eta_{C_o t}$ are unobservables, and $(X_Y, X_C) \perp (\eta_{Y_o t}, \eta_{C_o t})$ (Heckman and Navarro, 2007; Heckman and Vytlacil, 2007). We assume that $\eta_{Y_o t}$ and $\eta_{C_o t}$ follow a factor structure that separates the individual's endowments $\boldsymbol{\Theta}$ from uncorrelated variation (Carneiro et al., 2003; Hansen et al., 2004; Heckman et al., 2018). As in our conceptual framework in Section 2, these endowments include gender nonconformity and skills. Thus, $\boldsymbol{\Theta} = [\theta^{CGN} \quad \theta^H]$, where θ^{CGN} and θ^H represent the unobserved gender nonconformity and skills, respectively.

$$\eta_{Y_o t} = \alpha_t^{Y_o,G} \theta^{CGN} + \alpha_t^{Y_o,H} \theta^H + e_t^{Y_o}, \qquad \eta_{C_o t} = \alpha_t^{C_o,G} \theta^{CGN} + \alpha_t^{C_o,H} \theta^H + e_t^{C_o}$$

where $\boldsymbol{\Theta} \perp (e_t^{Y_o}, e_t^{C_o})$ and e's are mutually independent. We assume that, although the endowments are unobserved to the econometrician, they are known to the agent and are constant over time (Urzua, 2008). Thus, $\theta^H \in \mathcal{I}_0$ and $\theta^{CGN} \in \mathcal{P}_0$ as agents use them to make decisions just like they do with observable characteristics X_Y and X_C. The individual selects her occupation o^* by comparing the expected utility levels V_o across the different alternatives in the set $\mathcal{O}$. If we assume, for simplicity a linear utility function, and given the elements in sets $\mathcal{I}_0$ and $\mathcal{P}_0$, the occupation choice is given by

$$o^* = \arg\max_{o\in\mathcal{O}} \sum_{t=1}^{T} \rho^{t+1} \left(\mu_{ot}^{Y}(X_Y) + \alpha_t^{Y_o,G}\theta^{CGN} + \alpha_t^{Y_o,H}\theta^{H} + \mu_{ot}^{C}(X_C) + \alpha_t^{C_o,G}\theta^{CGN} + \alpha_t^{C_o,H}\theta^{H}\right)$$

Suppose there are two possible occupation types: STEM s and Non-STEM s' such that $\mathcal{O} = \{s, s'\}$. A person will choose a STEM occupation if

$$\begin{aligned}\mu_s^Y(X_Y) - \mu_{s'}^Y(X_Y) + \mu_s^C(X_C) - \mu_{s'}^C(X_C) + (\alpha^{Y_s,G} - \alpha^{Y_{s'},G} + \alpha^{C_s,G} - \alpha^{C_{s'},G})\theta^{CGN} \\ (\alpha^{Y_s,H} - \alpha^{Y_{s'},H} + \alpha^{C_s,H} - \alpha^{C_{s'},H})\theta^{H} > 0\end{aligned}$$

If $X_Y \subseteq X_C$, and given the independence of e's, we can describe the occupation choice as a function of $(X_C, \theta^{CGN}, \theta^H)$ such as STEM $= \mathbb{1}\left[\mu_t^C(X_C) + \alpha^{C_G}\theta^{CGN} + \alpha^{C_H}\theta^H + e^C > 0\right]$, where $\mathbb{1}$ is an indicator function that takes the value of 1 if the condition holds and 0 otherwise (Willis and Rosen, 1979). Depending on the occupational choice, we observe Y_o. If the individual's optimal response is $o^* = STEM$ then we observe Y_1, otherwise we observe Y_0. Thus, empirically, the model can be described by

$$\begin{aligned}\text{STEM} &= \mathbb{1}[\mathbf{x}_C\beta^C + \alpha^{C_G}\theta^{CGN} + \alpha^{C_H}\theta^H + e^C > 0] \\ y_0 &= \mathbf{x}_Y\beta^{Y_0} + \alpha^{Y_0,G}\theta^{CGN} + \alpha^{Y_0,H}\theta^H + e^{Y_0} \quad \text{if } D = 0 \\ y_1 &= \mathbf{x}_Y\beta^{Y_1} + \alpha^{Y_1,G}\theta^{CGN} + \alpha^{Y_1,H}\theta^H + e^{Y_1} \quad \text{if } D = 1\end{aligned} \tag{5}$$

G.2 Test scores as measurement system of latent factors

In order to estimate the Roy model of potential outcomes in (5), we rely on the factor structures governing η's that result in the independence of e's, once we identify $\mathbf{\Theta}$ (Heckman et al., 2006; Prada and Urzúa, 2017; Heckman et al., 2018).[32] For this

[32] Identification of the parameters of the Roy model require the assumption of $(e^C \perp e^{Y_0} \perp e^{Y_1})$. We assume that this assumption holds conditioned on observable $\mathbf{x}$ and unobservable characteristics θ^H and θ^{CGN}. Though $\mathbf{x}_C \neq \mathbf{x}_Y$, we recognize the lack of natural exclusion restrictions. Yet, they are not needed to formally secure the identification of the parameters of interest. Rather than natural exclusion restrictions, we rely on identification through functional form (Carneiro et al.,

purpose, we consider that ability and gender nonconformity are latent factors. In this sense, we acknowledge that we do not directly observe skills or the degree to which an individual conforms to the prevailing gender norms and prescriptions. Rather, we indirectly infer skills and conformity from the variation we observe in manifest scores (in the case of skills) or in responses to seemingly irrelevant questions about preferences and behaviors (in the case of gender nonconformity). In a latent factor framework, researchers recover unobserved variation $\mathbf{\Theta}$ using manifest information $\mathbf{T}$ that is known to be affected by said variation, some contexts $\mathbf{X}_T$ and some error $\mathbf{e^T}$ (Heckman et al., 2006; Bartholomew et al., 2011). That is, we consider a linear relation between the unobserved factors θ^{CGN} and θ^H, gender-nonconformity and skills, and the (vectors of) manifest variables $\mathbf{T}^{CGN}$ and $\mathbf{T}^H$. Namely,

$$\mathbf{T}^{CGN} = \mathbf{X}_T \beta^{T_G} + \alpha^{T_G} \theta^{CGN} + \mathbf{e^{T_G}} \tag{6}$$

$$\mathbf{T}^{H} = \mathbf{X}_T \beta^{T_H} + \alpha^{T_H} \theta^{H} + \mathbf{e^{T_H}} \tag{7}$$

where $\mathbf{X}_T$ is a matrix with all observable controls for each measurement and α^{T^G} and α^{T^H} are vectors containing the factor loadings in each measurement T. In Section G, we show that based on the system of equations (6) and (7), we can identify the distribution of the unobserved heterogeneity θ, clean from the influence of $\mathbf{X}_T$ or the error term $\mathbf{e^T}$ (Carneiro et al., 2003; Hansen et al., 2004). There are multiple advantages of pursuing this approach. First, we flexibly estimate the unobserved factors' distributions $f_{\theta^{CGN}}(\cdot)$ and $f_{\theta^H}(\cdot)$ using mixtures of normals. That help us fit the factor's true underlying distribution without strong functional form assumptions (Judd, 1998). Second, we identify the factor while controlling for predetermined characteristics $\mathbf{X}_T$ that have an influence on reporting of the measures we use. For instance, our results partial-out the correlation that SES might have on the *reporting* of the manifest variables and the outcomes. Third, the factor is continuous. That way, we observe the effects of different degrees of gender nonconformity on adult outcomes.

As we indicate below, identification of the unobserved heterogeneity requires at least three measures per factor. We estimate $f_{\theta^H}(\cdot)$ using three components of IQ—numeric, verbal and spatial ability—ascertained when students are 13 years old. We identify a gender-nonconformity factor $f_{\theta^{CGN}}(\cdot)$ using as manifest scores the reported

2003; Sarzosa and Urzua, 2016).

preferences for domestic interests, mechanical interests, and sports.[33] We estimate the joint models comprising measurement systems (6) and (7), and outcome equations (5) separately for men and women using maximum likelihood.[34] To ease interpretation, and given that gender-nonconformity and skills are unobserved, we rely on simulations of the expected outcome as a function of the unobserved heterogeneity. We randomly draw 20,000 θ^{CGN} and θ^{H} from the estimated distributions $\hat{f}_{\theta^{CGN}}(\cdot)$ and $\hat{f}_{\theta^{H}}(\cdot)$ and construct $E[Y|\theta^{CGN}, \theta^{H}]$.

G.3 Identification and Estimation of Models with Unobserved Heterogeneity

The type of models we use in Section can be described as a set of measurement systems that are linked by a factor structure.[35] We start with a measurement system which we use to identify the distributional parameters of q unobserved factors. The measurement system would have the following form:

$$\mathbf{T} = \mathbf{X}_T \beta^T + \alpha^{\mathbf{T},\mathbf{A}} \theta^A + \mathbf{e}^{\mathbf{T}} \tag{8}$$

where $\mathbf{T}$ is a $L \times 1$ vector of measurements (e.g., test scores, measures of behaviors), $\mathbf{X}_T$ is a matrix with all observable controls for each measurement and $\alpha^{T,A}$ is a vector containing the loadings of unobserved factor A in each mean measurement T. We assume that $\left(\theta^A, \mathbf{X}_T\right) \perp \mathbf{e}^{\mathbf{T}}$, that all the elements of the $L \times 1$ vector $\mathbf{e}^{\mathbf{T}}$ are mutually independent and have associated distributions $f_{e^h}(\cdot)$. To explain how the parameters of the measurement system (8) are identified, let us focus on the matrix $COV\left(\mathbf{T}\left|\mathbf{X}_T\right.\right)$ whose elements in the diagonal are of the form $COV\left(T_i, T_i\left|\mathbf{X}_T\right.\right) = \left(\alpha^{T_i,A}\right)^2 \sigma^2_{\theta^A} + \sigma^2_{e^{T_i}}$, and the off-diagonal elements are of the form $COV\left(T_i, T_j\left|\mathbf{X}_T\right.\right) = \alpha^{T_i,A}\alpha^{T_j,A}\sigma^2_{\theta^A}$.

[33] In fact, given how the manifest scores are set out, from measurement system (6), we identify the distribution of a *masculinity* factor separate for the samples of men and women. For both genders, higher scores of this measure implies behaviors or tastes that are more in line with the typical male. As in Section 3.2.2, we prefer men and women to be on the same scale going from gender conformity to nonconformity. Thus, we simply recode the identified factor for the male sample, so that for both genders high values in the factor mean greater gender-nonconformity.

[34] As controls for the measurement systems $\mathbf{X}_T$, we use a dummy of having a female head of household, father's education and home-ownership status. Table G.1 in the Appendix presents the estimates of measurement system (6) and (7).

[35] This Appendix follows closely the argument put forth in (Sarzosa and Urzua, 2016).

As it is, the model is underidentified. To see this, note that the is no way to use the off-diagonal elements of $COV\left(\mathbf{T}\,|\mathbf{X}_T\right)$ to come up with unique values for the parameters we intend to estimate. More precisely, note that

$$\frac{COV\left(T_2, T_3\,|\mathbf{X}_T\right)}{COV\left(T_1, T_2\,|\mathbf{X}_T\right)} = \frac{\alpha^{T_3,A}}{\alpha^{T_1,A}}, \frac{COV\left(T_2, T_3\,|\mathbf{X}_T\right)}{COV\left(T_1, T_3\,|\mathbf{X}_T\right)} = \frac{\alpha^{T_2,A}}{\alpha^{T_1,A}}, \frac{COV\left(T_1, T_3\,|\mathbf{X}_T\right)}{COV\left(T_1, T_2\,|\mathbf{X}_T\right)} = \frac{\alpha^{T_3,A}}{\alpha^{T_2,A}}$$

Therefore, identification requires some assumptions. First, we acknowledge that latent factors have no metric or scale of their own (Bartholomew et al., 2011). Hence, we need to normalize to unity one loading, and the remaining loadings should be interpreted as relative to the one used as nummeraire. If, with out loss of generality, we normalize $\alpha^{T_3,A} = 1$, the remaining loadings are identified from the quotients of the off-diagonal elements of $COV\left(\mathbf{T}\,|\mathbf{X}_T\right)$. This also shows that identification requires $L \geq 3$. That is, we need at least three scores per factor.[36] Having identified the loadings, we can further use the off-diagonal elements of $COV\left(\mathbf{T}\,|\mathbf{X}_T\right)$ to identify the factor variance σ_{θ^A} and the diagonal elements of $COV\left(\mathbf{T}\,|\mathbf{X}_T\right)$ to identify σ_{θ^A}. Equivalent steps across the q dimensions of unobserved heterogeneity yield the identification all the unobserved factors.

Now that we have identified all the loadings, factor variances and measurement residual variances, together with the fact that the means of θ^A, θ^B and $\mathbf{e}^{\mathbf{T}}$ are finite—in fact, equal to zero because we allow the measurement system (8) to have intercepts—we can invoke the Kotlarski Theorem to use the manifest variables $\mathbf{T}$ to non-parametrically identify the distributions of $f_{\theta^A}(\cdot)$ (Kotlarski, 1967).[37]

With the distribution of the factors in hand, we can consider a model linking the outcome variables we observe with the factor structure. That is,

$$\mathbf{Y} = \mathbf{X}_Y \beta^Y + \mathbf{\Lambda}^Y \Theta + \mathbf{e}^Y \tag{9}$$

[36] Analogously, we can also infer the minimum number of scores by acknowledging that we can use the $\frac{L(L-1)}{2}$ off-diagonal elements to identify $L-1$ loadings—taking into account we normalized one loading—and the factor variance (Carneiro et al., 2003) . We then need that $\frac{L(L-1)}{2} \geq (L-1)+1$. Thus $L \geq 3$.

[37] The basic idea of the Kotlarski Theorem is that if there are three independent random variables e_{T_1}, e_{T_2} and θ and define $T_1 = \theta + e_{T_1}$ and $T_2 = \theta + e_{T_2}$, the joint distribution of (T_1, T_2) determines the distributions of e_{T_1}, e_{T_2} and θ, up to one normalization. Note that, given that we have already identified all the loadings, we can write (8) in terms of $T_\tau = \theta + e_{T_\tau}$ by dividing both sides by the loading. See more details in Carneiro et al. (2003).

where $\mathbf{Y}$ is a $M \times 1$ vector of outcomes, $\mathbf{\Lambda}^Y$ is an $M \times q$ matrix containing the factor loadings for each of the M outcome equations and q dimensions of unobserved heterogeneity, $\mathbf{e}^Y$ is a vector of error terms with distributions $f_{e^y}(\cdot)$. We assume that $\mathbf{e}^Y \perp (\Theta, \mathbf{X_Y})$ and also that $e^{Y_m} \perp e^{Y_{m'}}$ for $m, m' = 1, \ldots, M$ and $m \neq m'$. This is the type of models considered, for instance, by Heckman et al. (2006) and Urzua (2008) often with $M = 1$ (e.g., employment or earnings). In the case of the Roy model $M = 3$, $\mathbf{Y} = [D \quad Y_0 \quad Y_1]'$, where D takes the value of one if the agent chooses sector 1 (e.g., a STEM occupation) or zero if the agent chooses sector 0 (e.g., a non-STEM occupation). Y_0 is the outcome observed for those who select into sector zero, and Y_1 is the observed outcome who sort into sector one. Note that the econometrician does not observe the actual value of Θ for each observation. Rather, in the first stage, s/he estimates the distributions they are drawn from and uses it to integrate it out in (9). We estimate the model using Maximum Likelihood. In the case of the Roy model, we considering the following likelihood function:

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

G.4 Additional Results

In this subsection, we present estimates of the model with unobserved heterogeneity (9) with $M = 1$. That is, we analyze the relationship between selected outcomes—not mediated by a choice—and gender conformity in the form of unobserved heterogeneity. Our results corroborate our regression estimates in Section 4 by showing clear CGN gradients. Figure G.1(a) shows that gender nonconformity is associated with lower 9^{th} grade GPA for boys, but higher scores for girls. The performance gaps between the extremes of the CGN distribution are sizable. The least gender-conforming boys (bottom 10%) score 0.16 points less than the most gender-conforming boys (top 10%). On the contrary, the least gender-conforming girls score 0.28 points *more* than the most gender-conforming girls. Figure G.1(b) indicates that pursuing a STEM track in upper secondary is mostly a masculine trait. While 83% of the gender-conforming boys choose a STEM track, only about half of the gender-nonconforming boys do. In the same vein, while only 43% of the most gender-conforming women choose a STEM track, 53% of the nonconforming ones do. Interestingly, the most gender-conforming men and the least gender-conforming women have roughly the same probability of selecting a STEM track in upper secondary.

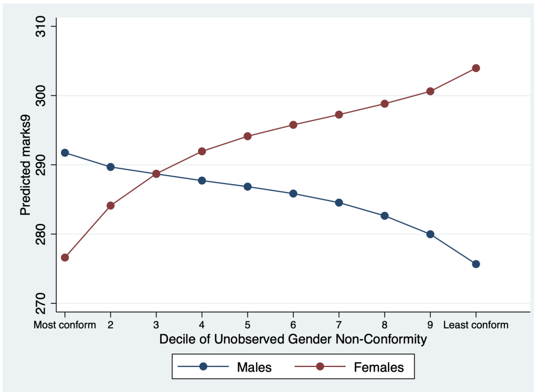
Figure G.1(c) presents a wide gap between gender-typical and gender-nonconforming women in the likelihood of them reaching any kind of tertiary education. CGN women are 7 percentage points (20% in relative terms) more likely to take on post secondary education than gender-typical women. This gap contrast with the almost flat relation between gender conformity a tertiary education attainment among men. Gender-typical women have about the same chances of going to tertiary education as men, while CGN women are about 16% more likely than men to do so. This is another example of how the education gaps in favor of women we have become accustomed to are driven by those who challenged gender norms during early adolescence.

Figure G.1(d) explores occupation choices. We zoom in on two types of occupations: STEM and Services & Sales. We choose them because they are opposites in terms of women's representation. Men dominate STEM occupations, while Services & Sales occupations are dominated by women. Figure G.1(d) shows that CGN men are twice more likely to sort into service and sales (12.9%) than into STEM (6.4%) occupations. On the contrary, gender-conforming men are about three times *more* likely to sort into STEM occupations (23%) than into service and sales (8%). In contrast, CGN women are 4 percentage points (18%) *less* likely to sort into a services or sales occupation than gender-conforming women.

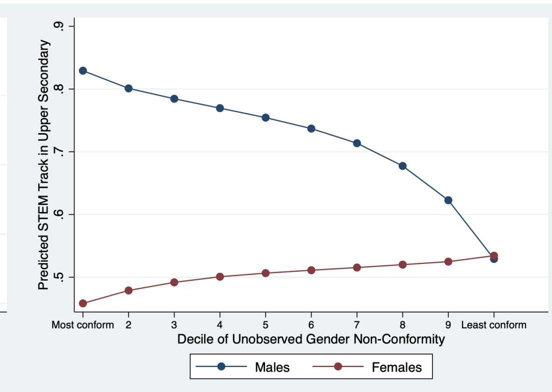
Finally, we show results on fertility. Figure G.1(e) corroborates our findings in Table 4. CGN women delay their first pregnancy relative to their gender-typical counterparts. Our estimations indicate that the gap between the gender-conforming and nonconforming extremes amount to about a quarter of a year.

Figure G.1: Gender Nonconformity and Education Outcomes

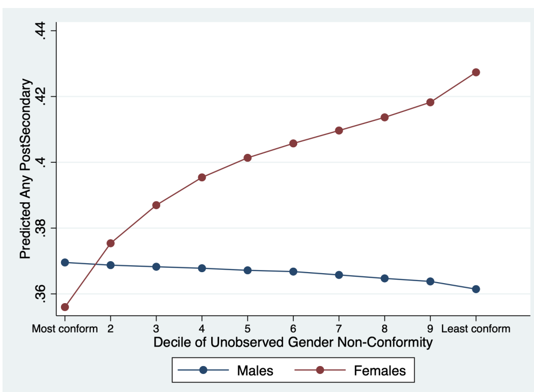
(a) GPA at 9^{th} Grade



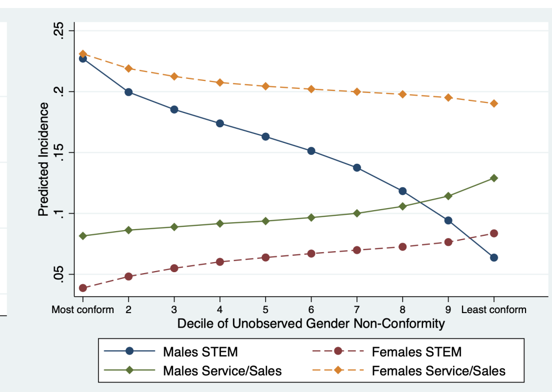
(b) STEM Track in Upper Secondary



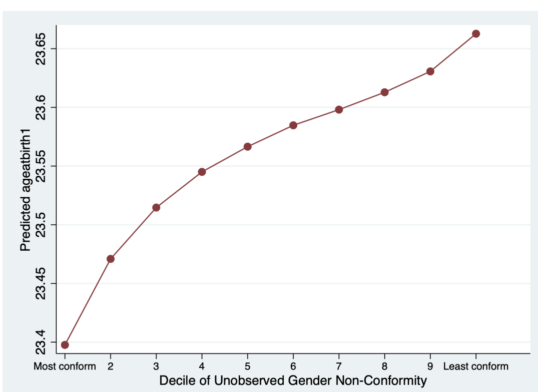
(c) Any Post Secondary



(d) Occupation Sorting



(e) Age at First Birth (Women Only)



Note: Each figure presents $E[Y|\theta^{CGN}]$ for GPA in $9th$ grade, the choice of a STEM track in upper secondary, the choice of going into any kind of tertiary education, the choice of STEM and Service & Sales occupations, and the age of first birth in the vertical axis. Each is the product of 20,000 simulations based on the findings model (9). The horizontal axes in all panels displays the deciles of the gender-nonconforming factor. Data from Stockholm Birth Cohort.

Table G.1: System of Manifest Variables and the Identification of Latent Cognitive Skills and Masculinity Factor

	Cognitive Scores			Male-biased Behaviors					
					(Males)			(Females)	
	Spatial	Verbal	Numeric	Outdoor	Domestic	Technical	Outdoor	Domestic	Technical
Cognitive	0.731***	0.711***	1						
	(0.020)	(0.019)							
Masculinity				5.435***	-0.147*	1	3.538***	-0.163***	1
				(0.463)	(0.084)		(0.175)	(0.040)	
Female	-1.532***	-0.160	-1.444***						
	(0.127)	(0.112)	(0.139)						
Female Head HHld	0.018	0.354	-0.294	0.298	-0.266	-0.361	-0.735*	-0.271	0.027
	(0.248)	(0.219)	(0.273)	(0.315)	(0.386)	(0.375)	(0.399)	(0.311)	(0.381)
FatherEduc: HS	1.638***	2.505***	2.437***	-0.504**	0.095	-0.071	-0.123	-0.686***	0.617**
	(0.175)	(0.155)	(0.193)	(0.226)	(0.264)	(0.257)	(0.272)	(0.224)	(0.273)
FatherEduc: College	2.131***	4.119***	4.384***	-0.649**	0.576*	-0.590*	0.144	-1.368***	1.635***
	(0.233)	(0.207)	(0.257)	(0.313)	(0.349)	(0.340)	(0.381)	(0.305)	(0.372)
Homeowner	0.562***	0.381**	0.273	-0.664***	-0.055	-0.013	-0.239	-0.750***	0.635**
	(0.169)	(0.150)	(0.186)	(0.222)	(0.256)	(0.249)	(0.278)	(0.218)	(0.267)
Constant	25.073***	24.936***	23.010***	37.901***	25.624***	36.968***	33.365***	34.591***	23.040***
	(0.207)	(0.184)	(0.228)	(0.122)	(0.123)	(0.120)	(0.136)	(0.103)	(0.127)
Observations			10,967			5,403			5,575

Note: This table provides the estimates of measurement system (6) and (7). Data from Stockholm Birth Cohort. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.