Can Educational Expansion of Parents Explain Polarised Earnings of Children?

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Abstract

This paper examines the impact of educational expansion on assortative mating and its effect on the earnings distribution of future generations. We show that higher college shares can lead to stronger assortative mating on the marriage market although preferences over the partner's education remain constant. If education is positively related to unobserved ability, a larger degree of educational assortative mating induces higher similarity of spouses, which can have substantial impact on the income distribution of their children. Using intergenerational data from the Panel Study of Income Dynamics, we find that the model can largely replicate observed trends in college education and earnings.

Keywords: Intergenerational mobility; assortative mating; education and inequality.
JEL Classification Numbers: J62, I24, J12, J11.

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Introduction

Labor markets in Western economies have experienced massive changes throughout the 20th century. As educational institutions became more accessible to disadvantaged social groups, the schooling level of the workforce, especially with respect to higher education, has risen considerably. At the same time, household composition with respect to educational attainment has changed towards a higher degree of positive assortative mating. Observational studies (Mare, 1991; Schwartz and Mare, 2005) show that spouses are increasingly likely to have a similar level of schooling. Another, more recent trend is the steady increase in wage polarisation. Starting in the 1970s, the earnings distribution has become more dispersed in the US and the UK (Katz et al., 1999; Heathcote et al., 2010). More recently, a similar trend has also been observed for Continental Europe, albeit to a lesser extent (Guvenen et al., 2013). In accordance with the hypothesis of skill-biased technological change, a large share of the rise in inequality can be explained by higher earnings differentials between college and non-college educated workers. However, wage dispersion has also increased to a substantial part among college graduates and within occupational groups (Eckstein and Nagypal, 2004).

In this paper, we argue that described trends in education have an intergenerational effect on the earnings distribution and can explain observed patterns in wage dispersion. We provide an intergenerational model of ability and educational attainment which takes into account assortative mating of parents. It assumes that educational expansion is partly driven by changing attitudes towards education that increase schooling of individuals from low-educated families. This expansion can in turn affect household composition. If future spouses are more likely to meet within educational groups, rising college attendance rates lead to higher assortative mating even though preferences over the partner's education remain constant. We show that this implies not only a stronger similarity of parents in terms of education but also with respect to unobserved ability. Assuming that ability is to some extent transmitted across generations, higher sorting of parents will lead to a polarisation in the ability distribution of future generations, which induces a more dispersed wage schedule.

Using intergenerational data on education and earnings from the Panel Study of Income Dynamics (PSID) between 1975 and 2011, we test the main implications of our model. Observed trends in assortative mating of parents and intergenerational mobility in college attendance are largely in line with the model predictions. Coinciding with a strong rise in attendance rates, the observed positive correlation in college attendance between parents of PSID respondents has increased steadily. This is due to a massive increase in the share of parents who both attended college which outpaces a modest rise in the share of families with only one college educated parent. Similarly, the intergenerational correlation in college attendance went up over the period of observation although the data show somewhat different patterns when we look at the share of college educated children by parents' attendance. Lastly, in accordance with previous studies, we observe an increase in the college premium as well as higher wage dispersion conditional on college education, which both could be the result of a more dispersed ability distribution.

With this paper, we contribute to a steadily growing literature that focuses on the causes and consequences of positive assortative mating. Theoretical studies have put forward several other explanations for the observed rise in assortative mating. Using an overlapping generations model, Fernández et al. (2005) show that a higher skill premium can lead to a higher degree of marital sorting with respect to skills. Using data from 34 countries, their empirical analysis confirms a positive correlation between skill premiums and positive assortative mating. A recent paper by Greenwood et al. (2012) provides a unified model which attempts to relate marriage decisions, educational attainment and female labour force participation. The authors argue that, due to technological progress, the value of household production has declined over time. Moreover, an increasing college premium as well as a decrease in the gender wage gap increases the benefit of education and labour force participation for females. As a consequence, non-monetary considerations of marriage have become more important. Assuming that individuals have a preference for a partner with similar education, the model can explain the rise in assortative mating.

Next to the causes of higher homogamy, several studies have analysed its consequences for economic outcomes. Greenwood et al. (2014) use US census data from 1960 to 2005 to analyse the impact of mating patterns on earnings inequality. They find that higher positive assortative mating in education combined with rising female labour force participation contributes substantially to the rise in income inequality that has been observed in the US. The overlapping generations model of Fernández et al. (2005) similarly shows that higher assortative mating induced by a rising college premium further amplifies income dispersion for future generations.

Only a few other studies have focused so far on the intergenerational effects of assortative mating.[1] Assuming linear transmission of education, Kremer (1997) analyses changes in marital and neighbourhood sorting and models their impact on inequality and intergenerational mobility. Exploring data from the PSID and the Matching Census Extract Data Sets, he does not find evidence for an increase in positive assortative mating. Moreover, the paper estimates that a decrease in sorting would only have moderate effects on intergenerational mobility and inequality. The study can, however, only explore data up to the late 1980s and therefore does not capture recent trends in mating patterns and intergenerational correlations of education. Fernández and Rogerson (2001) provide a dynamic model with exogenous marital sorting that takes into account fertility decisions, borrowing constraints and wage responses to the supply of high skilled workers. Calibrating the model to US data, the study shows that higher assortative mating decreases the supply of high skilled workers and thus drives up income inequality between high and low skilled workers through wage responses. Fernández (2002) uses a similar framework but models marital sorting as a function of segregation in the economy. She parameterises the model to UK statistics and finds that a higher degree of segregation favours skilled workers over unskilled workers but can be welfare improving from an ex-ante perspective.

All mentioned studies have in common that inequality operates either through the relative supply of skilled labour or borrowing constraints of low-income households. This paper takes a different route and focuses on the intergenerational impact of assortative matching on the ability distribution. Although ability is not observed, its relation to both education and income allows us to derive testable implications for future generations.

The remainder of this paper proceeds as follows. Section II provides the model and discusses its assumptions and implications. In section III, we describe the data and compare observed trends in education and earnings to simulations of our model. Finally, section IV concludes.

[1] Many empirical papers in the literature on intergenerational mobility take assortative mating into account. However, these studies focus almost entirely on partner choices of children rather than parents. (Lam and Schoeni, 1993, 1994; Chadwick and Solon, 2002; Ermisch et al., 2006; Blanden et al., 2004; Hirvonen, 2008; Raaum et al., 2007).

The model

To shed more light on the intergenerational impact of assortative mating, we propose a simple model that relates individual ability to educational choices. Taking into account costs and benefits of education, individuals may get educated if their level of ability is sufficiently high. In this model, ability can be thought of as the sum of unobserved characteristics such as inherited or learned traits and skills which drive up earnings and the likelihood to obtain education. In contrast to most studies in the economics literature, we further assume that only a fraction of individuals with sufficient ability obtains education. Henceforth, we will refer to these differences as *educational frictions* and analyse the impact of a decrease of frictions over time. The motivation comes from the sociology literature which argues that increasing levels of schooling are partly driven by changing attitudes towards education (see for instance Schofer and Meyer, 2005). As in the past higher education used to be the privilege of a small elite, many potential students did not consider college as a feasible career choice but rather followed role models of their social group. When in the course of the 20th century new social norms promoted educational equality to foster economic success independent of social origin, these attitudes changed steadily and contributed to the increase in enrolment rates. Our theoretical framework does not rule out demand effects for high skilled workers on the labour market but focuses in the analysis on diminishing educational frictions as the driving force behind educational expansion.

We show that the increase in higher education affects assortative mating and thereby also influences economic outcomes of future generations. Because individuals of the same educational group are more likely to meet, a larger share of educated individuals can lead to stronger assortative mating. As education and ability positively correlate, spouses also become more similar in terms of ability. Under very general assumptions on intergenerational transmission, it holds that ability will be more unevenly distributed for future generations, which in turn increases earnings inequality.

The remainder of this section will provide a formal description of the education decision, the matching mechanism and the intergeneration transmission process. The static model focuses on two generations, the parents and the children. Mothers, fathers and children will be denoted by subscripts m, f and c, respectively.

Education and earnings

In our model, we define education as a binary outcome e that takes value 1 if an individual attended college and 0 otherwise. Individuals can enter higher education as long as their ability level a is above threshold $\bar{a}$. The latter is determined by academic requirements of college education which, we assume, do not change over time. However, due to social norms, only a fraction p of individuals above the threshold attends college. Because attitudes towards higher education might be different for women and men, we allow this fraction to differ by gender. Denoting the cumulative density of ability as F, the share of college attendees is thus given by $q_m = p_m[1 - F(\bar{a})]$ and $q_f = p_f[1 - F(\bar{a})]$ for mothers and fathers, respectively. To keep the model tractable, we assume in the following that ability of parents follows a standard log-normal distribution $log(a) \sim N(0, 1)$.

Earnings are defined as $y = (1 + e\pi)wa$, where π describes an *ex-ante* college premium and w a uniform wage rate. Note that π differs from the observed college premium $\frac{E(y|e=1)-E(y|e=0)}{E(y|e=0)}$ as ability is positively correlated with education.

Similarly, we can define college attendance and earnings of the children. The main difference is that the next generation's ability distribution is endogenously determined and depends on the degree of assortative mating of parents.

Assortative matching

We assume that individuals have a fixed preference for their partner's level of education. Let $\lambda \in [0, 1]$ describe the rate at which educated males want to meet educated females.[2] If λ is larger than $\frac{1}{2}$, they have a preference for college educated women, whereas a value below $\frac{1}{2}$ indicates the opposite. They are indifferent if λ equals $\frac{1}{2}$. Clearly, the number of potential matches also depends on the fraction of higher educated individuals. As before, we denote the shares of college educated men and women (or fathers and mothers) as q_f and q_m. Normalising the total number of men and women to 1, educated males then meet λq_m educated and $(1 - \lambda)(1 - q_m)$ non-educated females. From all realised meetings individuals will choose a partner depending on individual preferences which are not related to ability or education.

Assuming that all individuals are matched, we can determine the degree of assortative mating as a function of λ and shares q_m and q_f. Let $\xi_k^j = P(e_m = k|e_f = j)$, $j, k \in \{0, 1\}$

[2] Equivalently, we can define this parameters for females as $\rho = \frac{\lambda(1-q_m)}{(1-q_f)-2\lambda(q_m-q_f)}$.

define the probability of having an (non-)educated spouse conditional on own education. It holds that $\xi_1^1 = \frac{\lambda q_m}{\lambda q_m + (1-\lambda)(1-q_m)}$, which is bound between $1 - \frac{1-q_f}{q_m}$ and $\frac{q_f}{q_m}$ due to supply constraints. Under market clearing, it follows that $\xi_0^1 = 1 - \xi_1^1$, $\xi_1^0 = \frac{q_m - q_f \xi_1^1}{1-q_f}$ and $\xi_0^0 = 1 - \xi_1^0$. Thus, all matching probabilities depend on the relative supply of college attendees. As education and ability are not independent, assortative mating in ability is likewise endogenously determined in this model.

Based on the matching probabilities ξ_k^j, we can derive the parent's joint distribution of college attendance as well as of ability. Let $\underline{f}(a_j)$ and $\bar{f}(a_j)$, $j \in \{m, f\}$ define the lower and upper tail of the ability distribution truncated at $\bar{a}$. Because ability levels between spouses are independent conditional on being below or above the threshold, the joint distribution can be written as

$$f(a_m, a_f) = \begin{cases} \underline{f}(a_m)\underline{f}(a_f) & if\; a_m < \bar{a} \,\&\, a_f < \bar{a} \\ \bar{f}(a_m)\underline{f}(a_f) & if\; a_m \geq \bar{a} \,\&\, a_f < \bar{a} \\ \underline{f}(a_m)\bar{f}(a_f) & if\; a_m < \bar{a} \,\&\, a_f \geq \bar{a} \\ \bar{f}(a_m)\bar{f}(a_f) & if\; a_m \geq \bar{a} \,\&\, a_f \geq \bar{a} \end{cases}$$

We provide the derivation of probabilities $P(a_m < \bar{a}, a_f < \bar{a})$, $P(a_m \geq \bar{a}, a_f < \bar{a})$, $P(a_m < \bar{a}, a_f \geq \bar{a})$ and $P(a_m \geq \bar{a}, a_f \geq \bar{a})$ in the appendix. These shares together with educational frictions p_m and p_f then give the joint distribution of college attendance.

Intergenerational transmission

Every family has exactly one child. Log-ability of children is defined as a linear combination of their parents' log-levels and an ability shock ϵ:

$$log(a_c) = r\frac{log(a_m) + log(a_f)}{2} + (1-r)\epsilon$$

where $r \in [0, 1)$ and $\epsilon \sim N(0, \frac{1-\frac{r^2}{2}}{(1-r)^2})$. r denotes the relatedness parameter which indicates to what extent log-ability is correlated across generations. The distribution of the ability shock ϵ is chosen such that the distribution of children's ability resembles that of parents under random matching.[3] It follows that $log(a_c)$ has mean zero and variance $1 + \frac{r^2}{2}Cov(log(a_m), log(a_f))$. Thus, changes in assortative mating of parents

[3] This functional form of intergenerational transmission is not crucial for the main implications of our model. It suffices to assume that a_c is a strictly increasing function of a_m and a_f.

may alter the ability dispersion of children. Given that the joint distribution of parents' ability is determined by the matching process, ability of the following generation follows a non-standard distribution and is not log-normally distributed unless ability levels of parents are entirely independent.

As for the parents, only a fraction p_c of children with $a \geq \bar{a}$ obtains education. The share of college attendees will be $q_c = p_c[1 - \tilde{F}(\bar{a})]$, where $\tilde{F}$ describes the CDF of children's ability. Again, earnings are defined as $y_c = (1 + e_c\pi)wa_c$.

Analytical solution

In the following, we use our model to analyse the impact of decreasing educational frictions ($p_m \uparrow$ & $p_f \uparrow$) on assortative mating, intergenerational mobility and the earnings distribution.

To evaluate the degree of assortative mating, we focus on the spouse correlations in ability and education. Given that ability levels of spouses are independent conditional on being above or below $\bar{a}$, the corresponding correlation is solely determined through shares $P(a_m < \bar{a}, a_f < \bar{a})$, $P(a_m \geq \bar{a}, a_f < \bar{a})$, $P(a_m < \bar{a}, a_f \geq \bar{a})$ and $P(a_m \geq \bar{a}, a_f \geq \bar{a})$. It can be shown that, if educated individuals have a preference for educated partners ($\lambda > \frac{1}{2}$), lower educational frictions will increase the number of spouses that are both below or both above the threshold. As a consequence, the ability correlation gets larger. Similarly, we can show that also the correlation in education increases when educational frictions diminish. The proof of both results is provided in the appendix.

An increase in positive assortative mating has further implications for intergenerational mobility. Again, we distinguish between correlations in ability and education. Because parents become more similar in terms of ability, the correlation between parents and children increases as well. If we, however, control for the second parent's ability, correlations between parent and child remain constant and correspond to the relatedness parameter r. Effects are somewhat different for intergenerational mobility of education. As educational frictions decrease for parents, education becomes a stronger signal of ability. Even when controlling for the other parent's education, the intergenerational correlation in education increases. Thus, the total correlation captures both a stronger partial correlation of education and a higher indirect effect through increasing similarity of parents.

As discussed in the previous section, changes in assortative mating of parents also influence the ability distribution of their children. Higher homophily of parents will lead to stronger ability dispersion and, in turn, affect the income distribution. Earnings differentials increase between college and non-college educated individuals as well as within both groups. The ex-post college premium is given by

$$\frac{E(y_c|e_c = 1) - E(y_c|e_c = 0)}{E(y_c|e_c = 0)} = \frac{(1+\pi)wE(a_c|e_c = 1) - wE(a_c|e_c = 0)}{wE(a_c|e_c = 0)}.$$

Since ability and education are positively correlated, higher dispersion induced by assortative matching of parents widens the difference $E(a_c|e_c = 1) - E(a_c|e_c = 0)$ and thereby increases the observed college-premium even when parameter π remains constant. Note that also decreasing frictions ($p_c \uparrow$) can contribute to an increasing college premium.

Next, we quantify dispersion within educational groups using the conditional variances $Var(y_c|e_c = 1) = (1+\pi)^2 w^2 Var(a_c|e_c = 1)$ and $Var(y_c|e_c = 0) = w^2 Var(a_c|e_c = 0)$. It can be shown that higher sorting of parents will lead to higher ability variances in both groups. As a result, earnings dispersion increases independent of education. However, diminishing frictions for children can attenuate the impact in this case. Because more individuals above the threshold level attend college, the variance among non-educated decreases in p_c whereas it is unaffected for college attendees. By construction, an increase in the ex-ante college premium π would generate opposite effects since the variance metric is not scale-independent. To avoid this scaling effect, we focus in the empirical analysis on percentile ratios.

Empirical analysis

Data

To test the predictions of our model, we use data from the Panel Study of Income Dynamics (PSID). Starting in 1968, the study has been collecting information about more than $9,000$ US households in (bi-)annual waves.

There are two reasons to use this dataset for our analysis. First, the PSID is a nationally representative longitudinal panel for the US and allows to estimate national trends in education and income over a long period of time. Second and most importantly, the survey collects data on education of parents which are crucial to estimate intergenerational effects.[4]

Respondents of the PSID correspond to the children's generation in our model.[5] To measure income from labor, total annual labour earnings are divided by annual working hours and deflated to 2010 dollars. Using education brackets for respondents and their parents, we construct dummy variables for college attendance.

For our empirical analysis, we make several sample restrictions. Because this study is ultimately interested in changes in the earnings distribution, the sample is restricted to male respondents aged 35 to 65 during the time of the interview. By doing so, we avoid measuring labour income at the beginning or the end of occupational careers, which is less representative for lifetime earnings. Next, we drop all observation with missing information on the respondents' or their parent's college attendance. Finally, we exclude the Latino and immigrant sample. This leaves us with in total 105,876 observations for 10,440 respondents in the years 1975 to 2011.[6] To include data from the non-representative Survey of Economic Opportunity (SEO) in the final sample and to account for sample attrition over time, all estimates are weighted using inverse household probability weights.

Trends in education and earnings

As shown in the previous section, our model has several predictions that are empirically testable. First, educational expansion leads to stronger positive assortative mating. The share of mixed marriages increases but less than share of parents with both college attendance. This raises the correlation in college attendance between spouses. Second, higher assortative mating increases intergenerational correlations in college attendance. Moreover, college education of parents becomes a better predictor of their children's education. Third, unobserved polarisation of the ability distribution leads to higher wage inequality. The wage differential between college and non-college individuals increases. Furthermore, wage dispersion within both educational groups rises.

To compare empirical trends to the model predictions, we simulate the impact of a decrease in educational frictions for a given set of parameters. We fix the ability threshold $\bar{a}$ at 0.8 and let frictions for parents diminish over time ($p_f : 0.2 \to 0.9$, $p_m : 0.1 \to 0.8$)

[4] As children of respondents are followed and, in many cases, included later on as respondents in the PSID sample, one could alternatively explore richer data on this subset. However, this will limit the period of observation and makes it more difficult to capture long run trends.

[5] Respondents are the head of a household as well as the spouse of the household head.

[6] Information on maternal education has only been collected since 1975.

such that the simulated attendance rates match observed trends. To observe the impact on education and earnings of children that is due to a decrease in frictions for their parents' generation, p_c is set to 1. Moreover, we assume that 80% of the children's log-ability is determined by their parents' ability and that the preference parameter on the marriage market (λ) is fixed to 0.8. The ex-ante college premium remains constant at 50%, and the wage rate is set to 10.[7] Statistics are calculated for 10 periods each based on $1,000,000$ family draws.

Figure 1 shows the simulated and observed trends in college attendance. By construction, simulated attendance rates of parents increase because frictions diminish over time. For chosen parameters, college attendance of children does not change. However, this does not hold in general. Because the ability distribution of children changes, the fraction of children above the ability threshold can be different even with constant p_c.

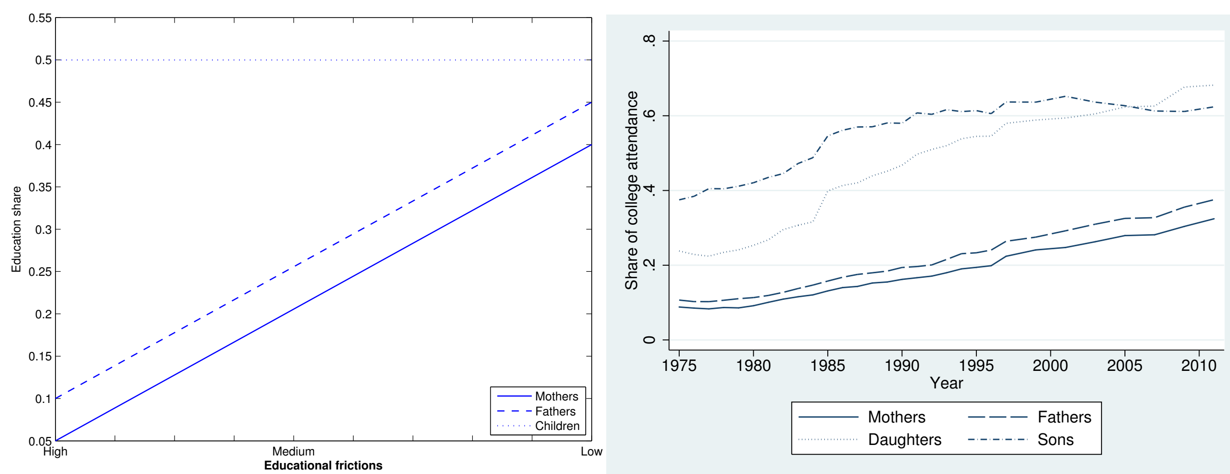
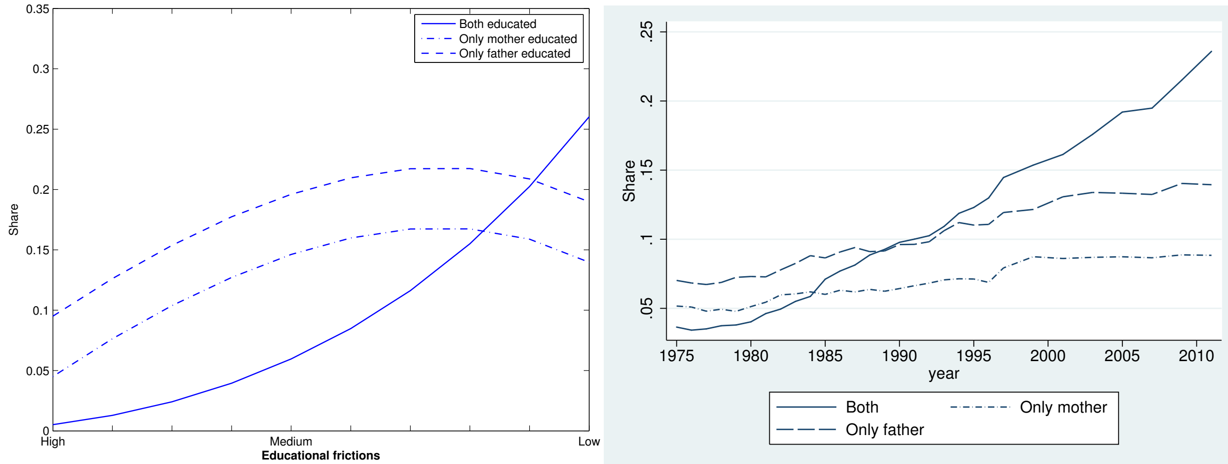


Figure 1: College attendance shares (Simulation (left) & PSID (right))

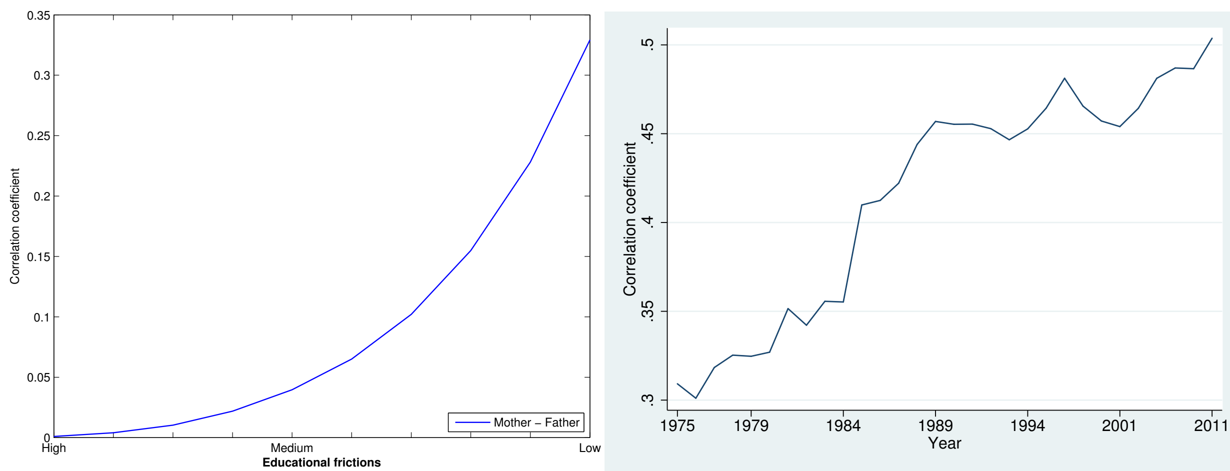
The figure on the right illustrates that parents of PSID respondents indeed experienced massive educational expansion. Whereas only 10% of parents went to college at the beginning of the sample period, this share has more than tripled in recent waves. The share of educated mothers is slightly lower than that of fathers and does not shrink over time. To illustrate the decreasing gender gap, we also plot college attendance separately for female and male respondents of the PSID. The two upper lines show that women catch up over time and even show slightly larger attendance rates in the last three waves.

Next, we analyse assortative mating of parents. Figure 2a plots the simulated and ob-

[7]The chosen parameters will soon be updated by estimates based on simulated moments.



(a) Shares of parents by college attendance



(b) Correlation in college attendance of parents

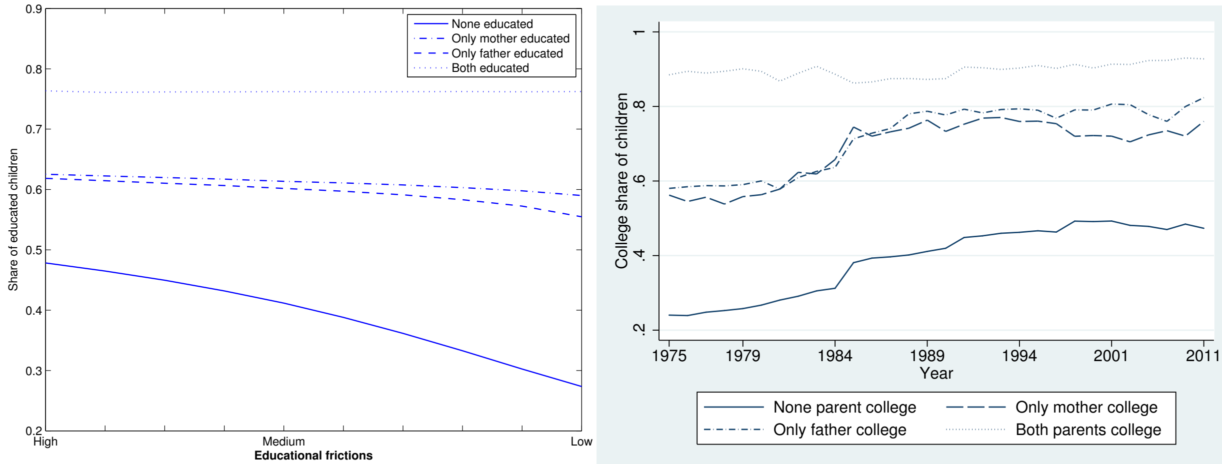
Figure 2: Assortative mating of parents (Simulation (left) & PSID (right))

served share of parents by college attendance. The graphs show that simulated fractions largely replicate patterns observed in the data. Educational expansion raises the share of families with one educated parent but by much less than the share of parents who both attended college. The simulated rise in assortative mating is so strong that the share of mixed parents even decreases somewhat for low frictions. As shown in Figure 2b, the corresponding correlation increases monotonically in both graphs. Although we already observe strong assortative mating of parents in the 70s, the PSID estimate further rises from approximately 0.3 to almost 0.5.

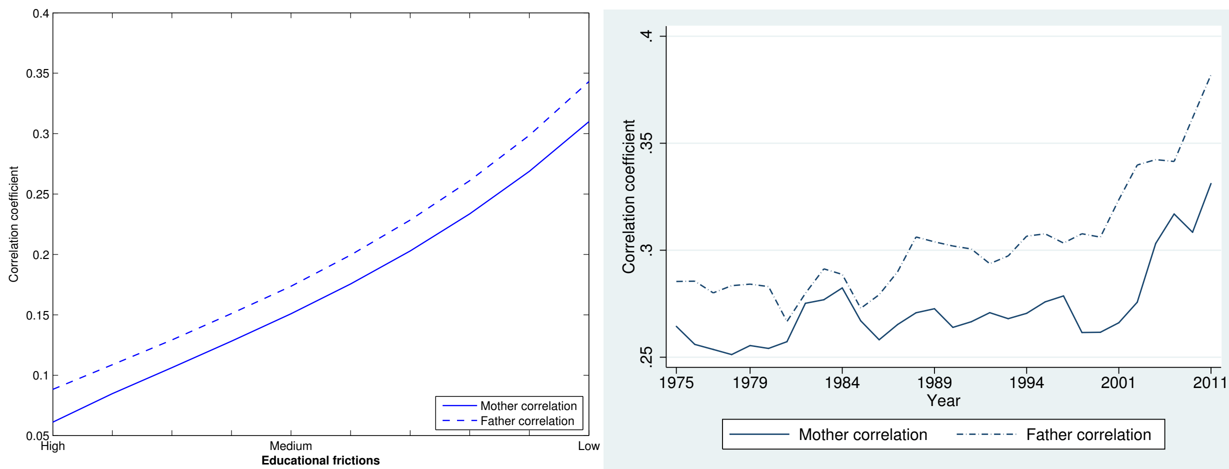
Figures 3a to 3c illustrate changes in intergenerational mobility of education. The first figure plots college attendance of children by college attendance of parents. As predicted, the observed share of college attendees with two educated parents remains relatively constant at a high level. About 90 percent of PSID respondents attend college if their parents obtained some college education as well. However, observed likelihoods for children from families with mixed or non-college educated parents do not align with our predictions. A decrease in frictions causes that no education becomes a stronger signal of low ability in the simulations. Keeping quality of education and frictions for children constant, children with non-educated parents are thus increasingly likely to fall below $\bar{a}$, and this effect is strongest if both parents did not go to college. Opposite trends in the data might be explained by the continuing increase of college attendance of PSID respondents. To reveal intergenerational effects due to higher assortative mating of parents, we keep educational frictions of the second generation constant. Higher attendance rates will automatically drive up the conditional shares depicted in Figure 3a, and difference by parental education can vary depending on the underlying ability distribution.

Figure 3b shows that both simulated and observed intergenerational correlations in college attendance increase over time. Due to opposing trends in the conditional attendance shares, the simulated change is larger than its empirical counterpart for the US. As predicted, the correlation between fathers and their children is somewhat higher than the estimate for mothers and the difference remains constant over time.

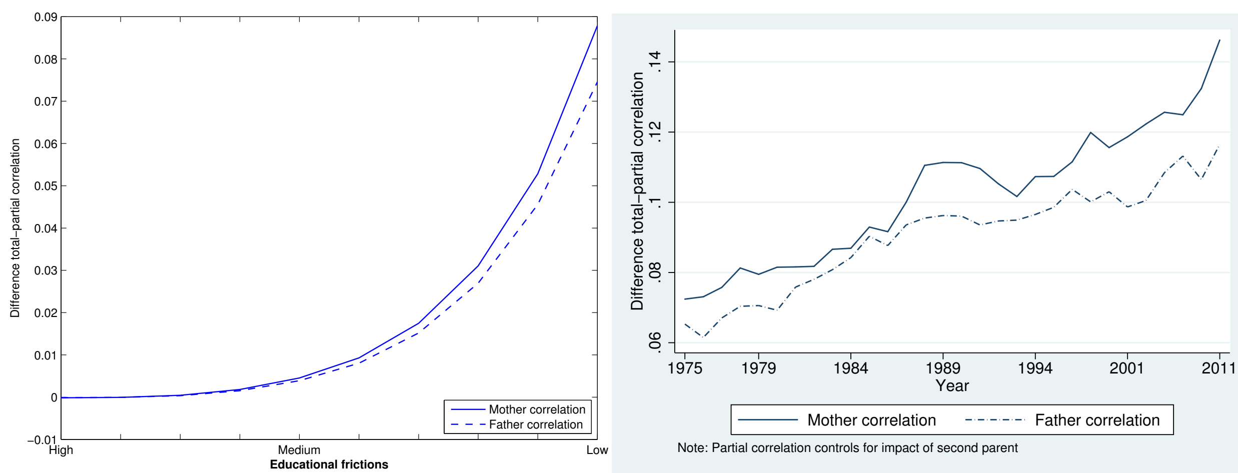
To quantify the impact of assortative mating for intergenerational associations in college attendance, we calculate the difference between the total and the partial correlation for both parents. The latter coefficient controls for education of the second parent and thereby isolates indirect effects, which increase in similarity of parents. By taking the difference between total and partial correlations in Figure 3c, we can measure the contribution of assortative mating to changes in intergenerational mobility. In accordance with predicted trends, we find that the difference steadily increases in the PSID sample. As parents become more similar, the total correlation rises due to higher indirect effects.



(a) College attendance of children by attendance of parents

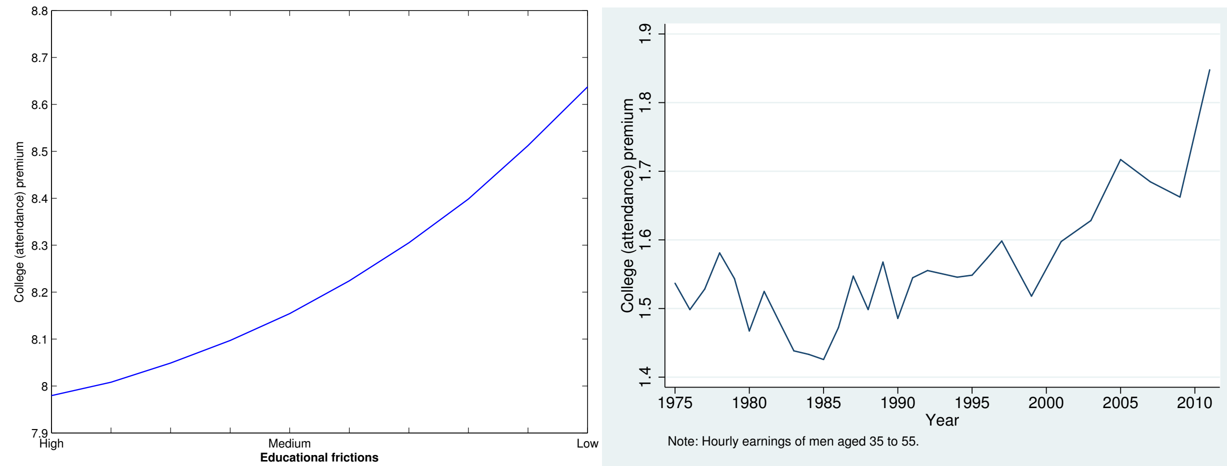


(b) Intergenerational correlation of college attendance

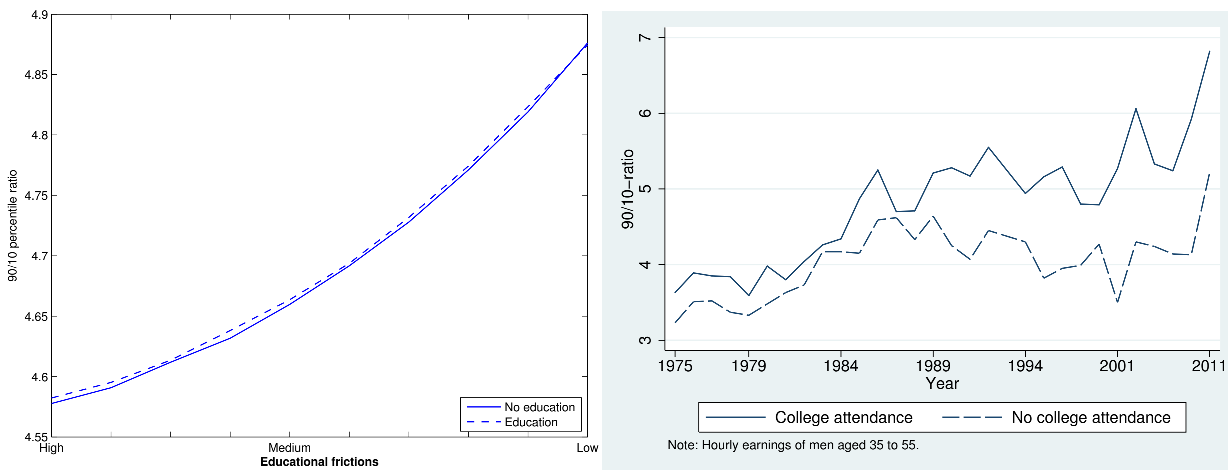


(c) Difference between total and partial correlation

Figure 3: Intergenerational mobility of college attendance (Simulation (left) & PSID (right))



(a) College premium



(b) 90-10-percentile ratio

Figure 4: Changes in the earnings distribution (Simulation (left) & PSID (right))

Lastly, Figures 4a and 4b focus on changes in earnings dispersion. Because ability is more dispersed under strong positive assortative mating, and education and ability are positively correlated, educational expansion of parents leads to a higher observed college premium in our simulations.[8] This is in line with empirical evidence from the PSID. Comparing average hourly wages by college attendance, we find that the premium increased over time from roughly 50 percent to more than 80 percent.

Figure 4b plots the 90-10-percentile ratios separately for college and non-college edu-

[8]Given our ad-hoc choice of parameters for the ability distribution of parents ($\mu = 0$, $\sigma = 1$), the simulated levels are unrealistically high. Fitting the model parameters to observed moments will partly correct for that. Also, the observed college premium underestimates the actual premium to some extent as earnings in the PSID are top-coded for very high levels.

cated workers to measure wage dispersion conditional on education. Our simulation results illustrate that stronger assortative mating of parents raises ratios in both groups. The right-hand graph shows that observed trends in the US align with this prediction. In addition, the increase in dispersion is more pronounced for college attendees, rising from 3.8 to almost 7. Note, however, that higher wage inequality among non-educated can be attenuated or even reversed in our model if we assume that educational frictions also decrease for children.

Conclusion

Contributing to the growing literature on earnings inequality, this paper shows how educational expansion can change assortative mating patterns and thereby polarise the income distribution through intergenerational transmission. In a simple two-generations model, we relate educational attainment to ability and demonstrate that higher college attendance rates can lead to increased homophily of spouses in terms of education and ability.

The idea behind this mechanism is straightforward. If educational expansion is in part driven by changing social norms regarding education, an increasing share of students with sufficiently high ability attends college. Assuming that individuals of the same education are more likely to meet, for instance on university campuses or at the workplace, changes in the supply of college-educated individuals will impact the degree of assortative mating even if preferences over the partner's education remain constant. Because the likelihood to attend college increases in ability, higher similarity in education causes likewise a stronger ability correlation of spouses.

Even under very general assumptions on the intergenerational transmission of ability, this mechanism leads to stronger intergenerational associations in education and a more dispersed ability distribution of future generations. Modelling labor income as the product of individual ability, a uniform wage rate and an ex-ante college premium, we show that changes in the ability distribution affect dispersion both across and within educational levels. Due to higher ability dispersion, the observed college premium increases even though wage differences by college attendance conditional on ability remain constant. Furthermore, the model predicts higher wage inequality for both college and non-college educated workers.

Using intergenerational data from the Panel Study of Income Dynamics, a nationally representative sample for the US, we test the predictions of our model with respect to assortative mating, intergenerational mobility of education, and the earnings distribution. The trends observed in the sample period (1975-2011) are largely consistent with the model implications. Parents of PSID respondents have experienced a massive expansion in college education although gender differences in attendance rates only dissolve for younger cohorts. Moreover, estimated correlations in college attendance document an increasing degree of positive assortative mating of parents. At the same time, the correlation of college attendance between children and parents has become stronger, and earnings of male PSID respondents show a steadily rising degree of dispersion. Consistent with our predictions, wage differentials have increased between college and non-college educated workers as well as within both groups.

The model provided in this study has made several simplifying assumptions. First, we abstract from borrowing constraints and assume that education is independent of parental income. It is straightforward to extend the model accordingly, which increases education inequality and the observed college premium but does not change the assortative mating mechanism. Second, we impose that every individual is matched on the marriage market. In an extension of the model, one could drop this assumption and analyse the impact of singles on assortative mating patterns. To provide further empirical evidence, future research may also aim to explore ability measures such as test scores and examine corresponding changes in correlations and dispersion over time.

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Appendix

Joint ability distribution

Define $t = P(a \geq \bar{a})$. It follows that $P(a_f \geq \bar{a}|e_f = 0) = \frac{(1-p_f)t}{1-t+(1-p_f)t} = \frac{t-q_f}{1-q_f}$. Using matching probabilities $\xi_k^j = P(e_m = k|e_f = j)$, $j, k \in \{0, 1\}$, we can derive the joint probability that parents are above or below the ability threshold:

$a_f \geq \bar{a}$ and $a_m \geq \bar{a}$:

$$P(a_f \geq \bar{a}|a_m \geq \bar{a}) = p_m[\xi_1^1 + \xi_0^1 P(a_f \geq \bar{a}|e_f = 0)] + (1 - p_m)[\xi_1^0 + \xi_0^0 P(a_f \geq \bar{a}|e_f = 0)]$$

$$P(a_f \geq \bar{a}, a_m \geq \bar{a}) = (p_m[\xi_1^1 + \xi_0^1 P(a_f \geq \bar{a}|e_f = 0)] + (1 - p_m)[\xi_1^0 + \xi_0^0 P(a_f \geq \bar{a}|e_f = 0)])t$$

$a_f < \bar{a}$ and $a_m < \bar{a}$:

$$P(a_f < \bar{a}|a_m < \bar{a}) = \xi_0^0 P(a_f < \bar{a}|e_f = 0)$$

$$P(a_f < \bar{a}, a_m < \bar{a}) = [\xi_0^0 P(a_f < \bar{a}|e_f = 0)](1 - t)$$

$a_f \geq \bar{a}$ and $a_m < \bar{a}$:

$$P(a_f \geq \bar{a}|a_m < \bar{a}) = \xi_0^0 P(a_f \geq \bar{a}|e_f = 0) + \xi_1^0$$

$$P(a_f \geq \bar{a}, a_m < \bar{a}) = [\xi_0^0 P(a_f \geq \bar{a}|e_f = 0) + \xi_1^0](1 - t)$$

$a_f < \bar{a}$ and $a_m \geq \bar{a}$:

$$P(a_f < \bar{a}|a_m \geq \bar{a}) = [p_m \xi_0^1 P(a_f < \bar{a}|e_f = 0) + (1 - p_m)\xi_0^0 P(a_f < \bar{a}|e_f = 0)]$$

$$P(a_f < \bar{a}, a_m \geq \bar{a}) = [p_m \xi_0^1 P(a_f < \bar{a}|e_f = 0) + (1 - p_m)\xi_0^0 P(a_f < \bar{a}|e_f = 0)]t$$

Correlation in ability

Proof Similarity in ability increases if educational frictions decline $\rightarrow$ Probabilities of being both below/above threshold increase with p_m and p_f

(I) Educational frictions of men (p_m)

- $\frac{\partial P(a_f<\bar{a}, a_m<\bar{a})}{\partial p_m} = P(a_f < \bar{a}|e_f = 0)(1 - t)t\frac{\partial \xi_0^0}{\partial q_m}$
- $\frac{\partial \xi_0^0}{\partial q_m} = \frac{\xi_1^1 - q_f}{(1-q_m)^2}$
- $\frac{\partial \xi_0^0}{\partial q_m} > 0 \Leftrightarrow \frac{\lambda q_f}{\lambda q_f + (1-\lambda)(1-q_f)} > q_f$

- Inequality holds if $\lambda > \frac{1}{2}$ (Preference for same education).

- Thus, $\frac{\partial P(a_f<\bar{a},a_m<\bar{a})}{\partial p_m} > 0$ if $\lambda > \frac{1}{2}$.

- Using $P(a_f < \bar{a}, a_m < \bar{a}) + P(a_f < \bar{a}, a_m \geq \bar{a}) = 1 - t$, we can show that $\frac{\partial P(a_f<\bar{a},a_m\geq\bar{a})}{\partial p_m} = -\frac{\partial P(a_f<\bar{a},a_m<\bar{a})}{\partial p_m} < 0$ if $\lambda > \frac{1}{2}$.

- Similarly, $\frac{\partial P(a_f\geq\bar{a},a_m<\bar{a})}{\partial p_m} < 0$ and $\frac{\partial P(a_f\geq\bar{a},a_m\geq\bar{a})}{\partial p_m} > 0$ if $\lambda > \frac{1}{2}$.

(II) Educational frictions of women (p_m)

- $\xi_0^0 = P(e_f = 0|e_m = 0) = P(e_m = 0|e_f = 0)\frac{1-q_f}{1-q_m}$.

- Then, $P(a_f < \bar{a}, a_m < \bar{a}) = [\xi_0^0 \frac{1-q_m}{1-q_f} P(a_m < \bar{a}|e_m = 0)](1-t)$

  $= \frac{1-q_m-q_f+q_m\xi_1^1}{1-q_f} P(a_m < \bar{a}|e_m = 0)](1-t)$

- $\frac{\partial P(a_f<\bar{a},a_m<\bar{a})}{\partial p_f} = \frac{q_m[\frac{\partial \xi_1^1}{\partial q_f}(1-q_f)-1+\xi_1^1]}{(1-q_f)^2} P(a_m < \bar{a}|e_m = 0)](1-t)t$

- It holds that $\frac{\partial \xi_1^1}{\partial q_f}(1-q_f) > 1 - \xi_1^1$ if $\lambda > \frac{1}{2}$. Then, $\frac{\partial P(a_f<\bar{a},a_m<\bar{a})}{\partial p_f} > 0$.

- As for p_m, it follows that $\frac{\partial P(a_f\geq\bar{a},a_m<\bar{a})}{\partial p_f} < 0$, $\frac{\partial P(a_f<\bar{a},a_m\geq\bar{a})}{\partial p_f} < 0$

  and $\frac{\partial P(a_f\geq\bar{a},a_m\geq\bar{a})}{\partial p_f} > 0$ if $\lambda > \frac{1}{2}$.

Correlation in education

Proof Correlation in education increases in p_m and p_f

$$\begin{aligned} Corr(e_m, e_f) &= \frac{Pr(e_m=1,e_f=1)-Pr(e_m=1)Pr(e_f=1)}{\sqrt{Pr(e_m=1)[1-Pr(e_m=1)]Pr(e_f=1)[1-Pr(e_f=1)]}} \\ &= \frac{\sqrt{\mathbf{p_m p_f}}[Pr(a_m\geq\bar{a}_m,a_f\geq\bar{a}_f)-Pr(a_m\geq\bar{a}_m)Pr(a_f\geq\bar{a}_f)]}{\sqrt{Pr(a_m\geq\bar{a})[1-\mathbf{p_m}Pr(a_m\geq\bar{a})]Pr(a_f\geq\bar{a})[1-\mathbf{p_f}Pr(a_f\geq\bar{a})]}} \end{aligned}$$

- As shown before, $\frac{Pr(a_m\geq\bar{a}_m,a_f\geq\bar{a}_f)}{\partial p_m} > 0$ and $\frac{Pr(a_m\geq\bar{a}_m,a_f\geq\bar{a}_f)}{\partial p_f} > 0$ if $\lambda > \frac{1}{2}$.

- Thus, numerator increases and denominator decreases in p_m and p_f.

- It follows that $\frac{Corr(e_m,e_f)}{\partial p_m} > 0$ and $\frac{Corr(e_m,e_f)}{\partial p_f} > 0$.