Gender Pay Gap of the Highly Educated in Early Career Trajectories: An Empirical Analysis on the USA

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Abstract

This article uses a longitudinal survey of registrants for the Graduate Management Admission Test (GMAT) to analyse the gender wage gap among Master of Business Administration (MBA) recipients. I find evidence that, despite an initial raw wage gap from the moment the individuals complete their MBA of 11.4% that grows to 23.2% after 5 years, variation in the industry individuals work in, the impact the birth a child has and the variation in confidence between men and women explain away the initial gap. I show evidence that confidence can also explain a large part of the wage gap in the first 5 years after completing an MBA. This contributes to many findings in experimental economics which suggest that the pay gap can be explained by different physiological traits between gender. Those who over predict their future earnings by more are those who earn more in the future. Those who already have children and are unemployed are more likely to under-predict their future earnings, even compared to those who have children one or two years after being asked their expectations. This suggests that individuals can internalise the impact their current situation has on the future but are unable to internalise potential future obstacles.

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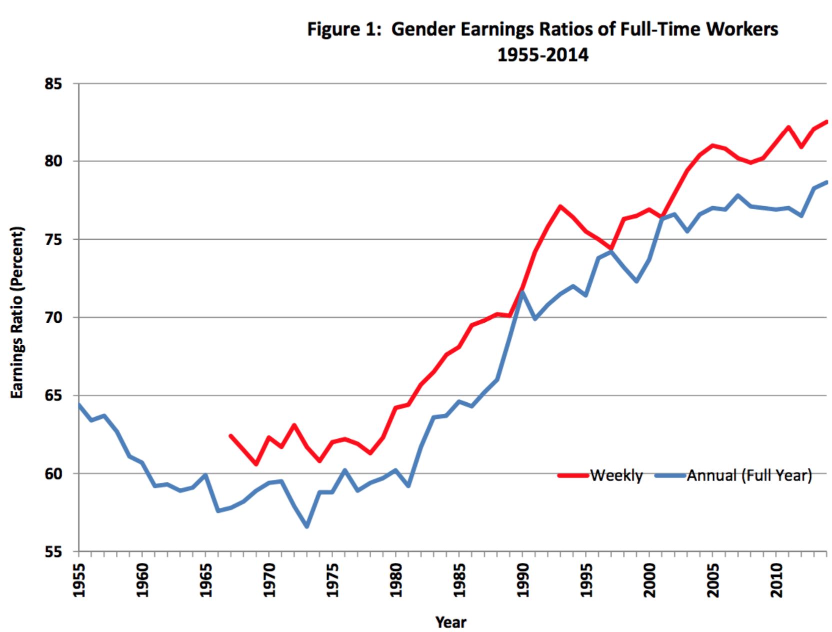
Contents

1 Introduction

The gender wage gap has been a thoroughly discussed research topic in economics and more recently become a common social discussion. In the UK, in 2018, for the first time, all companies and public bodies with more than 250 employees are legally obliged to publish their gender pay gap, their bonus pay gap and to reveal the proportion of men and women in each quartile of their business. It is more topical than ever to truly understand the root cause of the pay gap. Despite convergence of wages over time, a wage gap remains (see for example Blau and Kahn (2017)). Although there are a number of possible explanations for the gap, a full understanding of why it exists and how to deal with it has not been reached. In particular, a *glass ceiling* of female wages has been observed (see Bertrand, Goldin, and Katz (2010) for example). The phenomenon of a *glass ceiling* relates to the idea that women remain underrepresented in the upper part of the earnings distribution. This study will explore a particularly educated sample of relatively young individuals where the *glass ceiling* problem may be most prominent.

In the United States, there has been convergence of earnings. As seen in Figure 1, the fastest period of convergence was in the 1980s where the earnings ratio went from 60% to 70%. The convergence has slowed since then, and it has taken 20 years for less than 10% more convergence in terms of annual earnings. Therefore, despite analysing slightly dated data in the paper I present, focussing on the gender pay gap in the 1990s, there is clear evidence that the gap that existed then is still important to understand today.

Figure 1: Gender Wage Gap in US - Figure 1 of Blau & Kahn (2017)

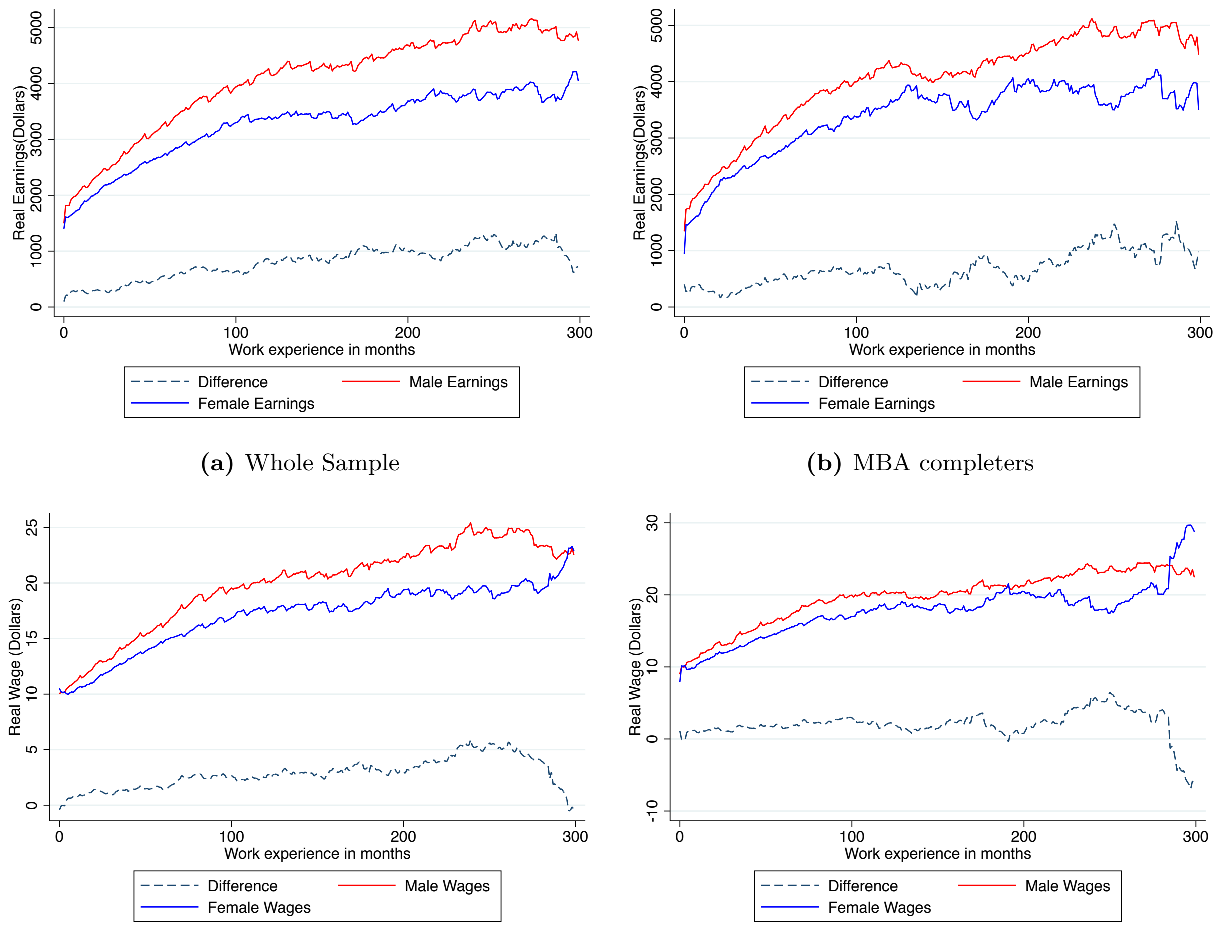


There is a rich discussion over why the wage gap exists. The human capital debate (e.g. Mincer and Polachek (1974) who extends the Mincer (1974) and Becker (1994) model of human capital) incorporates reasons why a female's human capital may be lower than a man's. Differences can come from different accumulation in work experience, different types of education and greater domestic commitments of women. However, even in early literature, using decomposition techniques, a gender gap was identified which could not be explained by observable human capital differences between men and women. Another potential explanation is the Job Shopping Hypothesis (e.g. Manning and Swaffield (2008)). This explains how women are more constrained in their opportunities to change jobs than men and are less concerned with earning more money when they do. More recently there has been an increasing discussion of an association between psychological attributes and non-cognitive skills and labour market outcomes. Early papers such as Eckel and Grossman (2002) use an experimental setting and ask subjects to choose from different gambles to test differences in risk aversion between men and women, finding that men on average choose riskier gambles. There are other studies that explore the association between personality traits such as self-esteem and earnings (e.g. Drago (2011)). There has also been literature looking at how competitiveness relates to earnings and gender (e.g. Niederle and Vesterlund (2007)).

However, despite an increase in recent research on non-cognitive skills, personality traits and norms, most of the cited literature that measures overconfidence and competition uses experimental economics (e.g. Reuben, Wiswall, and Zafar (2017)). This may partly be driven from the lack of data available that accurately measures these attributes. Therefore, my motivation comes from exploring the number of potential explanations for a gender wage gap including family status, degree choices, industries and also trying to use measures of overconfidence outside of experimental economics by making use of a rich survey data set. This paper uses a longitudinal survey of registrants for the Graduate Management Admission Test (GMAT) in USA. The GMAT is a test needed to apply for a Master of Business Administration (MBA). The registrants were surveyed 4 times during the period of 1990 and 1998. The data includes a number of questions which are rarely seen in surveys, such as expectations on their future earnings being matched with their realised future earnings. The group of individuals are a highly educated sample as they are at least considering taking the GMAT for an MBA. The interest will lie in the evolution of wages for those who complete an MBA from the time when they finish their studies. The main goal is therefore to explain gender differences in career starts of highly educated individuals.

Figure 2 presents the earning-experience profile and wage-experience profile of men and women and the difference between the two in two samples. In (a) and (c) I show the whole sample from the data set and in (b) and (d) I restrict the sample to just those who complete an MBA during the 4 surveys. One can see that the initial gap is close to zero in both samples and over time it rises to over \$1000/month for the full sample. There is a smaller gap amongst the MBA takers but at 100 months of work experience, the gap in earnings is around15%. Of course this is a naive relationship with the inclusion of different individuals at different points in the graph (as some individuals may only have a few years of experience by the end of the survey for example and some may start the survey with many years of experience). However, with this initial observation in mind, there seems to be evidence to support the exploration of the gender wage gap in this sample.

Figure 2: Earning-Experience and Wage-Experience Profiles



(a) Whole Sample

(b) MBA completers

(c) Whole Sample

(d) MBA completers

Note: Earnings is individuals real monthly earnings in $ whereas wage is hourly wages

This paper takes motivation partly from Manning and Swaffield (2008) and Bertrand et al. (2010) in trying to find the cause of the gender pay gap. The sample however is not representative of the whole population like it is in Manning and Swaffield (2008). I will look at a wealth of possibilities that could explain the gender wage gap amongst those who complete an MBA and conclude that the impact of confidence on wages exists. I present evidence to suggest that if women carried the same level of confidence as men, the gap would be reduced to insignificant in the first few years in the labour market. I use simple decomposition techniques including Oaxaca-Blinder. I accompany this with OLS regressions and panel regressions which allow me to plot the wage trajectories of reference individuals from the moment they complete their MBA. In addition I make use of matching and re-weighting techniques to overcome some short-comings of the other decomposition techniques and combine the weighting techniques with estimating wage trajectories. Lastly, I use a number of techniques to take a closer look at subgroups such as industry, children, confidence and part time workers to assess potential within group wage gaps.

What is clear is that a wage gap exists and it grows over time in the sample I am observing. Unlike (Manning & Swaffield, 2008), there is an initial raw gap between earnings (and wages). However, once controlling for industry of job and confidence in addition to the many typical observables that may explain part of the gap, the gap between women and men becomes insignificant at the point where they enter the work force after their MBA. Even three years later, once controlling for industry of job and confidence, the gap remains insignificant.

There seems to be three distinctive reasons for the wage gap in this sample, the first two, industry differences and children, are typical conclusions found in the literature. The impact that children has on labour supply of women and potential differences in preferences between children and career can create a gap in earnings between men and women and has been found to be true in a similar sample in Bertrand et al. (2010). The third distinctive reason seems to be differences in confidence in future earnings. What I find is that distinguishing people into confident and not, confident men and women see no wage gap and unconfident men and women see no wage gap, rather there is a gap between the groups, indicating a *confidence gap*. Women on average have much lower confidence in their earnings, hence leading to an observed wage gap. Those who already have children and are unemployed are more likely to under-predict their future earnings, even compared to those who have children one or two years after being asked their expectations. This suggests that individuals can internalise the impact their current situation has on the future but are unable to internalise potential future obstacles.

The paper will be structured as follows. Section 2 will review the relevant literature including both techniques to decompose the wage gap and explanations for the wage gap, looking at empirical, experimental and theoretical papers. Section 3 will give details about the dataset used in this study. Despite the crux of this paper being descriptive, there will be a discussion of traditional wage decomposition techniques to decompose the gender wage gap in Section 4, my empirical analysis of labour market trajectories are in Section 5. The non-parametric techniques used are in Section 6. Sub group analysis is found in Section 7. I finally conclude in Section 8. The Appendix and Bibliography are found at the end of the paper.

2 Literature Review

2.1 Economics of Discrimination

Economic theories of discrimination have been around since Becker (1957)'s seminal book. Discrimination can be defined as occurring when members of a minority group are treated less favourably than members of a majority group with identical productive characteristics. Typical discussions will focus on gender, ethnicity or race. The main focus of this paper will be gender. Economists typically distinguished between taste-based and statistical discrimination. Taste-based discrimination is described by Becker (1957) as a situation where employers have a negative taste for minority groups and hence the minority group have to compensate by being more productive at a given wage or accepting a lower wage for the same level of productivity as a majority individual. However, Becker (1957) predicts that in a competitive equilibrium, firms would not survive if they were discriminating.

Statistical discrimination is more of a signalling problem. Arrow et al. (1973) and Phelps (1972) are the drivers of this discussion. The idea is that firms have limited knowledge about the individuals applying for jobs and so they use easily observable characteristics such as gender and race to infer the expected productivity of the applicant. A key equilibrium issue is a self-fulfilling prophecy discussed by Coate and Loury (1993). The idea is that initially the minority and majority start the same but in equilibrium there is sustained discrimination (taste based or statistical), in this equilibrium, there are lower returns to education for the minority type and so they lower their levels of education and then fulfil the prophecy which confirms the original prejudice.

The early literature has used regression-based methods on observational data (such as labour force or household surveys) to test for discrimination. Oaxaca-Blinder (Oaxaca (1973), Blinder (1973)) approach decomposes the wage differentials between men and women into an 'explained' and 'unexplained' gap. The explained gap includes observable characteristics whereas the unexplained includes different returns to given characteristics - which could be thought to be the discrimination aspect (or unobservables). Results such as those summarised in Altonji and Blank (1999) suggest a large unexplained gap in gender wages and participation rates. However, it is important to note that survey data does not include all variables that are observed in reality and therefore the unexplained gap may include variables that are observed by an employer but not observed by the economist. An additional issue pointed out in the literature (see for instance Azmat and Petrongolo (2014)) is that if investment in human capital before entering the labour market is affected by expectations of discrimination then part of the impact of discrimination is actually seen in the observable productivity differences and hence the unexplained wage gap would underestimate the actual extent of discrimination. Therefore the two issues pointed out act in opposite directions whereby the first would lead to an overestimation of discrimination and the second, an underestimation.

An additional issue with the Oaxaca (1973)- Blinder (1973) decomposition is that it focuses on average gender gap over the whole population. The literature suggests that the wage gap may not be constant across the wage ladder. Therefore it is important to decompose the gap at different quantiles. Albrecht, Björklund, and Vroman (2003) for instance, see that, despite the mean gender wage gap being rather small in Sweden, the gap increases throughout the wage distribution. They conclude that the earnings potential of women seem to stagnate at the upper part of the distribution (this is the glass ceiling effect). Hence, assuming a constant wage gap throughout the wage distribution can be misleading because it could lead us to wrongly conclude that the gender wage gap is on average small, when in fact it is rather large for some proportion of the population. Hence, some attention in the empirical literature has shifted towards investigating the gender wage gap variation across the wage distribution. An early example can be seen in Fortin and Lemieux (1998) paper. The authors decompose changes in the US gender wage gap at various wage percentiles. They apply rank regressions and estimate the probability that an individual will be in a certain wage segment given their characteristics. More recently, studies use quantile regressions in order to decompose the gender wage gap at different points of the wage distribution. Pastore, Sattar, Sinha, and Tiongson (2016) use this quantile regression to estimate gender wage gap in Azerbaijan. They find that the wage gap is much stronger at the bottom and at the top distribution of earnings (which suggests for both sticky floor [2] and glass ceiling). They also show that the wage gap emerges around the childbearing age: starting from the age of 22, the wage gap increases with age. As wages tend to increase with time and experience, this could be part of the explanation for the existence of a glass ceiling. Gardeazabal and Ugidos (2005) weight the difference in returns to certain characteristics at a given quantile according to the proportion of the individuals with these characteristics at that same quantile. They use this approach to study the Spanish wage gap where they find that the gap due to different returns to characteristics (e.g. different returns for men and women from a degree or from having a child) falls throughout the wage distribution (perhaps a sticky floor effect). However, in my paper, the focus lies in a small subsample where the distribution of wages is limited to high earners. Therefore, quantile decomposition is less important than when observing a large spread of the population. So far I have introduced some basic decomposition techniques that I will use, outlining some downfalls. The details will be further explained in the Wage Gap Decomposition section.

[2]sticky floor is a similar concept to glass ceiling but at the bottom of the earning distribution. Therefore we may imagine a U-shape wage gap where it is largest at the two extremes of the wage distribution

2.2 Human Capital

2.2.1 Pre-Market

There is extensive literature looking at gender differences in pre-market human capital. The topic of educational differences between genders has had a large discussion around it. Educational differences can include a number of factors from preferences of parents, social roles and norms of subjects a gender should pick to discrimination in accessing higher education. Although in some countries, where preferences over certain children may exist, it may not be true in the USA. In USA and much of the developed world, where boys and girls share the same parents, families and society, there is arguably not such large differences in education level up to the end of secondary school. (In fact, according to the the National Center for Education Statistics (NCES) in the USA, in 2009-10, 57% of students in high school were women, and of those held back at any grade level, 60% of them were male.) Looking specifically at the USA (but relatable to UK and Western Europe), among workers who are entering the labour market now, or have done in the last couple of decades, the average years of education between men and women is not so different. However, older women on the labour market on average have lower education levels (Blau (1997)). Indeed, the convergence of education level between genders has been shown empirically to narrow the wage gap (see for instance Blau and Kahn (2000)).

Beyond number of years of education, what may be more important is the quality of education or the subjects taken. Machin and Puhani (2003) explores the differences in degree subject choice, making use of Oaxaca (1973) - Blinder (1973) decomposition to show that in the UK and in Germany in the 1990s, degree subject explains between 9 and 19 percent of the overall gender wage gap. Paglin and Rufolo (1990) look at students who take the Graduate Record Exam (GRE) finding that most variation in average starting salaries come from between college majors, rather than within. Other more recent papers such as Morgan (2008) also find that different degrees account for a large part of the gender wage gap. The magnitude however varies and no paper concludes that the gap is completely closed once controlling for degree choices.

However, in a lot of recent work, economists have shown that human capital does not account for a lot of the gender wage gap and this has become increasingly true over time as female educational choices have evolved. As Goldin (2014) puts it, *"as they [women] 'look' more like men, the human capital part of the wage difference has been squeezed out"*. The idea is that women have increased their education quantity, and increasingly made educational choices more similar to men and therefore the pre-market human capital argument becomes weaker whilst the gap remains.

2.2.2 Experience and Training

In a recent study, Dias, Joyce, and Parodi (2018) observe the evolution of the gender wage gap in the UK and associate differences in accumulated years of experience and working hours, often due to the arrival of the first child, as a large contributor to the wage gap. First exploring their representative sample of the UK (using British Household Panel Survey and Understanding Society Survey) they show that by the time their first child is 20, women have on average been in paid work for three years less than men (10 years less full time work and 7 years more part time work) and this gap is even larger for the low-educated. Some women have been employed less and some have moved into part-time work. Blundell, Costa Dias, Meghir, and Shaw (2016) explains that actually, despite 7 years of part time work, only full time work has benefits on experience accumulation that leads to higher wages, hence explaining the stagnation of earnings after the birth of a first child for a women. Beyond literally working less, it may be mothers choose different types of work where the benefits may come less in high wages and more in flexibility for example. Kleven, Landais, and Søgaard (2018) describe the effect outlined by Dias et al. (2018) as a post-child effect - women change their hours worked, occupation and so on in response to motherhood. An alternative effect is the pre-child impact where women, anticipating fertility, may invest less in education or choose careers where a family may be manageable in parallel.

Kleven et al. (2018) makes use of administrative data for the full population of Denmark, giving the advantage of a large representative data set. The authors' main findings, made clear in concise figures, are that women's careers are impacted due to children. The authors go so far to say that "almost all of the remaining gender inequality can be attributed to children". The explanation is that children affect the job characteristics of women relative to men in favour of benefits to help with having a family instead of salary rewards. Their technique of analysis diverts away from standard decomposition techniques, where econometricians aim to see if there is a wage gap if men and women are doing identical work. In this paper, the authors explain that having a child means women are much less likely to do the same work, and therefore occupation is in fact a transmission mechanism for children and not a variable they want to control for.

Occupation and industry segregation has been a discussed element of the gender wage gap. The logic follows that women select (or are selected) into lower paying jobs. Blau, Brummund, and Liu (2013) finds that since the 1970s there has been a reduction in segregation which is highly correlated with education. Their paper finds that those who are college graduates saw a large decrease in occupational segregation in the second half of the 1900s. Therefore, it is likely that within the group of MBA completers, occupational segregation may not be a reason for a pay gap.

2.2.3 Highly Educated Population

In Bertrand et al. (2010) paper they examine the earning trajectories of male and female graduates at the University of Chicago Booth School of business. The authors find that, 10 years after graduating, female graduates who are employed earn about 50% less than their male counterparts. The authors find that most of the gap comes from differences in labour supply between men and women. This includes working less hours per week but also having less labour market experience and also being more likely to take time out since graduating. Goldin (2014) shows that a lot of the gender wage gap can be explained within occupations by accounting for the elasticity of earnings in that occupation with respect to hours worked. Goldin (2014) shows that in higher paying occupations, women's earnings are a lower percentage of men's earnings. Goldin (2014) further shows that women are unable to match men's labor market achievement especially in the occupations where the rewards for working long hours are particularly large.

The previous literature mentioned in section 2.1 outlines the necessity to observe wage gaps at different points in the wage ladder. This is vital in understanding the glass ceiling, especially whenthe original sample is representative of the whole population. Examples of the use of quantile decomposition are explained above, see for example Albrecht et al. (2003). In the case of Azmat and Ferrer (2017), the sample observed is of young lawyers in the USA. In this case, they find that the wage gap can be attributed to having children younger than school age in the household and also differences between genders in aspirations to be promoted.

There is one cited paper in the literature that uses the same data set as this paper will. Montgomery and Powell (2003) attempts to answer the question of whether the *signal* of an advanced degree overcomes the negative signal of being a female or minority. They compare a group who have an MBA with those who considered an MBA and didn't take one. By focussing on takers of the GMAT test the paper focusses on a relatively homogeneous population in terms of pre-MBA human capital and career goals. To address sample selection into an MBA, the paper models the decision to obtain (or not obtain) an MBA simultaneously with the determination of wages. They estimate a degree-attainment equation jointly with a Tobit model of wages using full-info maximum likelihood (FIML). Their results suggest that women with advanced degrees do have a small gender wage gap. Their paper therefore gives some evidence against the glass ceiling hypothesis.

2.3 Reference Paper: Manning & Swaffield (2008)

Manning and Swaffield (2008) explore the reasons for the gender wage gap in early career paths in the UK using British Household Panel Survey (BHPS) in the late 1990s. They argue that understanding the evolution of the gender wage gap at the beginning of individuals careers can help find the primary cause of the overall gender pay gap. They find that wages are not particularly different when individuals leave education but they evolve quite differently to each other.

This article focuses on human capital (HC) hypothesis, job-shopping and psychological theories in trying to explain the gender wage gap in early-career wage growth. They find that HC theory can explain some of the gap but 50% of the gap that appears 10 years after entry into the labour market cannot be explained using HC theory. Of the explanation of HC theory, this includes actual differences in labour market experience (control for experience), differences in job-related training and differences in quantity of education (control for education level). In terms of the job shopping hypothesis, according to this paper, it can only explain 1.5 log points of the gender pay gap after 10 years in the labour market. Lastly, they look at attitudes to risk taking, competition, self-esteem and selflessness and find it explains a bit but the impact is not enormous. The motivation of the paper I propose is to explore the rich data we have and see if, with similar controls as Manning and Swaffield (2008) we come to the same conclusions, that is, a gap still exists. At this point we make use of the confidence measures to see how much difference in confidence between genders can explain the wage gap in early careers.

2.4 Non-Cognitive Skills

There is a growing wealth of literature which suggests that non-cognitive skills play an important role in explaining the gender wage gap. Mueller and Plug (2006) find that personality traits may be rewarded differently for different genders. The authors find that men were considerably more antagonistic (non-agreeable) than women and this trait led to significantly higher wages. Interpersonal skills are rewarded relatively more for females while agreeableness more for men. More specifically to confidence, Niederle and Vesterlund (2007) find that men are more overconfident, having higher self-worth whilst other papers such as Goldsmith, Veum, and Darity (1997) show that there is a positive correlation between self-worth and real-wages. This paper also finds that men hold a significantly more favourable view of self-worth than females. These two arguments combined suggest that confidence may lead to a gender wage gap. However, self-esteem and confidence although correlated are not identical concepts. Niederle and Vesterlund (2007) is a key paper that looks at confidence and competition between men and women in an experimental setting. Typically, there is a tournament like setting where individuals have to complete some puzzles, they are then told how they perform. In the next round they are told they are competing against other individuals - they can choose to get a flat rate for answering questions or a rate per question they perform better than others. Typically, the results suggest that men compete more often, even when they are less good at the task, suggesting a level of over-competitiveness. They find that *women shy away from competition* and choose to compete in a tournament half as much as men despite there being no differences in ability between the two genders. They find that their choice to compete less comes from men being overconfident and having greater preferences for competing. To measure overconfidence the individuals are asked how they think they rank in the group; famously 75% of men seem to think they are 1st in their group of 4 individuals. Of course this is interesting, but without empirical verification, it is hard to know what plays out in the real labour market.

Arguably, differences in earnings due to overconfidence can be attributed to the implications overconfidence has on productivity. For example, Brockner and Wallnau (1981) found that self-esteem influenced productivity positively in two ways. He explains that workers use their time more effectively as they need less direction from supervisors and that they are also more efficient in team work. Anderson and Kilduff (2009) look at how individuals who score highly in the personality trait dominance attain high levels of influence in groups. Potentially having this influence is a characteristic that can drive higher wages. Goel and Thakor (2008) find that managers who are overconfident are more likely to be promoted.

Differences between gender in bargaining power has also been discussed. Card, Cardoso, and Kline (2013) use longitudinal data on hourly wages of Portuguese workers matched with income statement information for firms and show that the impact of firm-specific pay differentials on the gender wage gap can be decomposed into a combination of sorting and bargaining effects. Small, Gelfand, Babcock, and Gettman (2007) measure bargaining power by direct observation in a laboratory setting and find results in a similar direction.

It has been found that confidence levels and competitiveness differ significantly depending on degree path. Specifically, those students who study subjects taught in business schools are more likely to be overconfident (Schulz and Thöni (2016)) and competitiveness is positively associated with choosing a more academic degree path (Buser, Niederle, and Oosterbeek (2014)). Further to this, conditional on degree major, overconfident and more competitive individuals expect to sort themselves into higher-paying occupations (Reuben et al. (2017)). Theoretical literature examines the difference in confidence and competition between men and women. A paper which looks at a comparable group of individuals to me is Kaniel, Massey, and Robinson (2010) which looks at job searches amongst MBA students. The authors find that those who are optimistic have significantly better job search outcomes than pessimists. An optimist places more weight on favourable states of nature when making these decisions than a pessimist does. The measure of optimism comes from a series of phrases of which the individual has to agree with or not, such as *'In uncertain times, I tend to expect the best'.* Of course, optimism and confidence are not synonyms by any means but one may think that someone who is optimistic may also be confident.

Empirically, early papers make use of simple econometric techniques such as OLS regressions with cross-sectional data. Obviously, this makes causal conclusions of any characteristic on the gender wage gap difficult. Therefore, despite observations of correlation between self-esteem and earnings, it is difficult to show that self-esteem leads to higher earnings. (See for example Waddell (2006) who looks at the impact self-esteem whilst at school can have on educational attainment and employment.) However, it may in fact be that high earnings boost individuals' self-esteem hence the positive correlation between the two. Drago (2011) addresses the issue of using cross-sectional data by using a longitudinal study and finds positive effect of self-esteem on earnings. In fact he finds that OLS underestimates the impact by about 2 fold (downward bias). Cattan (2013) looks at the role of psychological traits in explaining the gender wage gap. She critics existing empirical literature where they rely on an implicit model of wage inequality, which assumes that inequality in traits only determines the wage distribution by affecting productivity directly and uniformly across sectors. By ignoring the possible effects that traits have on wages through human capital investments and the sorting of workers across sectors of the economy, this model could fail to capture the full impact of traits on the gender wage gap. Also, she highlights the comment previously made in focussing on average gaps and ignoring gaps at other points of the wage distribution. To overcome these issues, Cattan (2013) models a multi-sector economy where traits shape wage distribution through occupation specific effects on productivity but also through their effect on occupation choice, education choice, fertility choice and so on. The model estimates in the paper show that workers sort into occupational categories according to their comparative advantage in self-confidence (and human capital variables). Self-confidence also has an impact on education and experience choices. Cattan (2013) estimates that gender differences in the joint distribution of cognition and self-confidence explain between 7% and 15% of the gender wage gap at the mean. Most of this effect comes from gender differences in self-confidence, which explains an increasing fraction of the gender wage gap over career trajectory. Cattan (2013) also finds that self-confidence has a bigger impact higher up the wage ladder, finding that self-confidence explains over double the gender wage gap at the 9^{th} decile compared to the 1^{st} decile of the wage distribution.

As can be seen, a lot of literature exploring norms, non-cognitive skills and psychological attributes uses experimental work. A typical issue with this work is that some psychological attitudes may be influenced by the context. For example, if women anticipates discrimination in the labour force, they may put less effort into building their human capital. Therefore the use of empirical analysis in the paper I set forth acts as a useful compliment to the already existing literature. As Blau and Kahn (2017) states *"The formation of norms and attitudes ... is a potentially fruitful area of research that has received relatively little attention by economists."*

2.5 Theoretical Literature on Personality Traits and Earnings

There is some theoretical literature worth mentioning, especially on the discussion of confidence. In labour economics, we learn about the signalling and screening models. The idea behind these is that one party has more information than another when a decision is being made. For example, when applying for a job, the interviewee knows more about their own ability than the interviewer who is trying to get as much information as they can from signals to predict the potential employee's ability. Santos-Pinto (2012) extends Spence (1974)'s signalling model by assuming that some workers are overconfident (defined as those who underestimate their marginal cost of acquiring education) and some are under-confident (overestimate the cost). There is information asymmetry in that firms cannot observe worker's productive abilities nor their beliefs of confidence but do know the proportion of high ability and overconfident workers in the population. This paper shows that if education raises productivity, which is a well-known stylised fact, and if men are overconfident and women under-confident, then women on average will earn less than men.

Bénabou and Tirole (2002) develop a framework identifying reasons why people may prefer optimistic self-views over accurate ones. One reason they give, defined as the *signalling value* is that if an individual believes (whether they are or not) that they possess certain qualities, it is easier to convince others of it. In an employment setting, being optimistic of ones ability may make it easier to convince an employer of this ability. Another reason is a *motivation value* where confidence in ones abilities can push individuals to be more ambitious. The authors examine ability and effort as compliments - in which case, under the premise that individuals are uncertain about their own ability, higher self-esteem leads to higher effort and hence higher earnings.

This literature review is not extensive of the literature and reasons that may explain gender wage gaps. What I have attempted to do is illustrate *(i)* how key explanations for a gender wage gap have evolved in recent years, some of which have been explored more than others and *(ii)* show that there are numerous explanations that are of course not mutually exclusive. There has been a certain focus on the different explanations that are important when looking at the glass ceiling and the highly educated sub sample that will be investigated in this paper.

3 Data

3.1 Summary Statistics

This paper uses a longitudinal survey of registrants for the GMAT in USA. The registrants were surveyed 4 times during the period of 1990 and 1998. 7006 individuals who registered to take the GMAT on test dates between June 1990 and March 1991 did the survey, of which only 5602 actually took the test. The sample is very select. All individuals are at least considering taking the GMAT which is necessary to take a MBA. Therefore the investigation set out is specifically looking at early career paths of the highly educated. In addition to the survey responses I have access to additional information on the individuals including their test scores (undergraduate GPA and if they took it, GMAT scores). I also have information about the schools which they went to for undergraduate studies and the schools of which they potentially apply to for an MBA from Barron's Profiles of American Colleges and Profiles of American Business Schools (1992).

The Graduate Management Admission Council (GMAC) who conducted the survey gives brief comparisons of the sample in the survey and the general population by comparing them to National Longitudinal Survey of Youth (NLSY) which should be a representative sample. We can see from Figure 3 a comparison of parent occupation and education. Clearly, the data set in this paper has a much higher level of educational attainment amongst the parents, the same is true for a higher percent of parents with professional occupations.

Figure 3: NLSY comparison to GMAT

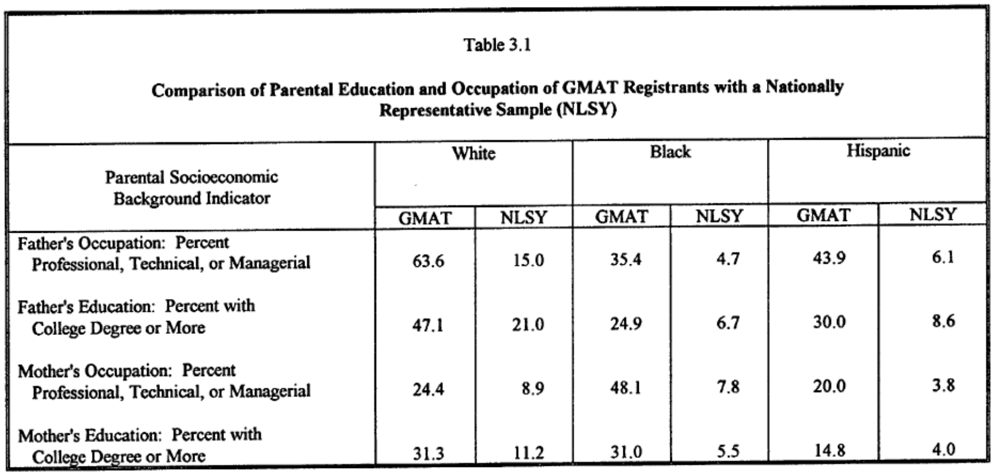


Table 3.1

Comparison of Parental Education and Occupation of GMAT Registrants with a Nationally Representative Sample (NLSY)

Parental Socioeconomic Background Indicator	White		Black		Hispanic	
	GMAT	NLSY	GMAT	NLSY	GMAT	NLSY
Father's Occupation: Percent Professional, Technical, or Managerial	63.6	15.0	35.4	4.7	43.9	6.1
Father's Education: Percent with College Degree or More	47.1	21.0	24.9	6.7	30.0	8.6
Mother's Occupation: Percent Professional, Technical, or Managerial	24.4	8.9	48.1	7.8	20.0	3.8
Mother's Education: Percent with College Degree or More	31.3	11.2	31.0	5.5	14.8	4.0

The 4 waves of data have been combined into a panel. The dates given for e.g. changing job or having a child are usually down to the month, therefore I have observations for each month for each individual. A great advantage of this data is how rich it is. When decomposing a wage gap, the question is, would a woman earn more if they had the same characteristics but were a man? In our case, we have a number of variables that help match individuals. Beyond grades, race, marital status, parents' education and other more common observables, the survey data asks a number of questions such as what the individuals' value more, family or work, what characteristics they believe to be important in being successful in business (such as initiative or communication skills) and also whether the individuals believe they have these characteristics. There are also questions on expectations, such as how much an individual expects to earn in 5 years time, I will discuss these more in Section 3.3.

I compare observables at the first wave of the survey between individuals who eventually get an MBA and those who do not (by the end of our observations). The summary statistics of the two groups are presented in Tables 1 to 4.

There are 1863 individuals who take the survey who complete an MBA by the time we stop observing them. There are 3933 individuals who do not complete an MBA by the time we stop observing them. 40 % of MBA takers are women, and 45 % of MBA non-takers are women. For those who are working in the first wave, the average wage is slightly lower amongst those who will complete an MBA (\$13.67 compared to \$14.21). The current age of an individual who completes an MBA is 26.2 whereas a non-completer is 27. A non-completer has more initial experience at nearly 70 months compared to an MBA completer who has 60 months experience when the first survey is completed. 33 % of individuals are married amongst those who do not complete an MBA and 31% amongst those who do. In both groups a higher proportion of men are married, but this may be driven by the higher average age of men. 16% of individuals who do not complete an MBA have children in wave 1 and 12% have children amongst those who do get an MBA. The mean GPA for individuals who do an MBA is 3.08 and for a non-MBA graduate it is slightly lower at 2.99. These values are statistically significantly different from each other at the 95% level. In both groups, women on average have a higher GPA score. In the group of individuals who do an MBA, the women's score are statistically significantly higher than men's. This is also true amongst the non MBA takers. Both the quantitative GMAT score and verbal GMAT score is statistically significantly higher on average for those who complete an MBA. Men's GMAT scores are on average higher than women's in both groups. Earning confidence, as described in Section 3.3 is lower for those who do an MBA than for those who do not, on average those who do an MBA overestimate their future earnings by $114/month. There is also a much smaller standard deviation of earning confidence amongst those who do an MBA. This indicates that they have a more accurate understanding of their future earnings, even though on average they have less months of previous work experience. Those who do an MBA overestimate quantitative and verbal score from their GMAT by less than those who do not complete an MBA. Women overestimate their scores by slightly more than men in both groups. Overall, looking at these observable characteristics, there are some differences between the two groups, but it does not seem as though the women are substantially more different than the difference that we exhibit between the men in the two groups.

Table 1: Summary Statistics at W1 of Individuals Who Complete MBA by End of Survey

	Total Count	Women Count	Men Count
Observations	1863	741	1122
Black	221	132	89
White	1,133	406	727
Hispanic	307	119	188
Asian	307	125	182
Other	19	8	11
Married/Cohabitating	584	195	389
US Citizen	1761	706	1055
Have A Child	226	79	147

Table 2: Summary Statistics at W1 of Individuals Who Complete MBA by End of Survey

	All			Women			Men		
	Count	Mean	SD	Count	Mean	SD	Count	Mean	SD
Real Earnings	1277	2617.53	1211.23	479	2361.54	1015.71	788	2770.99	1292.83
Real Wage	1311	13.67	5.62	492	12.86	5.02	809	14.13	5.81
Undergraduate GPA	1789	3.08	0.42	709	3.13	0.41	1068	3.04	0.42
Hours Worked	1821	137.77	93.59	718	125.49	91.48	1089	145.89	94.03
Work Experience	1800	59.11	63.22	705	54.65	58.97	1086	62.17	65.85
Number Children	1837	0.22	0.67	726	0.18	0.58	1101	0.25	0.72
GMAT Quant Score	1622	30.81	8.48	638	28.17	8.16	972	32.53	8.23
GMAT Verb Score	1622	29.7	7.83	638	28.99	7.92	972	30.16	7.73
Earning Confidence	1573	903.09	2770.03	630	334.86	2126.27	934	1291.01	3077.7
Confidence in Quant	1542	0.44	0.5	600	0.51	0.5	930	0.4	0.49
Confidence in Verb	1544	0.39	0.49	601	0.42	0.49	931	0.36	0.48
Opinion Index	1817	35.75	5.21	711	36.12	5.21	1098	35.52	5.2

Note: Earnings, Hours Worked and Experience are in Monthly terms. Earnings and Wages are in Dollars.

Table 3: Summary Statistics at W1 of Individuals Who Don't Complete MBA by End of Survey

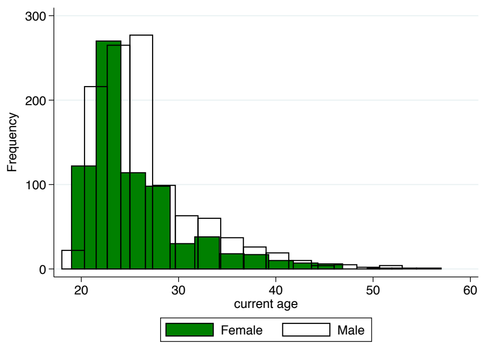
	Total Count	Women Count	Men Count
Observations	5796	2523	3,273
Black	830	495	335
White	3,243	1,308	1,935
Hispanic	978	416	562
Asian	1032	429	603
Other	19	34	41
Married/Cohabitating	1870	718	1152
US Citizen	5271	2340	2931
Have A Child	823	319	504

Table 4: Summary Statistics at W1 of Individuals Who Don't Complete MBA by End of Survey

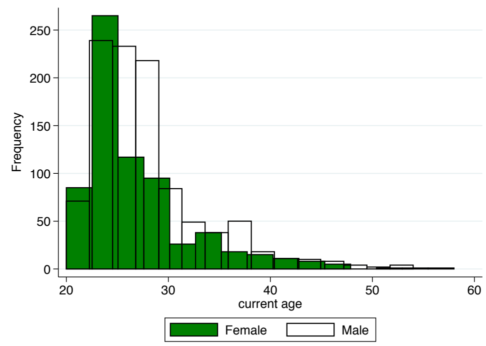
	All			Women			Men		
	Count	Mean	SD	Count	Mean	SD	Count	Mean	SD
Real Earnings	2560	2722.38	1392.17	1138	2399.98	987.37	1401	2976.75	1595.34
Real Wage	2631	14.21	6.81	1169	12.99	5.21	1439	15.19	7.67
Undergraduate GPA	3703	2.99	0.42	1671	3.04	0.42	2007	2.95	0.42
Hours Worked	3575	141.5	90.25	1596	136.39	88.05	1950	145.48	91.9
Work Experience	3536	69.92	68.23	1574	63.74	62.59	1945	74.9	72.21
Number Children	3874	0.27	0.69	1749	0.22	0.61	2107	0.3	0.75
GMAT Quant Score	3158	27.65	8.79	1377	25.1	8.15	1755	29.63	8.75
GMAT Verb Score	3158	26.54	8.27	1377	25.63	8.11	1755	27.24	8.32
Earning Confidence	2083	1017.05	4555.29	978	618.78	4784.33	1097	1363.35	4325.16
Confidence in Quant	2976	0.58	0.49	1296	0.63	0.48	1660	0.54	0.5
Confidence in Verb	2986	0.54	0.5	1299	0.57	0.49	1666	0.51	0.5
Opinion Index	3766	35.92	5.38	1691	35.99	5.27	2063	35.85	5.47

Note: Earnings, Hours Worked and Experience are in Monthly terms. Earnings and Wages are in Dollars.

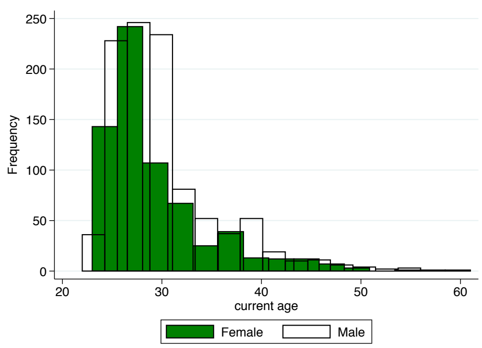
Figure 4: Age Distributions at each Wave



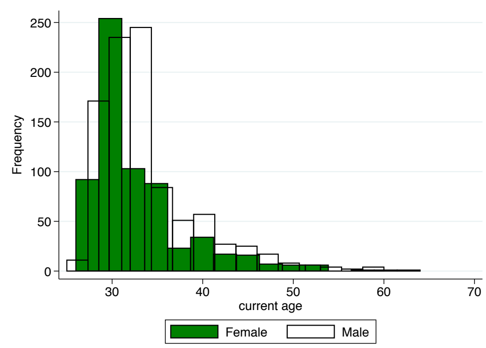
(a) W1



(b) W2



(c) W3



(d) W4

Figure 4 shows the male and female frequency of ages at each wave for MBA takers. In wave one, most individuals are in their 20s, by wave 4 most individuals are therefore in their early 30s. There are more men in the sample overall and hence there is a higher frequency of men at most ages, but the distribution of age seems to be relatively similar between men and women. Figure 5 shows the wage profile of men and women who complete an MBA. Just from observing this wage-age profile, it seems as though the wage gap grows as individuals get older and then starts to fall beyond the age of 45. However, this is purely a correlation between age and wage and does not control for anything. Also, as shown in the age-profiles, there are not many individuals older than 45 and hence the number of observations is much smaller at this point in the graph.

Figure 5: Wages by Age of those who complete an MBA

3.2 Real Wage and Real Earnings

This paper makes use of real hourly wages and monthly earnings in 1990 terms where wages and earnings are adjusted using CPI-U inflation measures. Typically using real wage is a useful tool over real earnings as it essentially controls for the number of hours worked. However, the useful variable asking what an individual expects to earn in 5 years time is in earnings. Hence making use of real earnings and then controlling in addition to hours worked is more practical in parts of this paper. We can see from the summary statistics that the average real wage is $13.67 per hour in the first wave for those who complete an MBA. Women have an average wage of $12.86 and men have an average wage of $14.13. I show summary statistics for MBA takers at each wave in the Appendix. By wave 4, the average wage is $21.27. Women have an average wage of $19.45 and men have an average wage of $22.42.

Some truncations have been made on the original data. As we have survey data, there are some outliers which seem to have been mis-announced. Looking in the literature, it often seems slightly arbitrary where the cutoffs are made, for example Manning and Swaffield (2008) choose to exclude hourly earnings below £1 or above £100. We have chosen to follow the same method but as it is dollars I choose to exclude hourly earnings below $1 or above $150.

Despite such a select sample, there is a large range of earnings within the sample. To see this, look at Figure 6 and Figure 7. The intuition of Figure 6 and Figure 7 is as follows: I Take $100 and divide it amongst 100 people who line up along the x-axis. The heights of the bars shows you how much each individual gets.

If all get the same, then everyone would get one dollar. However, according to the observed distribution, the right most person (i.e. the richest) would get around $4 of the $100. Looking at each gender individually, there seems to be greater inequality amongst women. The richest woman would get around $4.20 and the poorest about $0.10. The richest man would get around $3.75 and the poorest about $0.10.

Figure 6: Density of wage distribution of men and women in the population

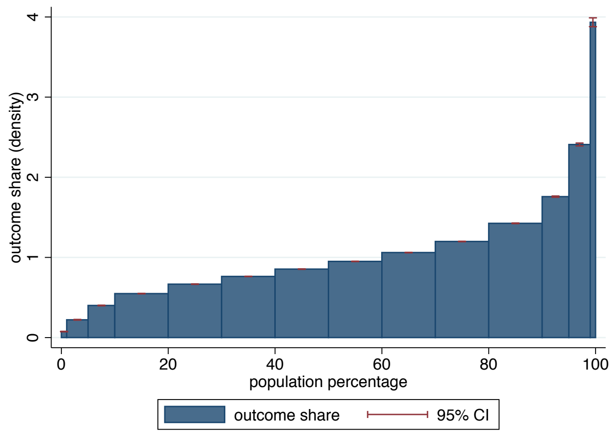
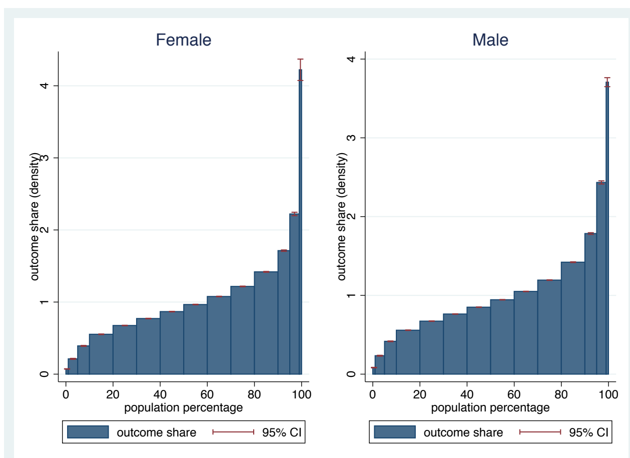


Figure 7: Density of wage distribution of men and women in the population



3.3 Overconfidence Variables

3.3.1 Potential Variables

The data allows us to exploit a number of variables that may indicate a measure of confidence. The main variables are:

- The first wave of the survey asks how much individuals expect to earn in 5 years. 5 years later, the individual's earnings are realised. The *confidence in earnings* variables is created by subtracting the actual earnings in 5 years from the expected. An individual can be labelled as *confident* in their earnings if this variable is greater than 0.
- The survey asks how well the individuals think they did in their GMAT and then their GMAT scores are realised. I explain how I create *confidence in quant* and *confidence in verb* variables in the discussion of potential issues below.
- The individuals are asked what type of job they expect to have and what managerial responsibility do they think they will have and then their managerial responsibility is realised. *Managerial Confidence* is a variable that takes the value from -1/0/1 where it takes -1 if an individual increases in managerial responsibility by less than expected, 0 if expectations are realised and 1 if responsibility increases by more than expected.
- There are a number of opinion variables. These variables ask the individual, on a 1-4 scale, how much they think they possess a certain characteristic. The characteristics include intuition, ability to organise and attractiveness, amongst others . I create an *opinion index* as explained in the potential issues below.
- I also have the individuals first choice university and the university they go to and the minimum or average GMAT or GPA scores they needed to get in to each university so we can understand if individuals aim too high or too low when applying.

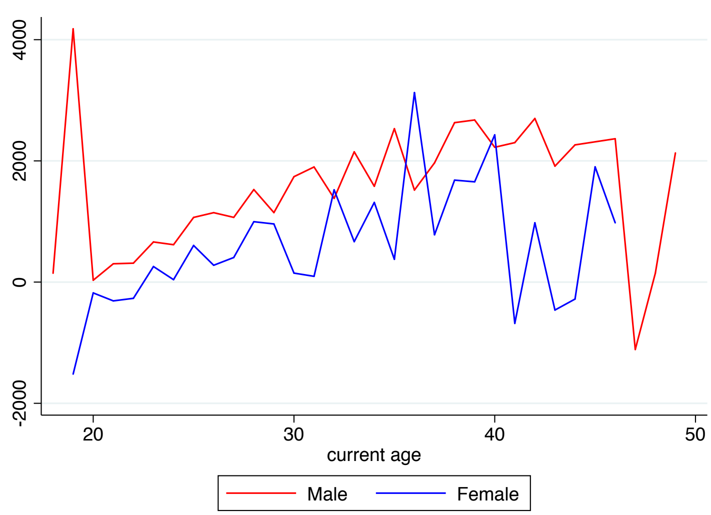
3.3.2 Potential Issues with Variables

There are a number of issues to discuss to acknowledge that these variables are not perfect confidence measures. The most interesting variable I have access to is the expected earnings in 5 years which we can then compare with actual earnings in 5 years time. However there is a potential heterogeneity of information which will impact the results. Some individuals may have a secure job when the first survey is done and hence have a realistic understanding of their future earnings whereas another individual may have been in education their whole life and therefore may be making more of a guess. Hence we may anticipate a higher variance amongst individuals who are not working at $t = 1$. In addition, we can only create a measure comparing what individuals estimate they will earn and what they do earn amongst those who are actually employed in 5 years time. It may be that individuals who are not working in 5 years hold certain characteristics that correlate with confidence.

The variables that look at what individuals predict how their GMAT went are also interesting. However, I cannot simply compare the variable indicating their actual test score and the variable indicating how well they think they did. The individuals are asked separately for their verbal exam and their quantitative exam whether they think they did "excellent", "above average", "average", "below average" or "poor". But obviously we can't simply claim that poor is bottom 20%. It may be better however to focus more around the average and separate the groups into above average, average or below average. As mentioned in Goldsmith et al. (1997), individuals may anchor their scales at different levels so interpersonal comparisons are useless (i.e. someone's *strongly agree* could be another person's *agree*). But, by asking if individuals opinion of a statement and then creating a two point scale where the individual can simply agree (accumulating all answers from somewhat agree to strongly agree) or disagree should not be affected as the anchoring is likely to come from level of agreement. Therefore it may be useful to group answers. I do this by creating a simple 1/0 dummy variable to measure separately confidence in quantitative score and verbal score. The value takes 1 if an individual estimated "excellent", "above average" and they got a grade that was average or below, or if an individual estimated "average" and they got below average and takes 0 otherwise.

Figure 8 shows the confidence in earning profile according to ages amongst the individuals who complete an MBA. Confidence in earnings is simply the amount individuals think they will earn in five years time (which they announce in the first survey) minus what they truly do earn in 5 years time. On average, at every given age up to around 37 years old, women overestimate their future earnings less than men do.

Figure 8: Confidence in Earnings - Age Profile



The difficulty in focussing on a confidence gap between men and women lies in the definition and accurate measurement of confidence as a characteristic. As explained by Moore and Healy (2008), the literature seems to define overconfidence in three different ways the three distinct ways. Firstly, overestimation of one's actual performance, secondly, over-placement of one's performance relative to others, and thirdly, excessive precision in one's beliefs to define overconfidence. Experimental literature seems to suggest that there are particular inconsistencies in results when defining confidence differently. The first definition of overconfidence is the most popular in empirical literature, and results such as that students overestimate their performance in exams Clayson (2005), have been found using this definition. The second definition, where individuals believe of themselves better than others, is likened to Niederle and Vesterlund (2007). It is important to differentiate that the first definition is overestimation whereas the second is over-placement. Clayson (2005) make an interesting distinction between *easy* and *difficult* tasks. The idea is that on easy tasks, where the probability of success is high, people tend to underestimate it (and the contrary is true for difficult tasks.) This is true also for *pessimism about the future* where for example, women may overestimate their chances of having breast cancer Woloshin, Schwartz, Black, and Welch (1999). In light of the confidence measure that looks at future earnings in the data set in this paper, it may be that those who are likely to have success may underestimate their future earnings and those are unlikely to have success overestimate their future earnings.

Another concern when trying to analyse the impact on confidence on wages is whether the traits are measured accurately. Existing studies of psychological factors for the gender wage gap rely on multi-item self-reported instruments and construct measures of cognitive and non-cognitive traits by averaging across items of various achievement and personality scales. Several studies have shown however that self-reported instruments are contaminated with measurement error (see for example Urzua (2008)). One option to deal with random measurement error is to average it has the restriction of assuming that each item in the index that is created has the same underlying issue for each gender. So when we are trying to analyse gender differences in traits there may be a bias.

3.4 Sample Selection

The sample is evidently very select. The sample by no means represents a whole population. The consideration of the paper is not to understand the whole gender wage gap, but to understand it amongst a sample that we observe, that is a highly educated group. However, there are still sample selection issues that can exist, even if the nature of the study is to look at a subsample. It is also always important to consider selection bias of those who choose to respond to the survey. 83.5 percent of those who were randomly sampled responded to the first wave of the survey. Although this is a high overall response rate, it is still important to compare the characteristics of respondents and nonrespondents to identify any potential differences in characteristics between the two groups.

There is data including age, race, gender, undergraduate grade-point average (GPA), years of work experience, when they expect to start the MBA and whether it will be full-time or part-time available on the GMAT registration for those who respond and those who do not respond. This wealth of information is incredibly useful and rare. The GMAC provide a comparison between respondents and non-respondents which is represented in Figure 9. In general, there are relatively minor differences between respondents and non-respondents on the characteristics that we can observe for both groups. It does seem however that respondents are more likely to be female and have a higher undergraduate GPA (except for Asians).

Figure 9: Comparing Respondents and Non-Respondents

Table B.1

Characteristics of Respondent and Nonrespondent Sample, by Race/Ethnicity

Characteristics	White		Black		Hispanic		Asian		Foreign	
	R	NR	R	NR	R	NR	R	NR	R	NR
Percent Female	40.6	30.9	60.8	50.0	42.3	33.1	43.4	40.7	34.4	25.6
Percent Age 25 or Less	54.6	51.2	47.8	51.9	47.4	46.6	60.7	53.7	47.2	55.7
Percent Age 35 or More	11.2	14.0	13.7	10.2	12.7	7.5	9.1	8.2	7.4	6.3
Percent GPA 2.9 or Less	35.4	39.7	56.2	63.4	47.6	46.9	39.3	26.4	33.5	39.6
Percent GPA 3.5 or More	20.9	17.7	7.6	2.9	13.9	12.2	19.2	13.2	23.5	18.9
Percent with at Least 5 Years' Work Experience	34.2	35.4	40.9	34.5	39.4	34.1	24.6	28.4	26.5	22.1
Percent Plan to Attend Full-Time Program	35.0	39.5	45.1	45.4	40.8	41.4	49.3	44.5	67.5	72.2
Percent Plan to Delay Entering MBA for 1 Year or More	8.7	7.6	9.3	10.7	8.4	11.3	15.3	11.9	10.4	11.7
Percent Sent GMAT Scores to 5 Schools or More	42.8	41.6	46.8	40.8	43.8	45.1	48.2	40.8	35.0	39.2
Percent Took GMAT on Scheduled Date	83.9	63.8	78.6	67.5	79.4	61.1	82.2	57.8	78.0	70.9
Sample Size	2,652	464	791	206	872	175	782	147	540	79

Source: Blau and Kahn (2017)

There is a potential additional issue of attrition. At the beginning of the survey, once the data has been cleaned of outliers, we have 5,851 observations. By wave 4 we only have 3,771 observations. The sample selection issue is therefore two fold; we have people who choose not to answer the survey in the first place and then we have people who choose to leave the survey. It is clear that the individuals who do not respond are not random, they may for example be more likely to not take the GMAT even if they have applied to do it. Within the sample, as we are aiming to compare men and women, if the *type* of man compared to the *type* of woman who chooses to respond to the survey differ then an issue will exist. However, if the *type* of man and *type* of woman who choose to respond/ who choose not to drop out are similar, then the analysis of comparison between men and women in the sample we observe can still be valid. Without adjusting for attrition in the sample, an assumption is made that the observations are 'missing completely at random' (MCAR assumption). I focus my paper on just the individuals who take an MBA. Therefore it is important to understand first if those who leave the sample are MBA takers or not. I present attrition levels at each wave amongst the MBA takers in Table 5. It seems as though the levels of attrition are relatively low compared to the whole sample. (If we include all individuals who take the survey, not just those who complete an MBA, the levels of attrition were over 10% at each wave. This is logical as those who do an MBA may more willing and interested in completing a survey that is targeted at those who take the GMAT and their future labour market outcomes. It seems as though the number of men and women who leave the sample are not largely different from each other, except in the last wave, where almost double the percentage of men leave the sample than women.

Table 5: Attrition in Each Wave

Wave	Number of Individuals	Female	Males	Attrition (%)	Female Attrition (%)	Male Attrition (%)
1	1863	741	1122			
2	1745	694	1051	6.3	6.3	6.3
3	1712	679	1033	1.9	2.2	1.7
4	1615	657	958	5.7	3.2	7.3

If one gender is more likely to leave the survey, this is important to note. But what we need to understand is if this gender who leave the survey are representative of that gender in the sample or if they hold certain characteristics, e.g. they earn less than the people who remain in the survey until the end. In Table 6 I present the initial wages of individuals who eventually complete an MBA (at the first survey date) and separate the means between those who remain in the survey until the 4^{th} wave and those who don't. The number of observations is lower than the total sample because many individuals are not working when we first observe them. It is hard to conclude much as there are not many observations at all for individuals who do not complete the survey. But, taking what we can see, it seems as though female non-completers have slightly higher wage (but a large standard deviation) and male completers have a slightly higher wage. There is no evidence at this point that higher earners are more likely to remain in the survey amongst those who complete an MBA.

Table 6: Summary Initial Earnings and Wages for Men and Women who Remain and who Leave the Survey

Group	No. Obs	Wage Mean	S.D.
Female Survey Enders	454	12.77	4.76
Male Survey Enders	717	14.14	5.77
Female Survey Non-Completers	38	13.94	7.50
Male Survey Non-Completers	92	14.05	6.12

I perform a test for attrition and report the results in the Appendix. One option is to perform a Probit where the outcome variable is the probability of responding to the final survey. I perform this on a number of observables from the first wave. The female dummy is not significant, nor is it significant when interacting it with wages or with having a child. This means that women are not more or less likely than men to drop out if they have low wages for example or when having a child. The results of this Probit regression are somewhat promising as it seems that even if individuals leave the sample non-randomly, no gender is more likely than the other to drop out for this reason.

4 Basic Wage Gap Decomposition

4.1 Oaxaca-Blinder

Oaxaca (1973) - Blinder (1973) decomposition divides the wage differential between the two genders into a part that is "explained" and a residual part that cannot be accounted for by such differences in wage determinants. It is interesting to conduct the simple cross sectional Oaxaca (1973) - Blinder (1973) decomposition as a first step, before moving onto a more interesting decomposition making use of the panel data. Below is a quick explanation of the decomposition:

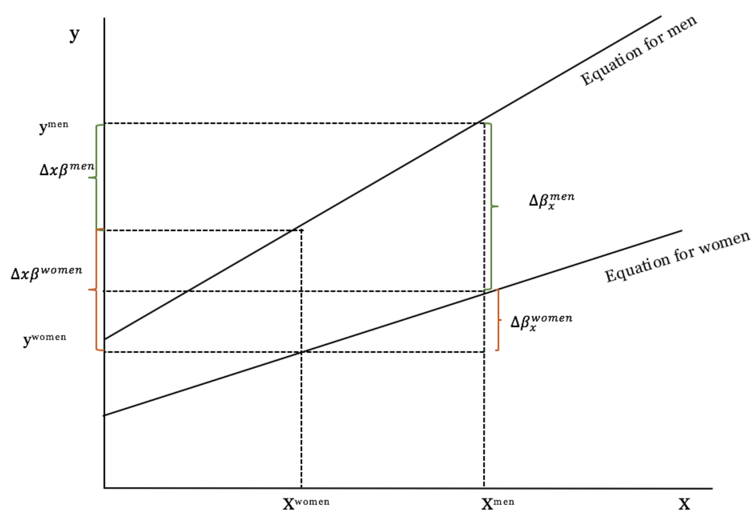
For each year t, estimate separate male and female OLS wage regressions for individual i:

$$Y_{gi} = \beta_{g0} + \sum_{k=1}^{K} X_{ik}\beta_{gk} + \nu_{gi}, \qquad g = F, M \tag{1}$$

Where Y is an earnings measure (wage, earnings, log of wages) and X is a vector of explanatory variables such as education, experience, number of children. Lastly, ν_{gi} is an error term.

In Figure 10 men are assumed to have a more advantageous regression line than women, meaning that at each value of X, the outcome of earnings is better. In addition, men are assumed to have a higher mean of X's. As a result, women have lower earnings than men.

Figure 10: Oaxaca-Blinder Decomposition



Source: Author

The estimated gap is given by:

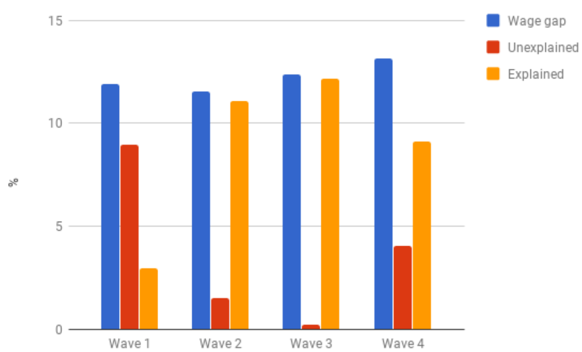
$$\hat{\Delta}_O^{\mu} = \bar{Y}_M - \bar{Y}_F \tag{2}$$

This gap can be decomposed as follows:

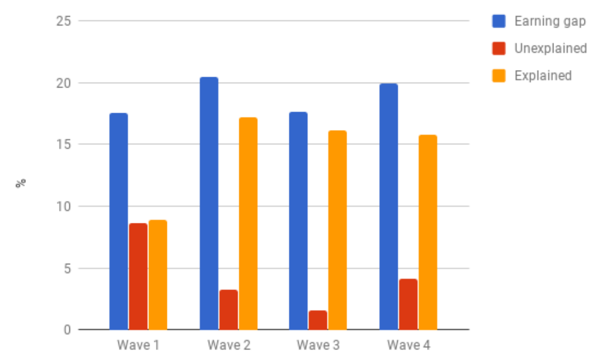
$$\hat{\Delta}_O^{\mu} = (\hat{\beta}_{M0} - \hat{\beta}_{F0}) + \sum_{k=1}^{K} \bar{X}_{Mk}(\hat{\beta}_{Mk} - \hat{\beta}_{Fk}) + \sum_{k=1}^{K} (\bar{X}_{Mk} - \bar{X}_{Fk})\hat{\beta}_{Fk} \tag{3}$$

Where the first 2 terms are the unexplained part and the last term is the explained part. The Oaxaca (1973) - Blinder (1973) decomposition allows the econometrician to decompose the gender wage gap into a part which reflects the mean difference in women's wages if they had the same characteristics as men (if for example, they on average had less experience, this is the explained part). There is then a component which expresses women's wages when applying men's coefficients to the women's characteristics.

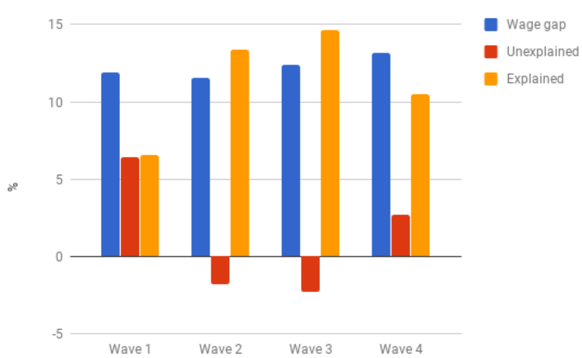
Figure 11: Oaxaca-Blinder decomposition at each wave



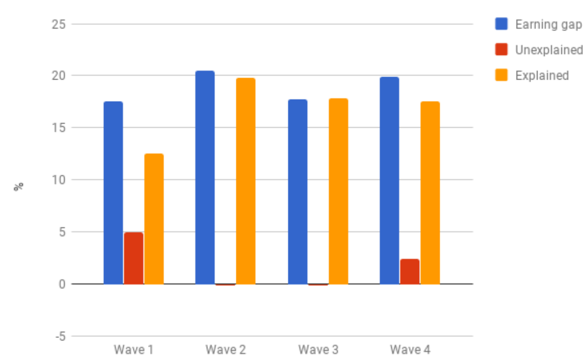
(a) Oaxaca-Blinder Decomposition of Wages



(b) Oaxaca-Blinder Decomposition of Earnings



(c) Oaxaca-Blinder Decomposition of Wages including confidence variables



(d) Oaxaca-Blinder Decomposition of Earnings including confidence variables

Note: The decomposition has controlled for GPA score, GMAT score, experience, marriage, hours worked, number of children, if individual is a US citizen, race, dummies for the industry of job and dummies for degree major at MBA. The outcome is defined in the captions. When confidence variables are included this includes a confidence measure for future earnings, for GMAT verb score, for GMAT quant score and an opinion index.

As always we have to be aware of a sample selection issue whereby we are only looking at individuals who are employed. Typically, in the population, there is a higher percentage of unemployed women than men. It may be that women who are employed hold certain characteristics and are likely to have a lower wage. Hence, omitting these women can underestimate the wage gap. I show in the next section that the employment levels between men and women who complete an MBA are fairly similar.

In Figure 11 I show the decomposition, using Oaxaca (1973) - Blinder (1973), of the wage and earning gap at each wave. I have controlled for education variables, experience, race, marriage, if individual is a US citizen, dummies for each number of children, dummies for industry of job and dummies for degree major in (a) and (b). I have included all of the above and confidence variables (confidence in earnings, confidence in quantitative score, verbal score and opinion index) in (c) and (d). Looking at Figure 11 there are a few clear observations. Firstly, the wage and earning gap exists at every wave. The earning gap is larger than the wage gap, which intuitively makes sense as looking at wages controls for hours worked. Secondly, the wage and earning gap grows over time. The level of unexplained gap has a U-shape pattern. It starts relatively large and then falls and then grows again. The reason the unexplained gap in wave 1 may be large may partly be driven by the fact that many people in the sample are not working so the sample to observe is small. Also, one possible explanation is if individuals are working whilst in education, job characteristics may be very different (flexible, part time) and wages could be considered more *random*. In (a), the gap is almost entirely unexplained in wave 1 but almost entirely explained in wave 2 and 3, the unexplained part returns in wave 4 and is substantial. In (b), the unexplained gap is smaller but substantial in wave 1 and wave 4. With the inclusion of confidence, the unexplained part shrinks by 20% in (a). This suggests that confidence may be an explanation for the wage gap. The story is the same for the other specifications. Looking at (c), the wage decomposition with confidence variables, the unexplained part of the gap is negative in wave 2 and wave 3 paired with an explained part that is larger than the gap itself indicates that there is potential positive discrimination to women on the observable characteristics included. I present a detailed decomposition of specification (c) in the Appendix. As expected due to the vast difference in how much the gap is explained with the inclusion of a confidence variable, confidence in earnings explains 80% of the explained gap in wave 1 and around 20% for all other waves. Some industries such as manufacturing and public explain a large part of the explained gap. Services has a negative coefficient suggesting that it explains a part of why the gap would shrink, i.e. suggesting that there is less of a wage gap within the service industry. Confidence and industry are two subgroups I will explore further later.

By using this decomposition technique, it seems as though much of the gap at each wave can be explained but not all of it. Decomposing at each wave is interesting but not the most insightful approach. There is some evidence to suggest that confidence may be an explanation for part of the wage gap. With this motivation, I move on to look at the wage gap from the point individuals complete their MBA and onwards.

5 Empirical Analysis of Labour Market Trajectories after Completing MBA

I estimate simple OLS regressions at fixed points in time to observe correlations between observables and wages with the inclusion of a female dummy. The specification is therefore:

$$Y_i = \alpha + \beta_1 X_i + \beta_2 \mathsf{Female}_i + \epsilon_i \ \textit{at time} = t \tag{4}$$

I combine this simple technique with a model to estimate real wages of individual i over a time period $t = 1$ to $t = T$ where time is measured as months since the individual left education, or I estimate wages over amount of experience.

$$Y_{it} = \alpha + \beta_1 X_{it} + \beta_2 \mathsf{Female}_i + \beta_3 \mathsf{Female}_i \times X_{it} + \beta_4 DOB \times Year + \beta_5 T \times \mathsf{Female}_i + \beta_6 T \times X_{it} + \epsilon_{it} \tag{5}$$

Where Y_{it} is real earnings of individual i at time t, X_{it} is a covariate matrix including a variation of controls which will be specified at each use, Female_I is a dummy variable that takes the value of 1 if the individual is a woman. T is a series of dummy variables for each time period after completing an MBA. There is an interaction term between all controls and each time dummy and the gender dummy. DOB is a cohort dummy which indicates which decade the individual was born in. I investigate cohort effects in the Appendix. The oldest individual was born in 1930s and the youngest was born in 1970s. Year is a series of dummies for each year that is in the panel. These go from 1990 to 1998.

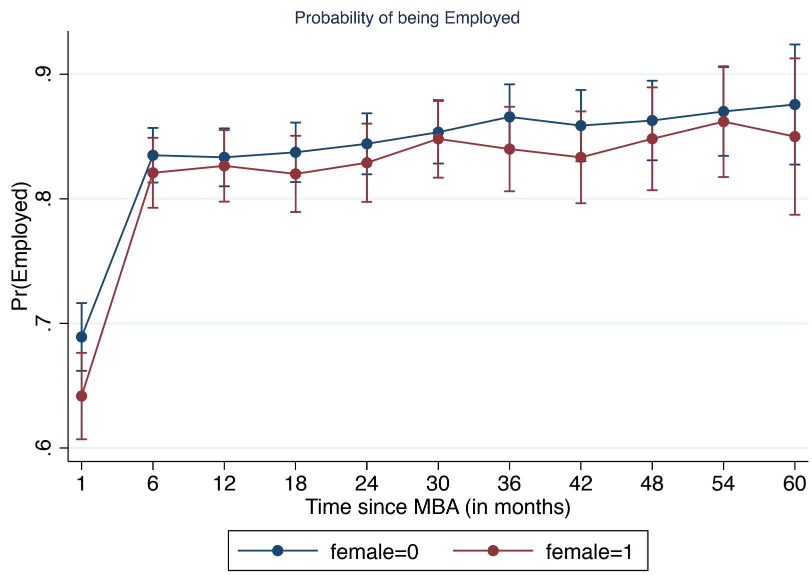
I can estimate wages at each time period after completing the MBA and then plot to see the trajectories of wages for men and women. The figures that follow therefore show the marginal effects at each time period after completing an MBA (unless stated otherwise). For each gender, the estimated earnings at each time period for the reference individual is estimated. I have de-meaned the variables so that the mean is 0. I do this so we are analysing individuals who have *average* characteristics. In the figures the vertical lines show the 95% confidence intervals.

As discussed, one issue that has arisen is that many individuals have actually completed education before the survey begins and although they take the GMAT they either do not do an MBA. Therefore we are unable to see their initial earning trajectory after completing education. This is the case for 2,533 individuals which amounts to almost half the data set. In addition, there are some individuals who complete their undergraduate studies after the first survey but then do not go on to complete an MBA. Lastly, there are some individuals who start their MBA but do not complete it. The option I have chosen is to reduce the sample just to those who complete an MBA and hence we observe the moment they finish and then some time after this. In total there are 1878 individuals who complete their MBA whilst we observe them.

Before estimating earning trajectories of men and women, I first estimate the likelihood of employment after they complete their MBA using a probit model. I plot the probabilities at every 6 month interval after completing their MBA for the first 5 years. This is presented in figure 12. Men and women follow a similar pattern, the first month after completing their MBA, men are slightly more likely to be employed, at just under 70% and women at around 65%. 6 months later, both men and women are much more likely to be employed, at just under 85%. Men and women seem to have a very similar probability of being employed, at each 6 month period, women are slightly less likely on average although the difference between the two does not seem to be significant. 5 years after completing an MBA, men and women have a probability of around 85% of being employed. The fact that men and women have similar probabilities of employment is promising for my analysis as it reduces the potential issue of selection bias. In the true population of USA, in 1990, the employment rate of women was just 44.2% and in 2000 it was around 45.6%. [3] In a situation where looking at the whole population, an econometrician would be worried that women who select into employment hold certain characteristics which those who do not participate in the labour force participation do not have. These characteristics are likely to be correlated with higher wages. Hence, without adjustments such as the Heckman procedure, an underestimation of the wage gap is possible. This however, is not the case in our sample, where men and women have similar probabilities of being employed.

[3] World Bank: Derived using data from International Labour Organization, ILOSTAT database and World Bank population estimates. Labor data retrieved in November 2017.

Figure 12: Probability of Employment From the Time Individuals Finished their MBA



Note: This graph estimates the probability of employment for men and women from the month after they finish their MBA. The vertical lines show the 95% confidence intervals at every 6 month period.

I present a preliminary set of results in Table 7 where I take the technique used by Bertrand et al. (2010) and regress log of real wages, log of monthly real earnings and also hours worked on a dummy variable for the number of years since the individual completes their MBA interacted with a female dummy. I include in this regression cohort × year dummies. I show the results only for when the female dummy is equal to one, i.e. showing the gap between men and women. The results show that the real wage gap 0 years after completing the MBA (i.e. the first period that individuals work) is 11.4 %. The wage gap grows to 23.2 % after 5 years. The earning gap shows the same pattern but is higher. Of course, by definition, this then controls for hours worked. As described in the literature review, the gap may be driven from hours worked in a direct and indirect way. Directly, women work less hours than men on average, indirectly, part time work or work with lower hours may give less training and hence reduce future earning potential. In terms of hours worked, it seems as though men work more hours initially but then women work more hours after, although the gap between them shrinks and becomes insignificant after 5 years. I have included no additional controls in this table and have not restricted the sample to individuals who do have information on all future controls that I use, hence the estimations may be slightly different to other estimations which focus on different sub-samples.

Table 7: Pooled OLS Estimates of the Difference between Female and Male Wages, Earnings and Hours Worked for the 5 Years after Completing an MBA

	(1) Log Wages	(2) Log monthly real earnings	(3) Hrs Wrkd
0 Years	-0.114***	-0.152***	-7.603**
	(0.001)	(0.000)	(0.033)
1 Year	-0.134***	-0.150***	-2.686
	(0.000)	(0.000)	(0.432)
2 Years	-0.142***	-0.201***	-7.105**
	(0.000)	(0.000)	(0.038)
3 Years	-0.155***	-0.236***	-9.942**
	(0.000)	(0.000)	(0.011)
4 Years	-0.144***	-0.226***	-8.716
	(0.007)	(0.001)	(0.059)
5 Years	-0.232***	-0.299***	-7.422
	(0.001)	(0.001)	(0.238)
Observations	2866	2856	2871
Cohort*Year	Yes	Yes	Yes

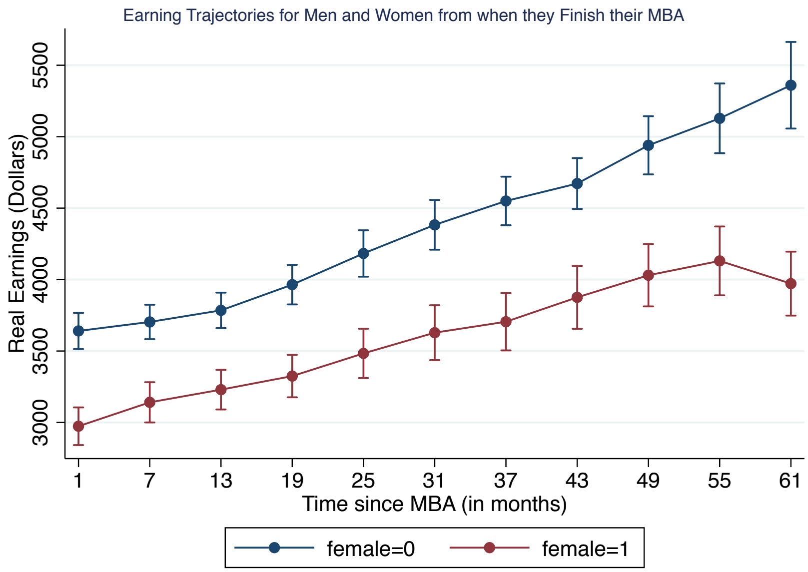
p-values in parentheses
** $p < 0.05$, *** $p < 0.01$

Note: Each regression includes cohort*year dummies and interactions between a female dummy and a dummy variable for the number of years since the individual completed their MBA. Wages are hourly wages and hours worked are monthly hours worked. The table reports the estimated coefficients on this interaction term. P-values are in parenthesis and the standard errors are clustered at the individual level.

Figure 13 shows the raw earnings gap. This is simply the average trajectory of earnings for men and women from the moment they finish their MBA and for 5 years after that point. There are two main findings from this graph. Firstly, a gap exists and secondly it increases over time. The initial gap is estimated to be 18.32% and after 5 years (or 60 months) it has increased to 25.91%. It seems as if the average female wage drops between 55 and 60 months after they finish their MBA. I will explore this further when exploring the explanations for the pay gap. This will be explored in more detail later on.

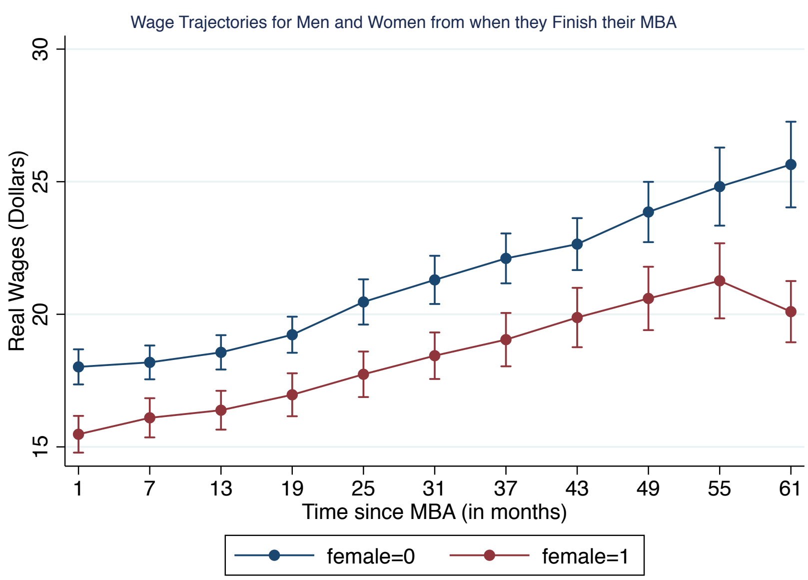
We can also look at a wage gap, rather than earning gap. The estimated initial wage gap is 14.10% amongst the sample. This is smaller than the earning gap as expected. The wage gap follows a similar pattern to the earning gap and increases over time. By 5 years after MBA completion, the wage gap is 21.64%, again smaller than the earning gap. The wage gap has therefore increased by 34.84% in 5 years and the earning gap increased by slightly less (29.30%). These figures are slightly different to the results found in Table 7. This is because in the figures I include the whole sample who have wages whereas in the regression analysis I limit the sample to those who have all observables that I will control for later on.

Figure 13: Raw Real Earning Gap From the Time Individuals Finished their MBA



Note: This graph estimates real earnings for men and women from the month after they finish their MBA. The vertical lines show the 95% confidence intervals at every 6 month period.

Figure 14: Raw wage gap from time finished MBA



Note: This graph estimates wages for men and women from the month after they finish their MBA.

I present OLS regressions in Tables 8 and 9 that show the correlations between variables and wages at the first period after completing the MBA. I focus on the coefficient on female dummy and how it changes as I include more observable characteristics. In the regressions I only include individuals who have all the observables I will include so that I am comparing the same sample throughout. This restricts us to 632 observations. When controlling for nothing, women suffer a 11.3% penalty. By including a quadratic in experience, the gap shrinks by almost to 10.4%.

With the inclusion of a standardised GMAT test score and Undergraduate GPA, the gap shrinks again to 8.7%. The inclusion of hours worked and marriage dummies does not seem to kill the gap. In fact the gap rises to 9.2%. The inclusion of dummies for children reduces the gap slightly to 8.8%. The inclusion of dummies for degree major reduces the but it still remains significant at the 5% level. Finally, including occupation dummies which are industry 1 digit codes [4], the gap reduces again but remains significant at the 5% level.

In Table 9 I explore the impact of the confidence variables on the female coefficient. In the first column, I return to the specification in column (5) of the previous table and include confidence in earnings. The coefficient on the female dummy is not significant, even without the inclusion of the controls for industry and degree majors. The magnitude of the coefficient is 30 % smaller than without the inclusion of the confidence variable. With the inclusion of the industry and degree major controls, the coefficient on the female dummy shrinks in magnitude to just 4.3%. However, the standardised earning confidence variable is large and significant. If an individual increased their earning confidence by one standard deviation, their wage is estimated to increase by 8.7%. It is not easy to decipher what this means in terms of the wage gap. As the coefficient of female becomes much smaller, this suggests that without the inclusion of the confidence in earnings coefficient, there was an downward bias, i.e. the female dummy was explaining a negative impact that is actually driven from lack of *confidence*. This suggests that confidence may have some part in explaining the gender wage gap. It suggests that, it is not that being a female is bringing down wages as such, but it is that having a smaller overestimation (or larger underestimation) of future earnings will lead to lower wages and this is perhaps more common in women. The fact that those who overestimate their earnings by more, means that in reality in 5 years, there is a bigger gap between their realised earning and what they expected to earn, i.e. they are less productive than they predicted. But it is these individuals, who are less productive than predicted, who earn the most. So this means that individuals set their bar so high, that even when they are further off than other individuals, they are earning more than other individuals. Of course, it may be that this is coming from an additional omitted variable bias in the confidence variable. Moreover, some individuals may have better insight on their future wage based on past experience and earnings. However, according to these results, this would mean that those who are well informed and hence less *overconfident* are actually less likely to have a higher wages.

[4] See the Subgroup Analysis section for more details of the 1 digit codes

Interestingly, the inclusion of additional confidence variables has no impact on the female coefficient. By removing the confidence in earning variable and including confidence in GMAT scores or the opinion index, the gap returns to around 7.5%. The opinion index is positive and significant. This suggests that an increase in 1 point in the index results in a 1% increase in wage. Column (5) in Table 9 includes all confidence in earning terms but without the industry and degree major dummies. The gap remains insignificant. With the inclusion of the additional dummies the gap remains insignificant.

The OLS regressions are informative and give motivation to return to exploring the earning trajectories over time. An analysis of gender wage gap by years since MBA graduation is given in Tables 10 and 11. Here I report the female coefficient (which was interacted with the year since MBA completion). The specification of these tables match those of 8 and 9. What is clear is that over time, the wage gap rises. Without any controls, the wage gap rises to 22.9%. The evolution follows a similar pattern even with the addition of many controls. Turning to 11. As we saw previously, the initial gap is not significant with the inclusion of confidence in earnings. However, just 1 year later the gap is significant at 6.9%. The gap rises to 18.5% in 5 years. With the inclusion of industry and degree major dummies the gap remains insignificant for the first 4 years but 5 years after completing the MBA, the gap is at 15.1% and significant.

Table 8: OLS Estimates of Log Wage at the first period after individuals finish MBA

	(1) Log Wages	(2) Log Wages	(3) Log Wages	(4) Log Wages	(5) Log Wages	(6) Log Wages	(7) Log Wages
Female	-0.113***	-0.104***	-0.087***	-0.092***	-0.088***	-0.078**	-0.073**
	(0.001)	(0.002)	(0.008)	(0.004)	(0.007)	(0.016)	(0.024)
Work Experience		0.004***	0.004***	0.004***	0.004***	0.004***	0.004***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Work experience		-0.000***	-0.000**	-0.000**	-0.000**	-0.000**	-0.000**
Squared		(0.008)	(0.016)	(0.015)	(0.028)	(0.017)	(0.030)
Undergrad GPA			0.077**	0.076**	0.076**	0.077**	0.079***
			(0.016)	(0.015)	(0.016)	(0.012)	(0.009)
GMAT score			0.094***	0.098***	0.099***	0.094***	0.094***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Hrs Wrkd				-0.001	-0.001	-0.001	-0.001
				(0.059)	(0.070)	(0.065)	(0.056)
Married/Cohabitating				0.042	0.030	0.032	0.027
				(0.071)	(0.211)	(0.178)	(0.250)
Observations	2866	2866	2866	2866	2866	2866	2866
Cohort*Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Degree Major Dummies	No	No	No	No	No	Yes	Yes
Industry Dummies	No	No	No	No	No	No	Yes

p-values in parentheses
** $p < 0.05$, *** $p < 0.01$

Note: P-values are in parenthesis. In addition to the variables shown, I control for race in each specification. From column (5) onwards I also include dummies for number of children. Experience and hours worked are measured in months.

Table 9: OLS Estimates of Log Wage at the first period after individuals finish MBA

	(1) Log Wages	(2) Log Wages	(3) Log Wages	(4) Log Wages	(5) Log Wages	(6) Log Wages
Female	-0.056	-0.043	-0.073**	-0.078**	-0.062	-0.049
	(0.074)	(0.170)	(0.024)	(0.015)	(0.051)	(0.122)
Work Experience	0.003***	0.003***	0.004***	0.004***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Work experience Squared	-0.000**	-0.000	-0.000**	-0.000**	-0.000**	-0.000
	(0.033)	(0.052)	(0.030)	(0.033)	(0.036)	(0.054)
Undergrad GPA	0.081***	0.083***	0.079**	0.080***	0.083***	0.085***
	(0.005)	(0.003)	(0.010)	(0.007)	(0.005)	(0.003)
GMAT score	0.083***	0.081***	0.095***	0.100***	0.083***	0.076***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Hrs Wrkd	-0.001**	-0.001**	-0.001	-0.001**	-0.001**	-0.001**
	(0.024)	(0.019)	(0.057)	(0.045)	(0.022)	(0.017)
Married/Cohabitating	0.027	0.024	0.027	0.026	0.027	0.024
	(0.231)	(0.279)	(0.256)	(0.274)	(0.238)	(0.293)
Earning Confidence	0.091***	0.087***			0.087***	0.084***
	(0.000)	(0.000)			(0.000)	(0.000)
Confidence in Quant			0.015		-0.002	-0.010
			(0.672)		(0.954)	(0.765)
Confidence in Verb			-0.011		-0.013	-0.019
			(0.740)		(0.686)	(0.544)
Opinion Index				0.010***	0.006**	0.006***
				(0.000)	(0.013)	(0.009)
Observations	2866	2866	2866	2866	2866	2866
Cohort*Year	Yes	Yes	Yes	Yes	Yes	Yes
Degree Major Dummies	No	Yes	Yes	Yes	No	Yes
Industry Dummies	No	Yes	Yes	Yes	No	Yes

p-values in parentheses
** $p < 0.05$, *** $p < 0.01$

Note: P-values are in parenthesis. In addition to the variables shown, I control for race in each specification. All columns include dummies for number of children. Experience and hours worked are measured in months.

Table 10: Estimates of Wage Gap Over First 5 Years After Completing MBA

	(1) Log Wages	(2) Log Wages	(3) Log Wages	(4) Log Wages	(5) Log Wages	(6) Log Wages	(7) Log Wages
0 Years	-0.113***	-0.104***	-0.087***	-0.092***	-0.088***	-0.078**	-0.073**
	(0.001)	(0.002)	(0.008)	(0.004)	(0.007)	(0.016)	(0.024)
1 Year	-0.133***	-0.121***	-0.104***	-0.104***	-0.100***	-0.090***	-0.084***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)	(0.005)	(0.008)
2 Years	-0.140***	-0.132***	-0.113***	-0.117***	-0.113***	-0.102***	-0.088**
	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)	(0.004)	(0.012)
3 Years	-0.153***	-0.149***	-0.130***	-0.136***	-0.132***	-0.119***	-0.099**
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.003)	(0.014)
4 Years	-0.141***	-0.140***	-0.121**	-0.126**	-0.121**	-0.108**	-0.088
	(0.009)	(0.008)	(0.017)	(0.012)	(0.018)	(0.032)	(0.079)
5 Years	-0.229***	-0.232***	-0.214***	-0.217***	-0.212***	-0.198***	-0.176***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.003)	(0.008)
Observations	2866	2866	2866	2866	2866	2866	2866
Cohort*Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Degree Major Dummies	No	No	No	No	No	Yes	Yes
Industry Dummies	No	No	No	No	No	No	Yes

p-values in parentheses

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

Note: The dependent variable in each equation is log of real hourly wages. In a regression without any controls, the sample is restricted to those survey respondents with non-missing characteristics that I include in later specifications. All regressions include cohort*year dummies and a dummy for race (white, black, hispanic, asian and other). The specification of each column matches with the OLS regressions in Table 8. Specification (1) includes no additional controls, specification (2) includes a quadratic in experience, specification (3) includes GPA and GMAT scores, specification (4) includes hours worked monthly and specification (5) includes a dummy if married. Specification (6) includes a dummy for each number of children. Specification (7) includes dummies for degree major choices and (8) also includes dummies for industries. P-values are in brackets and the standard errors are clustered at the individual level. Experience and hours worked are measured in months.

Table 11: Estimates of Wage Gap Over First 5 Years After Completing MBA

	(1) Log Wages	(2) Log Wages	(3) Log Wages	(4) Log Wages	(5) Log Wages	(6) Log Wages
0 Years	-0.056	-0.043	-0.073**	-0.078**	-0.062	-0.049
	(0.074)	(0.170)	(0.024)	(0.015)	(0.051)	(0.122)
1 Years	-0.069**	-0.054	-0.084***	-0.089***	-0.074**	-0.059
	(0.025)	(0.076)	(0.008)	(0.005)	(0.016)	(0.051)
2 Years	-0.085**	-0.061	-0.088**	-0.094***	-0.091***	-0.067**
	(0.012)	(0.067)	(0.011)	(0.006)	(0.007)	(0.044)
3 Years	-0.105***	-0.074	-0.100**	-0.106***	-0.111***	-0.079**
	(0.007)	(0.052)	(0.013)	(0.008)	(0.004)	(0.036)
4 Years	-0.094	-0.063	-0.089	-0.096	-0.101**	-0.069
	(0.050)	(0.186)	(0.077)	(0.054)	(0.036)	(0.148)
5 Years	-0.185***	-0.151**	-0.177***	-0.184***	-0.191***	-0.156**
	(0.005)	(0.019)	(0.008)	(0.005)	(0.004)	(0.015)
Observations	2866	2866	2866	2866	2866	2866
Cohort*Year	Yes	Yes	Yes	Yes	Yes	Yes
Degree Major Dummies	No	Yes	Yes	Yes	No	Yes
Industry Dummies	No	Yes	Yes	Yes	No	Yes

p-values in parentheses

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

Note: The dependent variable in each equation is log of real hourly wages. In a regression without any controls, the sample is restricted to those survey respondents with non-missing characteristics that I include in later specifications. All regressions include cohort*year dummies and a dummy for race (white, black, hispanic, asian and other). The specification of each column matches with the OLS regressions in Table 9. Specification (1) includes confidence in earnings but does not include dummies for industry and degree major. Specification (2) includes dummies for industry and degree major. Specification (3) includes confidence in GMAT scores (and not confidence in earnings), specification (4) includes opinion index (and no other confidence variables). Specification (4) includes all confidence measures but no dummy for industry and degree. Specification (5) includes all confidence measures and dummies for industry and degree. P-values are in brackets and the standard errors are clustered at the individual level. Experience and hours worked are measured in months.

6 Non-Parametric Matching Techniques

As discussed in the literature review, there are a number of short comings of the Oaxaca (1973) - Blinder (1973) (OB) technique. There are additional issues which motivate using a re-weighting technique. The OB technique does not address the problem known as the common support problem. Men and women may differ in age, education and so on but also the distribution of these variables may not overlap fully. For example, there may be a combination of characteristics where we can find a man that holds them but not a woman, for example majors in finance, married with a child that is one year old and working full time. This leads to individuals being compared when in fact they are not comparable. This problem of comparability is exaggerated when job characteristics are included in the explanation of the wage gap. The Oaxaca (1973) - Blinder (1973) technique fails to recognise the issue of gender differences in the support as it compares all men and women who are working without any restriction to individuals with comparable characteristics. As Ñopo (2008) explains, this means that the decomposition relies on the *'out-of-support assumption'* which means that it is necessary to assume that the linear estimators of the earnings equations are also valid out of the supports of individual individual characteristics for which they were estimated. Typically it has been shown that the decomposition therefore overestimates the part of the gap which is explained by differences in rewards for individual characteristics.

The solution to this is to estimate the gender gap only on the observations where the characteristics of men and women are comparable, i.e. within the common support. To determine the common support, authors in the literature have made use of non-parametric matching techniques. (see for example Ñopo (2008)). The idea is that gender is in fact a treatment. With that in mind, the technique selects a sub-sample of men and women who are comparable on observable characteristics and then see if there is a difference in outcome (earnings) if an individual is treated or not (i.e. if they are a woman or man).

There are three main parameters with this approach:

- ATE: the average treatment effect in the sample population (all indviduals) which is defined by $E(Y_{1i} - Y0i) = E(\beta_i)$
- ATT: the average treatment effect for 'treated' individuals (female workers) which is defined by $E(Y_{1i} - Y0i|T_i = 1) = E(\beta_i|T_i = 1)$
- ATNT: the average treatment for 'untreated' individuals (male workers) which is defined by $E(Y_{1i} - Y0i|T_i = 0) = E(\beta_i|T_i = 0)$

A matching approach starts by defining an outcome variable (real wages) and a (0,1) treatment variable (female). It seeks to establish whether a statistically significant difference exists in the wages between the treated (female) group and the control (male) group. I re-weight the sample using Inverse Probability Weights

(IPW) and estimate wage trajectories for early career outcomes on the matched group of individuals. The procedure selects a group from control (male) which is selected to be, as far as possible, identical in all other key characteristics to the treated (female) group. This process of creating a 'matched' control group is done by the creation of a propensity score, which is done by developing a probit model to identify the probability of the control group being a member of the treated group based on their characteristics. Following this, I compute a weighted average, using the inverse of the probability of being in each group.

A propensity score, $p(x)$ is created to estimate the ATE where:

$$p(x) = P(T = 1|X = x) \tag{6}$$

For women (the treated individuals), their outcome is weighted by:

$$w(x) = \frac{1}{p(x)} \tag{7}$$

And for men (the control group), the weight is:

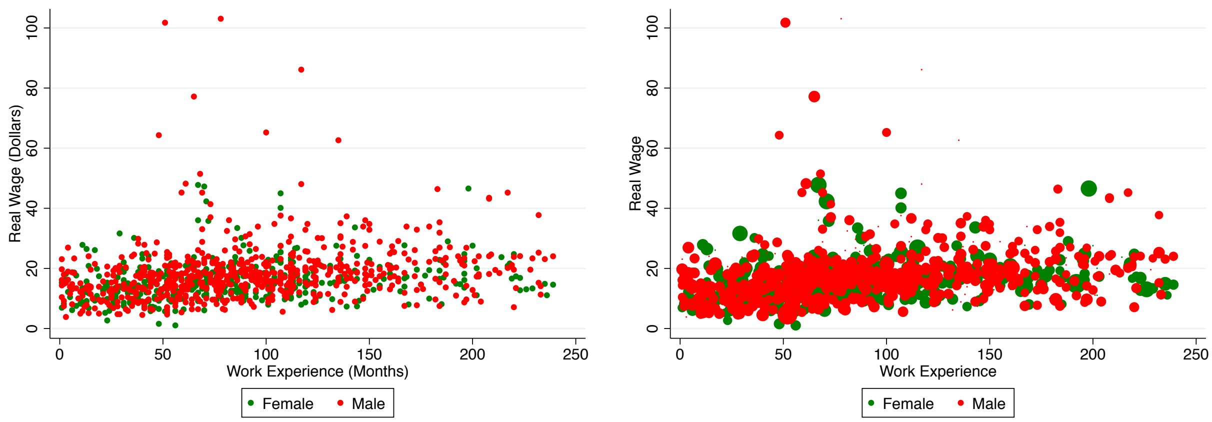
$$w(x) = \frac{1}{1 - p(x)} \tag{8}$$

However, these estimates are only valid if there are no residual systematic differences in observed baseline characteristics between the two genders in the sample weighted by the estimated inverse probability of treatment. There are a number of tests to assess whether measured baseline covariates are balanced between treatment groups in the weighted sample. I perform these in the Appendix.

Causal inference using the propensity score requires a number of assumptions: consistency, exchangeability, positivity, and no misspecification of the propensity score model. By consistency, that means that an individual's potential outcome under the treatment that they actually received is the same as the individual's observed outcome. Exchangeability means that we assume that there are no unmeasured confounders which means that we have included all variables that affect treatment selection and outcomes. Positivity is the assumption that all subjects have a probability greater than 0 of receiving each treatment.

I first estimate the 4 different sets of propensity scores. All sets are weighting based on characteristics observed at the first period after completing an MBA. Therefore, I attempt to match individuals at the point they enter into the labour market and then see how wages progress for the years following. The first set uses all observables from column (6) in Table 8, the second uses all observables from column (8), i.e. includes in addition degree major and industry dummies. I then reweight with the inclusion of confidence variables but without the degree and industry dummies and then lastly I also include the dummies with the confidence variables. Figure 15 compares the unweighted scatter (a) of wages according to work experience from the first period after completing an MBA to the first weighted scatter (b) (matching with observables from column (6) in Table 8. Because of the number of observations the Figures are not that clear but are useful for understanding, for example, of the 7 observations over $60/hour wage, 3 have got a very small weight and the other 4 a larger weight. I include the weighted scatters for the other 3 sets of propensity scores in the Appendix.

Figure 15: Estimated Wage Trajectories for Reference Individual



(a) Raw Scatter of Wages by Experience

(b) Weighted Scatter of Wages by Experience

I can now estimate wage trajectories, as I have previously, but with the inverse probability weights in use. The results are presented in Table 12. This essentially will give men who *look* (according to their observable characteristics) more like women a higher weight and those who *look* less like women, a lower weight. I estimate the wage trajectories using the four different sets of weights. With all 4 weight specifications, there is no significant initial wage gap. The magnitude on the female coefficients are all small (less than 5%). Over time, he wage gap becomes significant in all of the specifications. In the first two specifications, where confidence in earnings is not included, the gap is smaller in magnitute (less than 20%) and only significant at the 10% level. With the inclusion of confidence, the wage gap is around 20% and significant at the 5% level. Therefore, women who *look* like men on their initial characteristics at the point of entering the labour market, initially see no wage gap. However, over time the wage gap widens. This could be due to a number of differences that accumulate after individuals start working. It could be fact that there are differences labour market accumulation (e.g. hours worked) or differences in preferences towards working leading to different wage progression. These reasons will be investigated further in the sub group analysis that follows.

Table 12: Estimates of Wage Gap Over First 5 Years After Completing MBA with Weights

	(1)		(2)		(3)		(4)	
	Log Wages	Hrs Wrkd	Log Wages	Hrs Wrkd	Log Wages	Hrs Wrkd	Log Wages	Hrs Wrkd
0 Years	-0.050	-8.642**	-0.026	-4.226	-0.039	0.289	-0.031	-0.324
	(0.183)	(0.044)	(0.508)	(0.274)	(0.277)	(0.944)	(0.392)	(0.938)
1 Year	-0.086**	-0.514	-0.058	3.514	-0.081**	6.556*	-0.061	7.077*
	(0.027)	(0.884)	(0.151)	(0.326)	(0.031)	(0.083)	(0.111)	(0.073)
2 Years	-0.062	-5.231	-0.036	-1.221	-0.069	1.333	-0.076*	-0.799
	(0.206)	(0.183)	(0.472)	(0.759)	(0.129)	(0.739)	(0.087)	(0.844)
3 Years	-0.042	-7.412	-0.020	-3.257	-0.044	-3.600	-0.043	-6.304
	(0.474)	(0.127)	(0.725)	(0.509)	(0.420)	(0.457)	(0.412)	(0.255)
4 Years	-0.032	-3.200	0.024	0.714	-0.032	-0.272	-0.014	-1.889
	(0.687)	(0.558)	(0.772)	(0.900)	(0.662)	(0.960)	(0.844)	(0.753)
5 Years	-0.197*	-2.505	-0.182*	0.061	-0.203**	-3.811	-0.207**	-5.483
	(0.079)	(0.724)	(0.064)	(0.993)	(0.040)	(0.606)	(0.026)	(0.480)
Observations	3027	3027	3213	3213	2974	2974	2974	2974
Cohort*Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The dependent variable in each equation is log of real hourly wages. It is estimated by regressing log of wages on female multiplied by a dummy for each year after completing an MBA. All regressions include cohort*year dummies. The first 2 columns, specification (1) comes from the first weighting specification mentioned in the main text. (2) aligns to the second weighting specification, (3) to the third and (4) to the fourth. P-values are in brackets and the standard errors are clustered at the individual level.

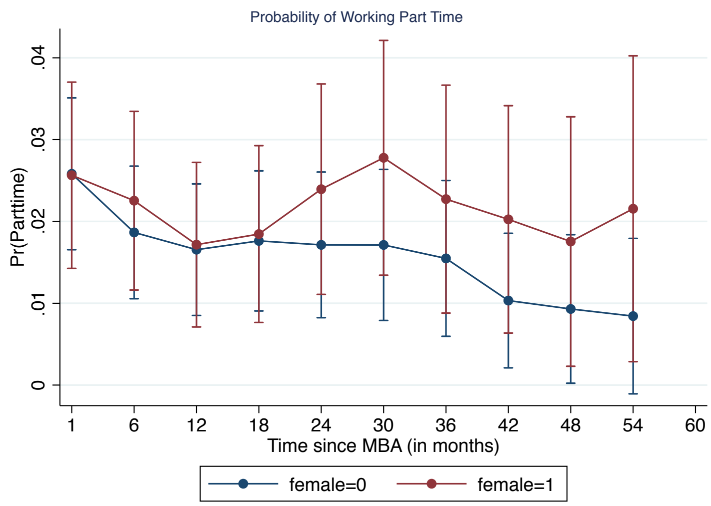
7 Additional Results: Subgroup analysis

7.1 Part Time / Over Time

There has been extensive discussion over the impact part time work has on wages, as discussed in the Literature Review Section. First, I estimate the probability for each gender of working part time after their MBA. I then estimate the impact that part time work now and also part time work in the past (measured by if an individual worked part time one year previously) has on wages. The average woman has worked part time for 2.18% of the time in the first 3 years after completing their MBA and the average man has worked 1.80% of the time. In some high paying industries, individuals are expected to work long hours, especially at the beginning of their career. There is discussion in the literature that suggests that sacrificing some of these hours can have a large penalty on wage rewards. Therefore it is interesting to look at over time work as well as part time work. Over time work can be defined as working more than 175 hours a month.

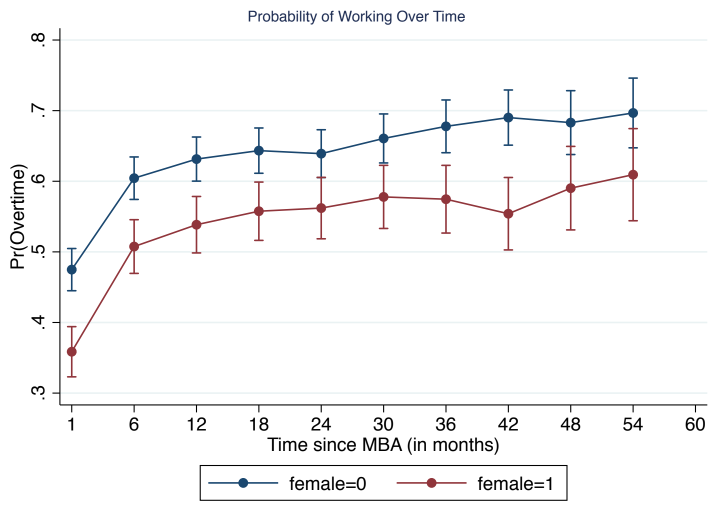
I predict the probability of working part time and over time at 6 month intervals after completing an MBA. The results are presented in Figure 16 and Figure 17. Both men and women in this sample are relatively unlikely to work part time (less than 3 % at every point in time that I observe). For the first year and a half, it seems as though men and women are as likely as each other to work part time. However, there is then a divergence, where men become less likely to work part time and women do not. The confidence intervals are large which makes it difficult to assess the significance in the difference between the probabilities. There is a much clearer separation in over time. At every given period, men are significantly more likely to be working over time than women. This suggests that a wage gap may grow over time as men accumulate more hours of experience each month.

Figure 16: Estimated Probability of Working Part Time



Note: This graph estimates the probability of working part time for men and women from the month after they finish their MBA using a Probit Regression. The vertical lines indicate the 95% confidence intervals.

Figure 17: Estimated Probability of Working OverTime



Note: This graph estimates the probability of working part time for men and women from the month after they finish their MBA using a Probit Regression. The vertical lines indicate the 95% confidence intervals.

Looking at column (1) of Table 13, working part time now has a negative significant impact on current wages but working part time in the past does not seem to correlate with current wages in a significant way. The reason women work part time more often than men can a lot be explained by taking time off or reducing work hours when having children. As an initial investigation, by separating between those who have a child and those who don't, suggests that there is a significant difference between male and female wages amongst those with children but not those without. The coefficient on part time becomes insignificant amongst those with children which suggests that the coefficient seen in column (1) suffered from omitted variable bias, absorbing the impact of having children on wages.

These results suggest that the wage gap may be partly driven by having children, which is very much in line with literature (e.g. Dias et al. (2018), Bertrand et al. (2010) and Kleven et al. (2018)). The motivation now turns to investigating the impact of having children on wages for men and women.

Table 13: OLS Estimates of Log Wage immediately after individuals finish MBA for Those With and Without Children

	Whole Sample	Without Children	With Children
Female	-0.085**	-0.035	-0.134**
	(0.031)	(0.472)	(0.034)
Undergrad GPA	0.032	0.034	0.046
	(0.494)	(0.563)	(0.530)
GMAT quant score	0.006*	0.005	0.007
	(0.053)	(0.194)	(0.137)
GMAT verbal score	0.010***	0.015***	0.008*
	(0.002)	(0.000)	(0.093)
Experience (Months)	0.003***	0.004***	-0.000
	(0.000)	(0.000)	(0.889)
Experience Squared	-0.000**	-0.000**	0.000
	(0.039)	(0.015)	(0.143)
Part time	0.183	0.584**	-0.102
	(0.305)	(0.043)	(0.652)
Part time last year	0.207	0.245	0.124
	(0.224)	(0.333)	(0.583)
Observations	570	349	221

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: p-values are in parenthesis. In addition to the variables shown, I control for race, us citizenship, tenure, marriage and children in each specification.

7.2 Children

I perform the same analysis as Bertrand et al. (2010) on selectivity in marriage and childbearing. I estimate predicted log monthly earnings for the first period after an MBA for different groups. I estimated the difference in predicted log earnings between men without children and women with children, women without children and men with children. I also estimate the difference in predicted log earnings between single men and single women, married women and married men. MBA women who become mothers might be selected on unobservables that could lead to lower wages in the absence of children. But, looking at Table 14, there is no evidence that women with children or married women do have lower earnings. In fact, married women seem to have higher earnings than unmarried women and married people in general seem to have higher earnings than single people. Men with children seem to have higher earnings than men without children.

Table 14: Selectivity in Marriage and Childbearing

	(1) Residuals	(2) Residuals
Female, Married	0.111**	
	(0.046)	
Female, Single	-0.097	
	(0.106)	
Male, Married	0.204***	
	(0.000)	
female_with_child		-0.111
		(0.100)
female_without_child		-0.052
		(0.249)
Male with child		0.109**
		(0.026)
Observations	854	911

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The dependent variable in each regression is predicted log monthly earnings. I construct the predicted earnings as follows: Firstly, in the sample of male respondents, I regress log monthly earnings on cohort*year dummies. The residual from that regression is then regressed on race, pre-MBA experience, GPA and GMAT score. Predicted log monthly earnings is the predicted value from the second regression. In the first column, I do not include the dummy for male single and hence am comparing the predicted earnings to this group. In the second regression I do not include the dummy for a male without a child and hence am comparing the predicted earnings to this group.

Because there seems to be a large difference in wages between men and women in the presence of children, I construct an analysis to explore career dynamics after the birth of a first child. I construct variables that indicate the number of years since an individual's first child is born. I estimate log of real earnings and include person-fixed effects, cohort $\times$ year dummies, a quadratic indicator and then the constructed variables indicating the number of years between the first birth and the year of the estimated earnings. Women's earnings (among those who remain unemployed after having a child) decline in the first and second year after having a child. In fact, they decline much faster in the second year. The fall in earnings of 28.1 log points compared to the year of birth of the child seems large but matches closely with the results found in Bertrand et al. (2010) that looks at a similar sample. 1 or 2 years before having a child, women had significantly higher wages than the year that they have their child. Unfortunately there are not sufficient observations of women who have a child 3 or 4 years after an MBA. In contrast, men with children do not see a change in earnings, if anything the coefficient is positive (although not significant). 4 years after child birth, men's earnings have in fact increased by 46.8 log points compared to the year of birth of the child. Women also reduce their hours worked significantly after the birth of their first child. One year after a child is born, a women decreases their monthly hours worked by 15 hours and two years later they have decreased their monthly hours worked by 36 hours. Men on the other hand increase their hours worked each year after having a child. From 1 or 2 years before having a child, to 2 years after having a child, a man increases their hours worked on average each year by 20 hours a month. This increases then starts to stagnate.

Table 15: Impact of First Birth on Earnings and Working Hours

	Women Log monthly real earnings	Men Log monthly real earnings	Women Hrs Wrkd	Men Hrs Wrkd
1 year since first child	-0.086**	0.136	-15.261***	25.439***
	(0.040)	(0.196)	(0.010)	(0.009)
2 years since first child	-0.281***	0.153	-36.203***	40.617**
	(0.000)	(0.243)	(0.000)	(0.012)
3 years since first child		0.214	-41.646***	46.039***
		(0.248)	(0.000)	(0.004)
4 years since first child		0.468*		51.557***
		(0.084)		(0.001)
1 or 2 years before first child	0.115***	-0.033	-0.415	-21.531**
	(0.000)	(0.501)	(0.907)	(0.050)
Observations	7561	16487	9911	20619

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Individuals who have a child before completing their MBA are not included in the regression. All regressions include cohort*year dummies, person fixed effects and a quadratic in age. Standard errors are clustered at the individual level.

Manning and Swaffield (2008) discuss the job shopping hypothesis whereby women may be less likely to find a good match of their skills as they are more constrained by job choices (because of fertility) or because they less likely choose to move jobs for monetary reasons. However the authors conclude that job-shopping models do not appear to be able to explain more than a small part of the gender gap in early-career wage growth. Bertrand et al. (2010) also investigate this hypothesis and look at the impact of the birth of a first child on why women may not work, or why they may leave a job. Unfortunately, I do not have enough observations to perform the same analysis that they have. However, there are 37 women who left their job for family-related reasons and only 15 men left for family-related reasons (and we have a larger sample of men).

I can also explore preferences towards work to see if women show clear preference towards family compared to men. In the survey, individuals are asked how important a number of aspects of life are including family, career and politics. In Table 16 I summarise the results for those who complete an MBA. A value of 1 indicates *very* important and a value of 4 indicates *not at all* important. Family seems to be the most unanimously important amongst men and women, with 88.42% of women and 06.94% of men saying it is very important. Almost 7% more women state that career is very important than men. [5] Women seem to value friends and free time slightly more highly than men. Men seem to value wealth slightly more

[5] You may expect that these preferences are quite different from non-MBA completers. In fact, women who do not complete an MBA vote 1 (*very*) to how important is career 69.64 % of the time, slightly higher than MBA completers. Full summary of these variables for MBA non-completers are in the Appendix.

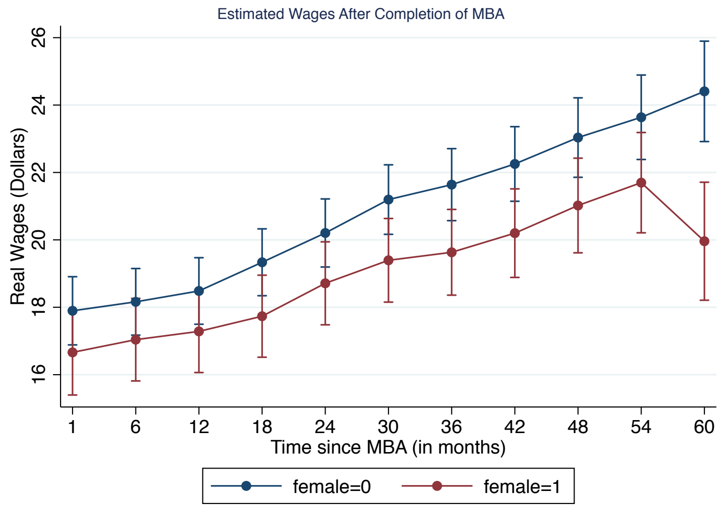
highly than women. However both groups show little commitment to stating that wealth is very important to them. There is a potential issue that individuals choose answers due to social pressures and not wanting to seem, for example, overly money driven.

Table 16: % of Each Group for 'How Important is...' (1 is highest, 4 is lowest)

All	1	2	3	4
Family	87.59	9.51	2.15	0.75
Wealth	22.68	61.45	14.26	1.61
Career	65.15	33.89	0.97	0
Friends	49.79	45.17	4.83	0.21
Free Time	49.2	45.71	4.4	0.7
Women	1	2	3	4
Family	88.42	9.4	1.36	0.82
Wealth	18.75	62.54	16.68	1.52
Career	69.02	30.16	0.82	0
Friends	52.65	41.63	5.44	0.27
Free Time	51.77	44.43	3.4	0.41
Men	1	2	3	4
Family	86.94	9.66	2.68	0.72
Wealth	25.27	60.54	12.68	1.52
Career	62.32	36.61	1.07	0
Friends	47.68	47.68	4.46	0.18
Free Time	47.54	46.56	5	0.89

Looking at Figures 18 and 19. It seems as if there is a wage gap between those who value their career as very important but no wage gap between those who value their career as somewhat important. Unfortunately I am limited in my analysis here due to the limited observations after individuals have children. In an ideal world I would investigate if those who value their career as very important see differences in wages due to the birth of a first child. This would be work I would suggest doing in the future with a data set that spreads over more years.

Figure 18: Estimated Wage Trajectories for Individuals who stated that Career was Very Important



Note: This graph estimates wages for men and women from the month after they finish their undergraduate studies. The vertical lines indicate the 95% confidence intervals.I have controlled for all observables that were included in specification (6) of 8. I have de-meaned all variables so the mean is 0. This means the trajectories are of the mean reference individual.

Figure 19: Estimated Wage Trajectories for Individuals who stated that Career was Somewhat Important

Note: This graph estimates wages for men and women from the month after they finish their undergraduate studies. The vertical lines indicate the 95% confidence intervals.I have controlled for all observables that were included in specification (6) of 8. I have de-meaned all variables so the mean is 0. This means the trajectories are of the mean reference individual.

7.3 Industry

Throughout this paper there has been evidence to suggest that different industry choices between gender can explain at least part of the gender wage gap. Due to the limitations of the sample size, I code the industries at the 1-digit level. I present the percentage of the total sample, percentage of the female sample and percentage of the male sample in the table below. There are some industries that are more popular for a particular gender; services and retail for women and manufacturing and finance for men. However, both genders share the 4 most popular industries: services, manufacturing, finance and public. I conduct similar regressions as I have with the full sample, estimating the coefficient on female interacted with the years since the individual completed their MBA. For all others, there are less than 50 observations in the regressions, making it difficult to come to conclusions.

I present the difference in wage trajectories between men and women in Tables 18 and Table 19. I present in Appendix the raw wage trajectories in the 4 most popular industries. They all have significant initial wage gaps except for services but after 5 years services has a large and significant wage gap and finance no longer has a significant wage gap. In 18 I have included all controls specified in the table notes, there is no control for confidence. There is an initial wage gap that remains in finance but not in the other industries. Note that in manufacturing the coefficient is very large but due to such small number of observations, there is little explanatory power. With the inclusion of confidence this initial wage gap disappears but in the second year (when we have a higher employment rate amongst our sample) there is a significant wage gap in finance and public services at the 10% level.

It is difficult to say whether we see within industry wage gaps due to the number of observations. Taking the results as given, it seems as if perhaps between industries there is more of a pay gap (as we saw a significant gap even once controlling for confidence after 5 years when looking at the whole sample). This suggests that some of the wage gap may be driven from the fact that women sort into different types of jobs. However, as the magnitude of the coefficients are still relatively large, I am not confident to say that between industry pay differences explains the wage gap.

Table 17: % of Individuals in Each Industry

Industry	% Total	% Men	% Women
Agriculture	6.1	5.03	6.71
Mining	3.54	3.28	3.76
Construction	0.82	0.22	1.21
Manufacturing	23.50	18.16	26.71
Transport	6.51	7.66	5.91
Wholesale	2.64	2.63	2.68
Retail	5.61	7.22	4.70
Finance	17.31	15.97	18.39
Services	26.22	32.82	21.74
Public	2.275	7.00	8.19

Table 18: Estimates of Wage Gap Over First 5 Years After Completing MBA

	Manufacturing	Finance	Services	Public
0 Years	-0.338	-0.137*	-0.033	-0.129
	(0.108)	(0.095)	(0.600)	(0.130)
1 Years	-0.395	-0.155*	-0.086	-0.143
	(0.107)	(0.057)	(0.202)	(0.103)
2 Years	-0.482*	-0.084	-0.108	-0.144
	(0.053)	(0.380)	(0.140)	(0.134)
3 Years	-0.476*	-0.118	-0.124	-0.155
	(0.068)	(0.294)	(0.146)	(0.150)
4 Years	-0.479	-0.048	-0.134	-0.163
	(0.124)	(0.713)	(0.185)	(0.208)
5 Years	-0.488	-0.062	-0.190	-0.149
	(0.162)	(0.720)	(0.104)	(0.327)
Observations	167	490	854	276
Cohort*Year	Yes	Yes	Yes	Yes
Degree Major Dummies	Yes	Yes	Yes	Yes

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The dependent variable in each equation is log of real hourly wages. In a regression without any controls, the sample is restricted to those survey respondents with non-missing characteristics that I include in later specifications. All regressions include cohort*year dummies and a dummy for race (white, black, hispanic, asian and other). All regressions in this table include the following variables: hours worked (measured monthly), a quadratic in experience, a dummy for if the individual is married, a dummy for if the individual is a US citizen, a set of dummies for the degree major and a set of dummies for the number of children. P-values are in brackets and the standard errors are clustered at the individual level. Experience and hours worked are measured in months.

Table 19: Estimates of Wage Gap Over First 5 Years After Completing MBA

	Manufacturing	Finance	Services	Public
0 Years	-0.292	-0.127	0.003	-0.135
	(0.175)	(0.137)	(0.955)	(0.102)
1 Years	-0.345	-0.142*	-0.050	-0.148*
	(0.173)	(0.072)	(0.441)	(0.086)
2 Years	-0.424	-0.079	-0.075	-0.150
	(0.105)	(0.356)	(0.289)	(0.115)
3 Years	-0.410	-0.115	-0.092	-0.160
	(0.142)	(0.249)	(0.251)	(0.136)
4 Years	-0.405	-0.045	-0.099	-0.167
	(0.224)	(0.694)	(0.295)	(0.194)
5 Years	-0.418	-0.056	-0.152	-0.153
	(0.266)	(0.720)	(0.160)	(0.311)
Observations	167	490	854	276
Cohort*Year	Yes	Yes	Yes	Yes
Degree Major Dummies	Yes	Yes	Yes	Yes

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The dependent variable in each equation is log of real hourly wages. In a regression without any controls, the sample is restricted to those survey respondents with non-missing characteristics that I include in later specifications. All regressions include cohort*year dummies and a dummy for race (white, black, hispanic, asian and other). All regressions in this table include the following variables: hours worked (measured monthly), a quadratic in experience, a dummy for if the individual is married, a dummy for if the individual is a US citizen, a set of dummies for the degree major a set of dummies for the number of children and the standardised measure of confidence in earnings. P-values are in brackets and the standard errors are clustered at the individual level. Experience and hours worked are measured in months.

A note on occupation: As discussed in the wage decomposition approach used by Blau and Kahn (2017), it may be that women select into jobs that have lower returns or it may be that they get lower returns in the same jobs as men select into. Sample sizes preclude using more than 1-digit occupation definitions (and even then the sample sizes are relatively small). Over 99 percent of individuals fall into two categories: legislators (senior officials and managers) and professionals. This is unsurprising having completed an MBA. 11 % of women and 14% of men are legislators. 52% of women and 53 % of women are professionals. Therefore estimating within occupation wage gaps is not interesting as we find similar results to the whole population for professionals and the sample is small for legislators. I present some results on occupation in the Appendix. Amongst legislators, there seems to be no significant gap under any specification. However, the magnitude of the female coefficient changes in the direction we would expect, it becomes increasingly less negative and then increasingly positive as the coefficients are included. The professionals do see a negative and significant at the 5% level wage gap of 9.3 % when just a quadratic in experience, race and grades are controlled for, the gap shrinks slightly to 8.4 % with the inclusion of controls for marriage, children, job tenure and us citizenship. The gap becomes insignificant and reduces in magnitude by almost 50% with the inclusion of the confidence in earnings variable.

7.4 Confidence

So far there has been some evidence to suggest that confidence, or at least, confidence as defined in the variables in this data set, can explain a large proportion of the wage gap amongst these highly educated individuals. To confirm this, I firstly need to explore the difference in confidence between genders.

66.52 % of all males who eventually complete an MBA have a confidence in earning variable larger than 0, i.e. they over estimate their future earnings. In comparison, only 48.57 % of woman over estimate their future earnings. By performing a simple probit, to predict the probability of being a woman based purely on the confidence in earnings variable. The probability of being a woman decreases as the confidence in earning variable increases. For example, the probability of being a woman and having a confidence in earning variable of -1000 (i.e. underestimating their future earnings by 1000) is 47.38 % but the probability of being a woman and having a confidence in earning variable of 1000 is 39.41 %. This is of course a linear relationship that I predicted, in reality it is likely to be more complicated.

I perform a similar analysis in Figure 20 to the previous Figures I have presented, but I look at subgroups, separating men and women into confident and not, according to the confidence in earnings variable. I have interacted the female variable with all included variables and have interacted each time dummy with every variable. Therefore the specification is as follows:

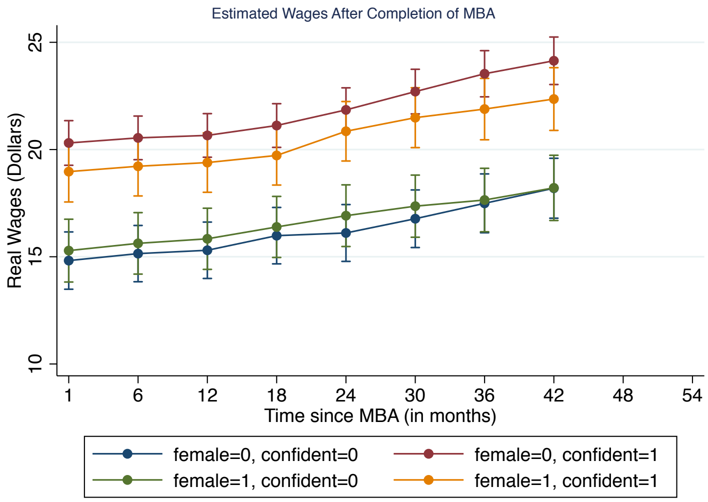
$$Y_{it} = \mathsf{Female} \times X_{it} + X_{it} + \mathsf{Female}_i + \mathsf{DOB} * \mathsf{Year} + \mathsf{Time} \times X_{it} + \epsilon_{it} \tag{9}$$

Some of the observables included in X do not vary over time, for example grade scores. However, interacting it with time means that the return to the observables may vary over time. For example, one may expect that returns to grade scores decreases over time, as individuals become increasingly experienced.

Figure 20 has a very striking result. There are initially two distinctive groups: confident and under-confident. Men and women who are confident start with a slight wage gap although it is arguably not significant. Confident men have an initial estimated wage of around $20. Under confident men and women have an initial wage of around $15, 25% lower. Therefore there is a distinctive gap between men who are confident and men who are under-confident and the same is true for women. This suggests a *confidence gap* in earnings. Overtime, confident men see the fasted wage growth, meaning that there is a slightly larger gap between confident men and women after 3 and a half years. Underconfident men and women see very similar wage trajectories. Reuben et al. (2017) find in an experimental setting that, amongst highly educated individuals, those who are confident have higher expectations about their future earnings. This result found in an experimental setting gives some support that I am at least partly capturing confidence in the measures I have used. The conclusions that come from these findings match with the findings of Reuben et al. (2017) in that women seem to be systematically less confident and this is having a negative impact on their early labour market outcomes. When asked what an individual expects to earn in the future, individuals may respond with a goal they have set for themselves. Therefore, a higher answer may indicate a higher level of effort that the individual is willing to exert. The Oscar Wilde phrase seems fitting here, *Shoot for the moon. Even if you miss, you'll land among the stars.*

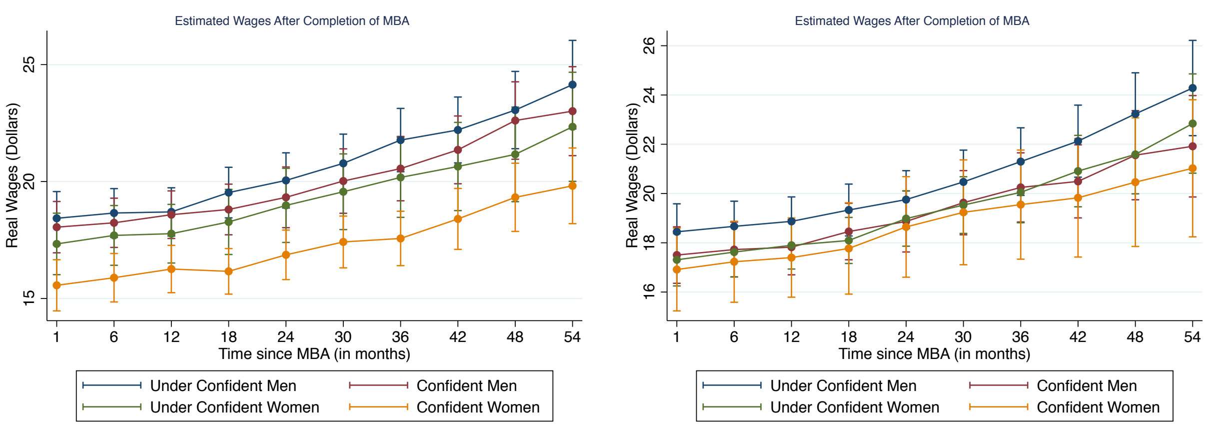
I repeat the same analysis in Figure 20 but with a different measure of confidence: confidence in GMAT quantitative and verbal scores. There is not the same striking relationship between confident and under-confident individuals. Looking closely at the initial wages in the left side panel (quantitative confidence), under-confident and confident men begin at the top of the ranking, followed by under-confident women and then confident women. Confident women have a statistically significant initial wage to both groups of men. Over time, all men and under confident women have significantly higher wages than confident women. In some ways it is unsurprising that those who over estimate their GMAT scores have higher earnings. An accurate estimate of ones own ability (and hence not an over estimation) may represent some level of intelligence. If one can correctly predict their own test scores, therefore having a better understanding of what they got right and what they got wrong in the tests, they may also have a better understanding of the best job matches, for example. Now looking at the right side panel (verbal confidence), under confident men have a higher initial wage than the other three groups, although it is arguably not significantly different. Although it is hard to make any conclusions due to the large confidence intervals, under confident women and men see slightly faster wage growth than confident men and women. Again, the interpretation of this could be that more accurate estimation of ones own ability could be an indicator of some kind of ability.

Figure 20: Estimated Wage Trajectories separated by Confidence and Gender



Note: This graph estimates wages for men and women from the month after they finish their MBA. The vertical lines indicate the 95% confidence intervals. I have controlled for all observables that were included in specification (4) of 8. I have de-meaned all variables so the mean is 0. This means the trajectories are of the mean reference individual. Confident = 0 means that individuals underestimate their future earnings and confident = 1 means that individuals overestimate their future earnings.

Figure 21: Estimated Wage Trajectories separated by Confidence and Gender



Note: This graph estimates wages for men and women from the month after they finish their MBA. The vertical lines indicate the 95% confidence intervals. I have controlled for all observables that were included in specification (4) of 8. I have de-meaned all variables so the mean is 0. This means the trajectories are of the mean reference individual. Under Confident means that individuals underestimate their grade score as explained in the Data section and Confident means that individuals overestimate their grade score.

From the conclusions found previously, I am encouraged to see if individuals who have children in the future have lower expectations of their future earnings. In an ideal world, I would work out the probability of being confident given that individuals will have children in the next few years. However, I am limited by my data size and hence cannot calculate this for many years. I can calculate the probability of being confident on future earnings if an individual has a child 1 year after they are asked or two years after they are asked. I find that men and women who have a child one year after they are asked about their future earnings have roughly the same probability of over predicting, at about 60%. Of those who have a child 2 years later, men have a lower probability of over predicting. Therefore there does not seem to be evidence that women who have children in the future have lower expectations of their future earnings. However, this is a very naive and preliminary investigation and is something that should be researched further.

Table 20: Estimated Probability of Being Confident at Wave 1 if have child 1 Year or 2 Years after

	Prob Confident	
	Men	Women
1 Year	59.77	59.50
2 Years	42.41	50

Note: The probabilities are calculated using a probit where the outcome takes the value 1 if an individual over estimates their future earnings and 0 if they under estimate. I then calculate the margins, so we are left with the probability for the reference individual.

It is also interesting to see if individual who have children at the moment that they are asked about their future earnings predict less than those who do not have children. I repeat same technique as I did previously in Table 14 but this time I estimate the selectivity in children and marriage on confidence in earnings. I estimate predicted confidence in earnings. I report the results in Table 21. As we know, on average women predict lower earnings than men. It seems as though women who have children have lower predicted confidence in earnings then women who do not have children. Men who have children do not seem to have lower predicted confidence in earnings than men who do not have children. Married and Single women are predicted lower confidence in earnings then men. Single women seem to have lower predicted confidence in earnings then married women. This information suggests that women may internalise the impact that having children can have on their future earnings.

Table 21: Selectivity in Confidence

	(1) Residuals	(2) Residuals
Married Female	-593.995***	
	(0.005)	
Single Female	-734.163***	
	(0.001)	
Married Male	293.718	
	(0.115)	
Female With Child		-1253.375***
		(0.000)
Female Without Child		-764.731***
		(0.000)
Male With Child		-78.940
		(0.720)
Observations	1154	1239

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: I repeat the same exercise as in Table 14. The dependent variable in each regression is predicted confidence in monthly earnings. I construct the predicted confidence as follows: Firstly, in the sample of male respondents, I regress log monthly earnings on cohort*year dummies. The residual from that regression is then regressed on race, pre-MBA experience, GPA and GMAT score. Predicted confidence in earnings is the predicted value from the second regression. I do not include the dummy for male single or male without a child and hence am comparing the predicted earnings to this group.

The confidence in earning variable currently includes actual earnings in 5 years time and hence may be correlated with earnings now. In fact, the correlation coefficient between earnings at the first period after an MBA and the confidence in earnings variable is 0.4155. To factor this in, I look at actual expectations and do not subtract future earnings from this (i.e. do not construct the confidence variable). By regressing the typical observable variables I have previously included (quadratic of experience, test scores, children, hours worked and race) on expected future earnings and predicting the residuals, I can then create quintiles of the residuals and see how many women are in each group and what the associated average wage is in each group. I present these results in Table 23. What is clear is that in the highest quintiles, i.e. those who have a larger residual, the average wage is higher and there are less women. Intuitively this makes sense, those who have higher wages at the time they are asked to predict their future wages, predict higher future earnings. But what is less obvious is why those who over estimate their future earnings by more, have higher earnings in the future.

I repeat the same technique as I did previously in Table 14 but this time I estimate the selectivity in confidence. I estimate predicted log monthly earnings for the first period after an MBA. It seems as though all under confident individuals and even confident women have lower predicted earnings compared to confident men. Under confident women and under confident men have 38 log points lower predicted earnings

Table 23

Quintile	Share Women	Average Wage
1	52.25	14.67
2	42.34	16.06
3	39.22	17.05
4	40.64	17.83
5	25.44	22.88

and confident women have 16.2 log points. Therefore confident women have much higher predicted earnings then under confident individuals but confident men have the highest predicted earnings.

Table 22: Selectivity in Confidence

	Predicted Log Monthly Earnings
Confident Female	-0.162***
	(0.002)
Under Confident Female	-0.360***
	(0.000)
Confident Male	-0.388***
	(0.000)
Observations	825

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: I repeat the same exercise as in Table 14. The dependent variable in each regression is predicted log monthly earnings. I construct the predicted earnings as follows: Firstly, in the sample of male respondents, I regress log monthly earnings on cohort*year dummies. The residual from that regression is then regressed on race, pre-MBA experience, GPA and GMAT score. Predicted log monthly earnings is the predicted value from the second regression. I do not include the dummy for male confidence and hence am comparing the predicted earnings to this group.

One potential issue concerning the confidence in earning variable is that some individuals are working when asked about future earnings in the first survey and some individuals are not. It may be that individuals who have worked have a better understanding of potential wages. It may also be that an individual who is unemployed may have a less optimistic prediction of the future and hence it is the labour market status of the individual that is driving the confidence variable. [6] In Table 24 I present the average confidence in earnings for employed and unemployed individuals in wave 1. It is clear that unemployed do over estimate their future earnings by less, but that means they have more accurate estimations of their future earning, despite the fact that they are not working when asked to estimate.

[6] Although it may be fair to say that unemployment leads to loss in confidence which can lead to a larger negative impact on wages than the unemployment spell itself.

Table 24: Mean Confidence in Earnings by Gender and Employment

Employed

	Mean	S.D	Number
Total	1061	2824.233	1167
Men	1419.338	3160.19	721
Women	484.4761	2062.044	446

Unemployed

	Mean	S.D	Number
Total	440.8691	2553.225	396
Men	861.003	2743.6323	213
Women	-24.19657	2244.591	183

Overall, it seems as though individuals may not anticipate the impact of future children, according to Table 20 but women who have children in wave 1 do have less confidence in their future earnings. Those who are unemployed also have lower confidence in their future earnings. So unemployed and women with children over estimate their future earnings by less but are also those who in fact do earn less.

As I previously found, it seems as though some of the gender wage gap can be explained by industry choices. I next investigate whether choice of industry, which seems to explain a substantial part of the gender gap, depends on confidence (conditional on field of the MBA). As an initial observation, I look at the average confidence in earnings in each industry. This is presented in Table 25. In every given industry, women have lower men confidence in earnings compared to men. Finance, agriculture and construction have the highest confidence in earnings, but with such small sample sizes, agriculture and construction may not give consistent estimates. I next estimate, in a similar fashion to previously, the selectivity on confidence in earnings, but now based on industry. The results are presented in Table 26. The omitted industry is Public. I find that, there are 3 industries which have higher predicted confidence in earnings than the Public industry. That is Agriculture, Construction and Finance. Therefore, of the 4 most popular industries, Finance is the only one which seems to take in more confident people. This indicates that in this industry in particular, choice of industry may depend on confidence - i.e. more confident people work in this industry. Looking at the summary statistics in table 25, the second highest mean confidence in earnings for women is in the finance sector. This suggests that confidence can be one factor that leads individuals into certain industries or jobs. This would be a topic I suggest to investigate further with a data set that has a larger sample within each industry and holds more job characteristics, matched with some confidence measures.

Table 25: Mean Confidence in Earnings by Industry

Industry	Mean Confidence in Sample	Mean Female Confidence	Mean Male Confidence
Agriculture	1586.58	873.34	1931.70
Mining	930.73	494.015	1196.55
Construction	2339.65	-1112.08	2723.17
Manufacturing	1035.02	423.63	1291.68
Transport	903.31	555.36	1179.88
Wholesale	294.33	10.82	489.25
Retail	15.82	-264.94	394.23
Finance	1431.81	659.24	1840.07
Services	710.89	310.1422	1106.44
Public	501.71	227.51	674.17

Table 26: Selectivity in Confidence based on Industry

	(1) Residuals
Agriculture	1149.270**
	(0.044)
Mining	351.626
	(0.550)
Construction	2162.610**
	(0.030)
Manufacturing	674.731*
	(0.090)
Transport	371.929
	(0.466)
Wholesale	87.139
	(0.896)
Retail	66.604
	(0.902)
Finance	979.325**
	(0.018)
Services	482.693
	(0.218)
Observations	856

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: I repeat the same exercise as in Table 14. The dependent variable in each regression is predicted confidence in monthly earnings. I construct the predicted confidence as follows: Firstly, in the sample of male respondents, I regress log monthly earnings on cohort*year dummies. The residual from that regression is then regressed on race, pre-MBA experience, GPA and GMAT score. Predicted confidence in earnings is the predicted value from the second regression. I do not include the dummy for the Public industry and hence am comparing the predicted confidence in earnings to this group.

8 Conclusions

I have examined gender differences in wage and earning trajectories of individuals who have graduated with an MBA between the years of 1990 and 1998. I observe an initial raw wage gap of around 14% that grows after 5 years to 23%. I identify three key factors that can explain a large proportion of the gap: firstly, the impact of children on female earnings and not on male earnings, that seems to be driven partly by the impact on hours worked. Secondly, the difference in industry choices between men and women. And lastly, and most uniquely to my paper, the difference in confidence in earnings between genders. The last factor suggests that if women had the same level of confidence in future earnings, the gap would shrink.

There are some distinctive groups who are more likely to over estimate their future earnings than others. Employed individuals on average have higher confidence in their future earnings than unemployed. This is unsurprising and suggests that being unemployed may be a knock on ones confidence, although in reality they are the individuals who have a smaller gap between their expected and realised earnings. Women who have children when asked about their expected future earnings have lower over confidence - this suggests that they may internalise the impact having children has on their career and hence expect the lower wages that they do in fact receive 5 years later. However, women who have children just 1 or 2 years after asked about their future earnings are as likely to be confident as a man. Assuming that women who have a child in 1 or 2 years to have some pre-expectation of having children, this result suggests that women may not internalise the impact that having children will have on their career until they actually have a child. Lastly, I show some evidence that more confident people work in the finance industry. This suggests that confidence can be one factor that leads individuals into certain industries or jobs. The results are preliminary and researching this further would be recommended.

While working on this project, a number of issues have become increasingly clear. Despite so many individuals taking the GMAT test, as explained, less than 30% of these individuals actually complete an MBA by the 4^{th} wave of the survey. This makes analysis difficult, especially when looking at subgroups as the number of observations becomes increasingly small. Moreover, despite following the individuals for around 8 years, many individuals do not complete their MBA until about 4 years after the first wave of survey. This means that for many individuals I can only see the first 4 or 5 years on the labour market. Although this is interesting in itself, many findings such as in Manning and Swaffield (2008) and Dias et al. (2018), it is clear that the wage gap grows over time, and can be at its largest much later than what I am able to observe in my data. With some evidence to suggest that differences in confidence in future earnings between gender explains some of the wage gap, future exploration with other measures of confidence and longer trajectories of earnings once completing education would be insightful.

I am wary that the confidence variables being used, although interesting, may not be capturing confidence as such. I have attempted to address some issues with the confidence in earnings throughout my paper. Firstly, it is heavily correlated with earnings that individuals are earning when they are asked to estimate their future earnings. If we take an individual who is unemployed and with a wage of 0, as I have observed, it is very likely that they will be employed 5 years later, but based on their current employment status, they estimate their future earnings to be less than an individual who is employed now. Therefore the confidence in earnings variable is systematically correlated with earnings in wave 1.

The sample I have examined is interesting in itself and may be applicable to a wider population of educated individuals. However, an MBA may not be representative of all highly educated individuals. An MBA is a particular master degree that has its focus on business. The industries that people enter after an MBA is very different to say someone who has a PhD in chemistry or literature. The industries these individuals go in to may have different job characteristics and also, if discrimination does exist, different levels of discrimination.

Taking the results as given, the policy implications are complicated. If women are systematically less confident than men and this is leading to lower wages for them, then an initial suggestion may be to implement policy to boost female confidence. However, one may question whether society and the economy will in fact benefit from women being more like men in their attributes. As we have seen that women work a lot less when having children, there may be some policy implication to provide child care to help women work more hours. Saying that, preferences may be leading women to choose to work less. Lastly, there may be direct policy implications towards certain industries such as implementing quotas for high paying positions in industries where we see less women.

This paper has attempted to dig deeper into the wage gap question - the results are somewhat in line with previous findings. The impact children have on female labour force participation has been found in Dias et al. (2018) and Bertrand et al. (2010). However, Bertrand et al. (2010) does not find an initial wage gap after completing an MBA whereas I do, this is likely to be driven by the level of experience individuals held before getting their MBA. The addition of confidence is quite unique to my paper and compliments the work in the field of experimental economics. I describe my paper as motivation to the further discussion of the gender confidence gap.

A Appendix

A.1 Summary of Variables

Table 27: Summary Stats at W2 for those who complete an MBA

	(1) All count	mean	sd	(2) Women count	mean	sd	(3) Men count	mean	sd
Female	1745	0.40	0.49						
Real Earnings (Dollars)	1254	2495.11	1307.03	485	2190.48	1060.39	757	2681.77	1408.12
Real Wage (Dollars)	1300	13.47	6.60	500	12.36	4.97	787	14.12	7.31
Undergrad GPA	1674	3.07	0.42	663	3.14	0.41	1000	3.03	0.42
Hrs Wrkd (Months)	1685	142.16	88.40	665	132.62	86.36	1007	147.73	89.40
Work Experience (Months)	1688	71.66	65.30	662	66.52	60.66	1018	75.12	68.12
Black	1758	0.11	0.31	694	0.17	0.37	1051	0.07	0.26
Hispanic	1758	0.16	0.37	694	0.16	0.37	1051	0.16	0.37
Asian	1758	0.16	0.37	694	0.16	0.37	1051	0.16	0.37
Other	1758	0.01	0.10	694	0.01	0.10	1051	0.01	0.10
current age	1727	27.55	5.45	686	27.10	5.44	1039	27.85	5.44
Married/Cohabitating	1750	0.39	0.49	689	0.33	0.47	1048	0.43	0.49
Children?	1748	0.15	0.35	689	0.12	0.33	1046	0.16	0.37
N. children	1748	0.25	0.69	689	0.20	0.60	1046	0.28	0.74
GMAT quant score	1524	30.98	8.44	598	28.36	8.03	915	32.68	8.26
GMAT verbal score	1524	29.97	7.75	598	29.30	7.75	915	30.41	7.71
Earning Confidence	1498	870.91	2740.00	601	291.70	2007.85	889	1265.95	3084.31
Confidence in Quant	1453	0.43	0.50	563	0.50	0.50	879	0.39	0.49
Confidence in Verb	1455	0.38	0.48	564	0.41	0.49	880	0.35	0.48
Opinion Index	1703	35.66	5.20	668	36.09	5.23	1028	35.39	5.17

Table 28: Summary Stats at W3 for those who complete an MBA

	(1) All count	mean	sd	(2) Women count	mean	sd	(3) Men count	mean	sd
Female	1712	0.40	0.49						
Real Earnings (Dollars)	1409	3095.55	1513.26	544	2772.22	1339.15	855	3298.44	1583.21
Real Wage (Dollars)	1443	15.86	7.75	557	14.54	6.89	875	16.65	8.15
Undergrad GPA	1650	3.07	0.42	654	3.13	0.41	984	3.04	0.42
Hrs Wrkd (Months)	1654	172.53	79.34	648	166.63	80.71	993	176.60	78.14
Work Experience (Months)	1660	91.65	67.33	649	86.60	63.58	1002	95.10	69.64
Black	1725	0.11	0.32	679	0.18	0.38	1033	0.08	0.27
Hispanic	1725	0.16	0.37	679	0.16	0.36	1033	0.17	0.37
Asian	1725	0.16	0.37	679	0.16	0.37	1033	0.16	0.37
Other	1725	0.01	0.10	679	0.01	0.11	1033	0.01	0.10
current age	1696	29.78	5.36	673	29.42	5.46	1021	30.03	5.28
Married/Cohabitating	1590	0.51	0.50	630	0.45	0.50	948	0.54	0.50
Children?	1701	0.21	0.40	668	0.15	0.36	1020	0.24	0.43
N. children	1701	0.34	0.75	668	0.22	0.57	1020	0.42	0.84
GMAT quant score	1498	30.84	8.46	591	28.21	8.09	895	32.57	8.25
GMAT verbal score	1498	29.82	7.80	591	29.14	7.94	895	30.27	7.66
Earning Confidence	1457	850.45	2456.49	583	332.07	2079.04	865	1205.39	2628.46
Confidence in Quant	1424	0.44	0.50	555	0.51	0.50	857	0.39	0.49
Confidence in Verb	1426	0.38	0.49	556	0.42	0.49	858	0.35	0.48
Opinion Index	1674	35.71	5.21	654	36.05	5.21	1012	35.50	5.21

Table 29: Summary Stats at W4 for those whocomplete an MBA

	(1) All count	mean	sd	(2) Women count	mean	sd	(3) Men count	mean	sd
Female	1615	0.41	0.49						
Real Earnings (Dollars)	1375	4312.53	2365.32	531	3788.87	2163.13	831	4646.57	2435.90
Real Wage (Dollars)	1400	21.27	12.58	544	19.45	11.79	843	22.42	13.00
Undergrad GPA	1567	3.07	0.42	635	3.13	0.41	920	3.03	0.42
Hrs Wrkd (Months)	1492	193.97	67.16	589	182.51	71.42	890	201.48	63.30
Work Experience (Months)	1581	125.50	71.40	633	119.00	66.11	939	130.15	74.61
Black	1629	0.12	0.32	657	0.18	0.39	958	0.07	0.26
Hispanic	1629	0.17	0.37	657	0.16	0.37	958	0.17	0.38
Asian	1629	0.14	0.34	657	0.14	0.34	958	0.14	0.35
Other	1629	0.01	0.09	657	0.01	0.10	958	0.01	0.09
current age	1598	33.35	5.44	649	32.92	5.42	947	33.65	5.45
Married/Cohabitating	1492	0.68	0.47	605	0.62	0.49	874	0.73	0.44
Children?	1580	0.38	0.49	639	0.31	0.46	927	0.43	0.49
N. children	1580	0.65	0.97	639	0.47	0.80	927	0.77	1.05
GMAT quant score	1421	30.79	8.47	574	28.10	8.16	835	32.62	8.20
GMAT verbal score	1421	30.12	7.65	574	29.42	7.75	835	30.61	7.54
Earning Confidence	1574	907.77	2775.38	630	334.86	2126.27	935	1299.48	3084.51
Confidence in Quant	1354	0.44	0.50	541	0.52	0.50	801	0.40	0.49
Confidence in Verb	1356	0.37	0.48	542	0.42	0.49	802	0.34	0.47
Opinion Index	1578	35.72	5.13	633	36.21	5.12	937	35.40	5.13

A.2 Cohort Effects

I check for cohort effects to see if older individuals are earning more than younger individuals. I estimate the wage trajectories of men and women born in each decade from 1930 to 1970. (Dob = 50 means the individual was born in the 1950s, Dob = 60 means the individual was born between 1950 and 1960 and so on...). In the figure 22 there seems to be some evidence that older cohorts earn more than younger cohorts. The highest earning group are those born in 1940, followed by 1950, 1960 and then 1970. There are very few observations for those born in 1930 and 1970 and hence the confidence intervals are extremely large.This is true for men also as seen in 23. Although these figures are not overly conclusive, In any case, I control for experience in my specifications and when mention I include cohort dummies, which should absorb any impact of older cohorts.

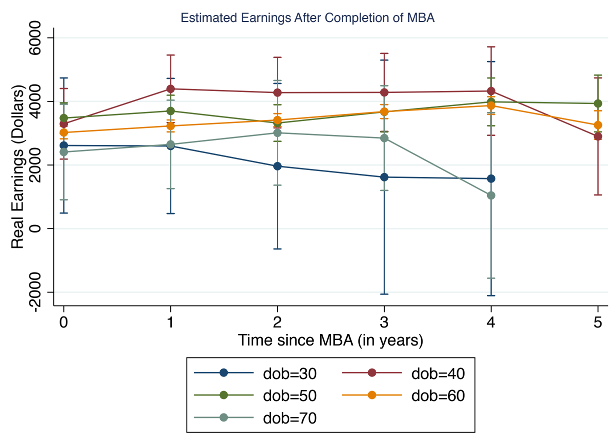


Figure 22: Earnings since finishing education for different cohorts of women

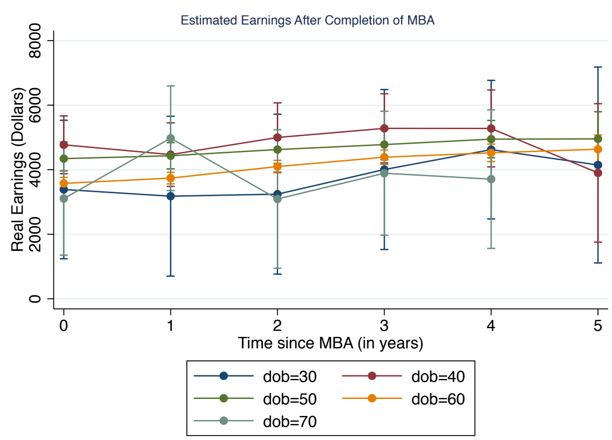


Figure 23: Earnings since finishing education for different cohorts of men

A.3 Testing for Sample Selection and Attrition Bias

One way to test for attrition bias is to estimate a probit in which the dependent variable takes the value one if the individual leaves the sample after the first wave, second wave or third wave and zero otherwise. The explanatory variables can include any variables that are believed to affect the outcome and also any variables that characterise the interview process.

The regression will take the following form:

$$Y_i = \alpha + \beta_1 X_i + \beta_2 Female_i + \beta_3 Female_i \times X_{2_i} + \epsilon_i \tag{10}$$

	Pr(End Survey)	
Real Wage	-0.0234	(-1.27)
Undergrad GPA	-0.104	(-0.60)
GMAT quant score	0.0203	(1.86)
GMAT verbal score	0.00535	(0.45)
Female	0.590	(1.46)
Married	-0.392*	(-2.54)
White	-0.0745	(-0.21)
Black	-0.339	(-0.85)
Asian	-0.602	(-1.61)
Hispanic	-0.0243	(-0.09)
Other	-0.741	(-1.30)
Have a Child at W1	0.166	(0.51)
Have a Child during Survey	1.039***	(4.71)
Experience	0.0610	(1.52)
Age	-0.0648	(-1.71)
FemXWage	0.00179	(0.06)
FemXChildFuture	-0.0594	(-0.13)
Observations	881	

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A.4 Oaxaca-Blinder Details

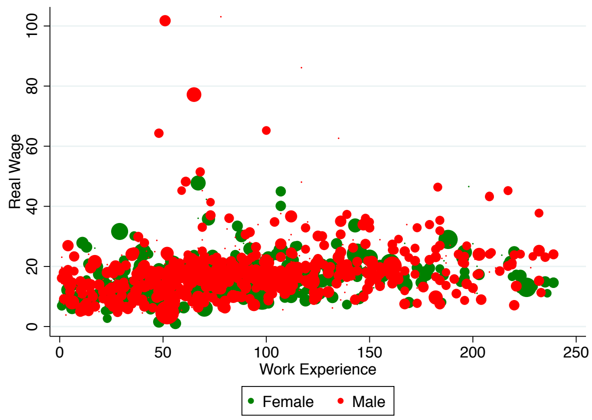
	W1		W2		W3		W4	
	Coefficient	% Explained	Coefficient	% Explained	Coefficient	% Explained	Coefficient	% Explained
Total Explained	6.58		13.4		14.7		10.5	
Quant	3.39	51.51975684	6.67	49.7761194	8.15	55.44217687	3.49	33.23809524
Verb	0.41	6.23100304	-1	-7.462686567	-0.56	-3.80952381	0.03	0.285714286
GPA	-0.5	-7.598784195	-0.54	-4.029850746	-0.05	-5	0.34	3.238095238
White	-0.01	-0.151975684	0.44	3.28358209	0.46	3.129251701	-0.7	-6.666666667
Black	-0.23	-3.495440729	-1.44	-10.74626866	-2.32	-15.78231293	0.26	2.476190476
Hispanic	-0.03	-0.455927052	-0.02	-0.149253731	-0.05	-0.340136054	-0.02	-0.19047619
Other	0	0	-0.09	-0.671641791	-0.07	-0.476190476	0.06	0.571428571
Asian	-0.02	-0.589970501	-0.03	-0.223880597	0.18	1.224489796	-0.11	-1.047619048
Experience	4.77	72.49240122	6.87	51.26865672	6.668	45.36054422	0.7	6.666666667
Experience Sq	-1.93	-29.33130699	-3.55	-26.49253731	-2.97	-20.20408163	1.04	9.904761905
Hours Worked	-1.85	-28.11550152	0.35	2.611940299	-0.71	-4.829931973	-0.05	-0.476190476
Married	0.52	7.902735562	0.97	7.23880597	0.05	0.340136054	0.07	0.666666667
US Citizen	-0.03	-0.455927052	0.28	2.089552239	0.04	0.272108844	-0.24	-2.285714286
0 Children	-3.47	-52.73556231	2.33	17.3880597	-3.59	-24.42176871	-1.24	-11.80952381
1 Child	0.61	9.270516717	-1.19	-8.880597015	1.21	8.231292517	2.71	25.80952381
2 Children	1.13	17.17325228	-0.91	-6.791044776	1.67	11.36054422	0.84	8
3 Children	-0.21	-6.194690265	-0.31	-2.313432836				
Confidence in Earnings	5.28	80.24316109	2.3	17.1641791	2.61	17.75510204	2.82	26.85714286
Confidence in Quant	-0.25	-3.799392097	-0.81	-6.044776119	0.69	4.693877551	0.75	7.142857143
Confidence in Verb	-0.31	-4.711246201	1.26	9.402985075	0.87	5.918367347	-0.02	-0.19047619
Opinion Index	0.23	3.495440729	-0.23	-1.71641791	-0.92	-6.258503401	-0.92	-8.761904762

	W1		W2		W3		W4	
	Coefficient	% Explained	Coefficient	% Explained	Coefficient	% Explained	Coefficient	% Explained
Major1	-0.35	-5.319148936	1.49	11.11940299	0.7	4.761904762	2.25	21.42857143
Major2	0.55	8.358662614	-0.47	-3.507462687	-0.22	-1.496598639	-0.92	-8.761904762
Major3			0.65	4.850746269	0.36	2.448979592		
Major4	0.01	0.151975684	0.06	0.447761194	-0.02	-0.136054422	0.03	0.285714286
Major5	-0.15	-2.279635258	2.61	19.47761194	2.67	18.16326531	3.4	32.38095238
Major6	-0.45	-6.838905775	-1.1	-8.208955224	-0.48	-3.265306122	-1.21	-11.52380952
Major7	0.25	3.799392097	-0.3	-2.23880597	-0.85	-5.782312925	-0.42	-4
Major8	-1.12	-17.0212766	0.07	0.52238806			0.5	4.761904762
Major9	0.1	1.519756839	-0.19	-1.417910448	-0.62	-4.217687075	-1.79	-17.04761905
Major10	-0.23	-3.495440729	-0.45	-3.358208955	-0.06	-0.408163265	-0.47	-4.476190476
Major11	-0.05	-0.759878419	-1.06	-7.910447761	-0.66	-4.489795918	-1.78	-16.95238095
Major12	-0.1	-1.519756839	1.29	9.626865672	1.11	7.551020408	1.21	11.52380952
Major13	-0.02	-0.303951368			0.01	0.068027211	0.03	0.285714286
Major14	0.05	0.759878419	-0.04	-0.298507463	0.38	2.585034014	0.08	0.761904762
Major15								
Major16								
Major17	0.26	3.951367781	-0.63	-4.701492537	-0.67	-4.557823129	-1.47	-14
Industry1	0.03	0.455927052	-0.23	-1.71641791				
Industry2	0.13	1.975683891	0.2	1.492537313	-0.75	-5.102040816		
Industry3	0.06	0.911854103					0.19	1.80952381
Industry4	1.14	17.32522796	0.08	0.597014925	-1.71	-11.63265306	-0.83	-7.904761905
Industry5	0.41	6.23100304	0.11	0.820895522	0.27	1.836734694	-0.14	-1.333333333
Industry6					-0.87	-5.918367347	0.51	4.857142857
Industry7	0.41	6.23100304			1.3	8.843537415	1.64	15.61904762
Industry8	0.13	1.975683891	-0.06	-0.447761194	-2.19	-14.89795918		
Industry9	-2.8	-42.55319149	-0.01	-0.074626866	5.73	38.97959184	2.6	24.76190476
Industry10	0.95	14.43768997			-0.15	-1.020408163	0.17	1.619047619

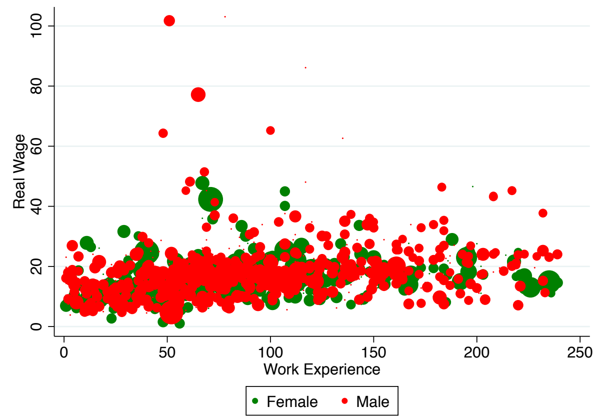
A.5 Additional Information on Re-Weighting

A.5.1 Scatter of Wages by Experience for 3 additional weightings

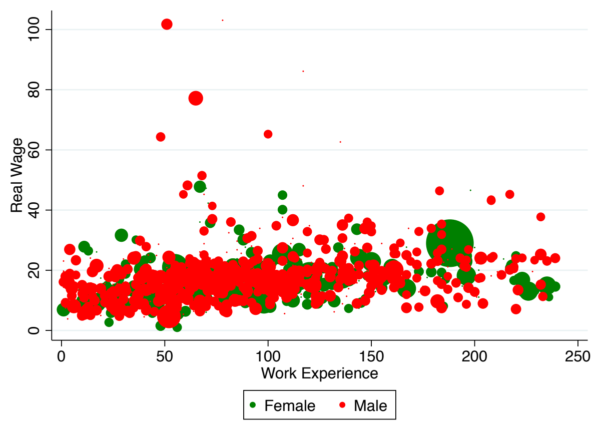
Figure 24: Estimated Wage Trajectories for Reference Individual



(a) Raw Scatter of Wages by Experience



(b) Weighted Scatter of Wages by Experience



(c) Weighted Scatter of Wages by Experience

A.5.2 Checking Balance of Re-Weighting

Using the first set of weights I proposed, a preliminary test is to compare the t-stat coefficient when regressing the female dummy on wages (at the first period after completing MBA) with and without the weights. The good news is that the female coefficient in the weighted sample is no longer significant.

Table 30

	Coefficient	Standard Error	T-statistic
Unweighted	-2.66	.59	-4.51
Weighted	.67	1.59	0.42

Table 31

Coefficient	P-Value Unweighted	P-Value Weighted
Female	0.04	0.644
GPA	0.067	0.131
GMAT	0.001	0.732
White	0.151	0.828
Black	0.036	0.766
Hispanic	0.160	0.935
Other	0.336	0.817
Asian	0.016	0.060
Experience	0.000	0.551
Experience Squared	0.136	0.489
1 Child	0.029	0.058
2 Children	0.564	0.322
3 Children	0.491	0.413
Hours Worked	0.065	0.108
Married	0.004	0.014
US Citizen	0.176	0.489

One simple method is to compare the means of observed baseline covariates between treated and control subjects in the weighted sample. For a continuous variable, let $\bar{x}_C$ and $\bar{x}_T$ denote the sample mean of X in the treated and control groups.s_T^2 and s_C^2 denote the standard deviation of each group. I calculate a standardised difference which is essentially the same as a t-test but it is not influenced by sample size.

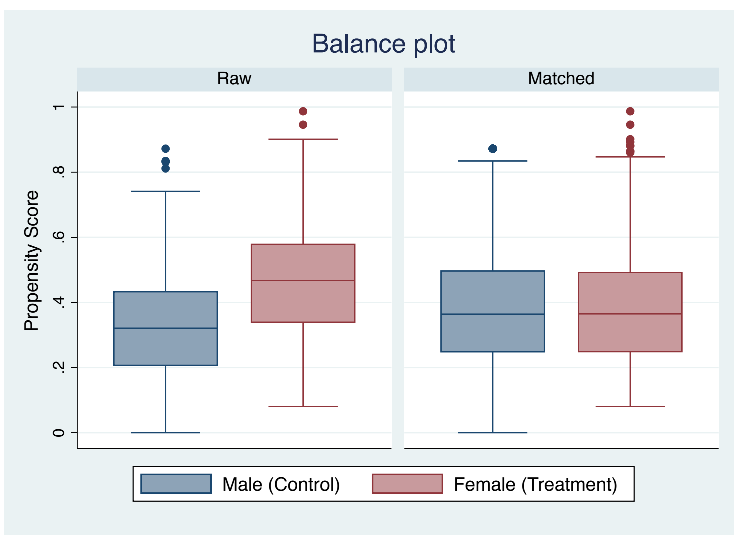
$$\mathsf{SMD} = \frac{\bar{x}_T - \bar{x}_C}{\sqrt{\frac{s_T^2 + s_C^2}{2}}} \tag{11}$$

An ideal SMD would take the value of 0. The good news is that we can see that most SMD are less than 0.06 except for confidence in earnings and hourly wage. This is due to the fact that these variables have such a large variation.

	Raw	Matched
Number of Observations	862	1724
	331	862
	531	862

	Standardised Differences		Variance Ratio	
	Raw	Matched	Raw	Matched
Verbal Score	-0.103	-0.02	1.034	1.046
Undergrad GPA	0.283	0.044	1.048	0.963
White	-0.257	0.027	1.175	0.98
Black	0.394	0.025	2.691	1.062
Hispanic	0.004	0	1.009	1
Asian	-0.02	-0.055	0.956	0.875
Other	-0.004	-0.037	0.964	0.669
Experience	-0.154	0.034	0.748	0.859
Experience Squared	0.155	0.058	0.668	0.859
Hours Worked Monthly	-0.263	-0.126	0.84	0.873
Married	-0.16	-0.026	0.921	0.985
Age	-0.168	-0.022	0.882	0.92
Age Squared	-0.152	-0.026	0.903	0.92
Tenure	-0.034	-0.016	2.396	0.915
US Citizenship	-0.066	0	1.363	1
Confidence in Earnings	-0.32	0.106	0.449	1.515
Confidence in Quant Score	0.226	0.058	1.05	1.014
Confidence in Verb Score	0.128	0.034	1.078	1.02
Opinion Index	0.205	-0.031	0.971	1.11

Figure 25: Box Plot of Balance in Groups Before and After Propensity Score Matching



A.6 Additional Tables

Table 32: % of Each Group for 'How Important is...' (1 is highest, 4 is lowest) for Non-MBA Completers

All	1	2	3	4
Family	87.67	9.18	2.48	0.67
Wealth	26.14	58.18	13.55	2.12
Career	66.85	32.12	1.00	0.03
Friends	49.44	44.14	6.14	0.28
Free Time	49.94	44.44	5.32	0.31
Women	1	2	3	4
Family	87.27	9.51	2.49	0.74
Wealth	22.57	61.60	13.12	2.71
Career	69.64	29.23	1.07	0.06
Friends	50.06	43.71	6.06	0.17
Free Time	52.12	43.02	4.47	0.40
Men	1	2	3	4
Family	87.98	8.92	2.49	0.61
Wealth	29.12	55.28	13.95	1.64
Career	64.52	34.59	0.89	0
Friends	48.94	44.48	6.20	0.38
Free Time	48.05	45.66	6.06	0.23

Table 33: Estimates of Wage Gap Over First 5 Years After Completing MBA

	Manufacturing	Finance	Services	Public
0 Years	-0.392**	-0.202**	-0.055	-0.207**
	(0.026)	(0.011)	(0.405)	(0.025)
1 Year	-0.388**	-0.210***	-0.128*	-0.226**
	(0.017)	(0.010)	(0.055)	(0.019)
2 Years	-0.461***	-0.128	-0.150**	-0.241**
	(0.006)	(0.219)	(0.043)	(0.022)
3 Years	-0.478**	-0.149	-0.167*	-0.252**
	(0.020)	(0.210)	(0.052)	(0.038)
4 Years	-0.480*	-0.071	-0.182*	-0.279*
	(0.056)	(0.607)	(0.072)	(0.066)
5 Years	-0.455*	-0.065	-0.237**	-0.269
	(0.054)	(0.713)	(0.046)	(0.134)
Observations	167	490	854	276
Cohort*Year	Yes	Yes	Yes	Yes
Degree Major Dummies	No	No	No	No

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The dependent variable in each equation is log of real hourly wages. In a regression without any controls, the sample is restricted to those survey respondents with non-missing characteristics that I include in later specifications. All regressions include cohort*year dummies and a dummy for race (white, black, hispanic, asian and other). P-values are in brackets and the standard errors are clustered at the individual level. Experience and hours worked are measured in months.

Table 34: MBA Major Choices by Gender

Major	Total (#)	Total (%)	Women (#)	Women (%)	Men (#)	Men (%)
General Management	312	18.91	107	16.61	205	20.38
Accounting	135	8.18	67	10.40	68	6.76
Economics	25	1.52	5	0.78	20	1.99
Entrepreneurial Management	41	2.48	16	2.48	25	2.49
Finance	316	18.97	77	11.96	236	23.46
Health Care Administration	46	2.79	33	5.12	13	1.29
HR Management	64	3.88	43	6.68	21	2.09
Industrial Management	37	2.24	6	0.93	31	3.08
International Business	188	11.39	79	12.27	109	10.83
Management Information Systems	134	8.12	53	8.23	81	8.05
Marketing	194	11.76	99	15.37	95	9.44
Production/Operations Management	56	3.39	10	1.55	46	4.57
Public Policy or Public Admin	21	1.27	9	1.40	12	1.19
Real Estate	26	1.58	8	1.24	18	1.79
Statistics	5	0.30	1	0.30	4	0.4
Transportation	2	0.12	1	0.16	1	0.10
Other	51	3.09	30	4.66	21	2.09
Total	1650		644		1006	

Table 35: OLS Estimates of Log Wage immediately after individuals finish MBA for 6 most popular Degree Majors

	General Managment	Accounting	Finance	International Business	Management Info Systems	Marketing Marketing
0 Years	-0.182**	-0.034	-0.036	-0.051	-0.028	-0.211*
	(0.013)	(0.725)	(0.592)	(0.665)	(0.830)	(0.092)
1 Years ×	-0.201***	-0.053	-0.126*	0.073	-0.135	-0.222**
	(0.009)	(0.535)	(0.083)	(0.562)	(0.359)	(0.040)
2 Years	-0.217**	-0.085	-0.230***	0.212	-0.181	-0.166
	(0.013)	(0.396)	(0.004)	(0.156)	(0.236)	(0.105)
3 Years	-0.179**	-0.130	-0.120	0.104	-0.205	-0.176
	(0.046)	(0.323)	(0.230)	(0.533)	(0.242)	(0.164)
4 Years	-0.122	-0.026	-0.122	0.012	-0.218	-0.127
	(0.251)	(0.866)	(0.293)	(0.960)	(0.290)	(0.371)
5 Years	-0.219*	0.132	-0.113	-0.163	-0.303	-0.328*
	(0.060)	(0.448)	(0.396)	(0.703)	(0.198)	(0.053)
Observations	585	216	489	313	238	356
Cohort*Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummies	No	No	No	No	No	No

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The dependent variable in each equation is log of real hourly wages. In a regression without any controls, the sample is restricted to those survey respondents with non-missing characteristics that I include in later specifications. All regressions include cohort*year dummies and a dummy for race (white, black, hispanic, asian and other). P-values are in brackets and the standard errors are clustered at the individual level. Experience and hours worked are measured in months.

Table 36: OLS Estimates of Log Wage immediately after individuals finish MBA for 6 most popular Degree Majors

	General Managment	Accounting	Finance	International Business	Management Info Systems	Marketing Marketing
0 Years	-0.142**	-0.022	0.029	-0.066	-0.012	-0.163
	(0.035)	(0.796)	(0.693)	(0.570)	(0.925)	(0.208)
1 Year	-0.156**	-0.051	-0.056	0.032	-0.162	-0.160
	(0.031)	(0.558)	(0.407)	(0.769)	(0.258)	(0.148)
2 Years	-0.162**	-0.087	-0.174**	0.142	-0.198	-0.095
	(0.049)	(0.376)	(0.028)	(0.255)	(0.177)	(0.355)
3 Years	-0.117	-0.139	-0.069	0.002	-0.192	-0.090
	(0.206)	(0.255)	(0.483)	(0.989)	(0.228)	(0.440)
4 Years	-0.068	-0.044	-0.085	-0.057	-0.210	-0.052
	(0.541)	(0.759)	(0.428)	(0.757)	(0.240)	(0.694)
5 Years	-0.138	0.119	-0.085	-0.206	-0.298	-0.247
	(0.250)	(0.441)	(0.423)	(0.510)	(0.120)	(0.133)
Observations	585	216	489	313	238	356
Cohort*Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The dependent variable in each equation is log of real hourly wages. In a regression without any controls, the sample is restricted to those survey respondents with non-missing characteristics that I include in later specifications. All regressions include cohort*year dummies and a dummy for race (white, black, hispanic, asian and other). All regressions in this table include the following variables: hours worked (measured monthly), a quadratic in experience, a dummy for if the individual is married, a dummy for if the individual is a US citizen, a set of dummies for the industry of job and a set of dummies for the number of children. P-values are in brackets and the standard errors are clustered at the individual level. Experience and hours worked are measured in months.

Table 37: OLS Estimates of Log Wage immediately after individuals finish MBA for 6 most popular Degree Majors

	General Managment	Accounting	Finance	International Business	Management Info Systems	Marketing Marketing
0 Years	-0.071	-0.048	0.048	-0.039	0.017	-0.153
	(0.242)	(0.527)	(0.505)	(0.740)	(0.883)	(0.237)
1 Year	-0.083	-0.070	-0.032	0.062	-0.117	-0.149
	(0.194)	(0.363)	(0.622)	(0.588)	(0.373)	(0.183)
2 Years	-0.090	-0.110	-0.156**	0.178	-0.146	-0.085
	(0.202)	(0.175)	(0.049)	(0.158)	(0.276)	(0.400)
3 Years	-0.043	-0.167	-0.051	0.037	-0.134	-0.080
	(0.582)	(0.101)	(0.586)	(0.785)	(0.358)	(0.482)
4 Years	0.007	-0.085	-0.068	-0.020	-0.149	-0.043
	(0.943)	(0.479)	(0.516)	(0.915)	(0.357)	(0.726)
5 Years	-0.053	0.053	-0.065	-0.175	-0.232	-0.233
	(0.608)	(0.661)	(0.523)	(0.589)	(0.175)	(0.141)
Observations	585	216	489	313	238	356
Cohort*Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The dependent variable in each equation is log of real hourly wages. In a regression without any controls, the sample is restricted to those survey respondents with non-missing characteristics that I include in later specifications. All regressions include cohort*year dummies and a dummy for race (white, black, hispanic, asian and other). All regressions in this table include the following variables: hours worked (measured monthly), a quadratic in experience, a dummy for if the individual is married, a dummy for if the individual is a US citizen, a set of dummies for the job industry a set of dummies for the number of children and the standardised measure of confidence in earnings. P-values are in brackets and the standard errors are clustered at the individual level. Experience and hours worked are measured in months.

Table 38: OLS Estimates of Log Wage immediately after individuals finish MBA for Professionals and Legislators

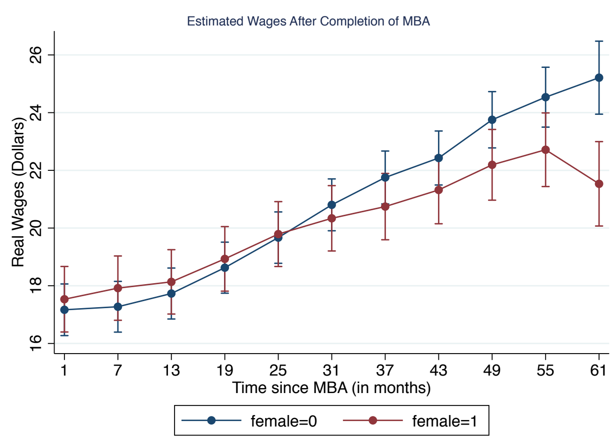
	Legislators	Professionals	Legislators	Professionals	Legislators	Professionals
Female	−0.070	−0.119***	−0.051	−0.107***	−0.016	−0.069*
	(0.325)	(0.001)	(0.449)	(0.004)	(0.805)	(0.057)
Undergrad GPA	−0.086	0.123***	−0.078	0.128***	−0.065	0.120***
	(0.257)	(0.009)	(0.283)	(0.006)	(0.349)	(0.007)
GMAT score	0.095**	0.065***	0.095***	0.065***	0.088**	0.054***
	(0.011)	(0.001)	(0.009)	(0.001)	(0.011)	(0.006)
Work Experience	0.003**	0.005***	0.003**	0.003***	0.002	0.002***
	(0.031)	(0.000)	(0.028)	(0.001)	(0.128)	(0.007)
Work experience in months squared	−0.000	−0.000***	−0.000	−0.000	−0.000	−0.000*
	(0.225)	(0.002)	(0.152)	(0.126)	(0.401)	(0.097)
Earning Confidence					0.077***	0.084***
					(0.000)	(0.000)
Observations	152	582	152	582	152	582

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: P-values are in parenthesis. In addition to the variables shown, I control for race, us citizenship, tenure, marriage and children in each specification. The specification is that the first two columns match the specification (2) of the original OLS tables (8 and 9), the second two columns match the specification (5) in the same tables and the last 2 columns match the specification (1) of Table 9.

Figure 26: Estimated Wage Trajectories for Professionals



Note: This graph estimates wages for men and women from the month after they finish their MBA. The vertical lines indicate the 95% confidence intervals. I have controlled for all observables that were included in specification (5) of 8. I have de-meaned all variables so the mean is 0. This means the trajectories are of the mean reference individual.

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