Risk Aversion and Science, Technology, Engineering and Mathematics (STEM) Labour Diversity in the UK

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INTRODUCTION

A growing concern for many post industrial economies is a widening gap between the labour supply and labour demand within Science, Technology, Engineering and Mathematics (STEM) related industries. As well as a general shortfall of STEM skilled workers within the economy, studies have identified STEM participation gaps within socio-economic groups, namely gender, ethnicity and disability. This paper aims to explore the role of risk aversion within STEM career selection, focusing on whether differences in risk preferences within these socio-economic groups are a contributory factor for their gaps in STEM uptake. This is achieved through a survey analysis, conducting and comparing a number of logistic regressions. Despite females making up 50.4 percent of the total workforce, in the sample used only 18.6 percent of the STEM workforce were women. Similarly, individuals of Black and Pakistani heritage are found to be underrepresented in STEM in relation to their population size. Those identified as having Chinese and Indian ethnicity have higher STEM uptake than population rates. All proxy measures of physical disability saw significant STEM uptake gaps. Individual's whose health issues limit the ability to climb stairs 'a lot' make up 2.9 percent of the working population, but only 1.4 percent of the STEM workforce.

LITERATURE REVIEW

THE STEM GAP

Employment in fields related to Science, Technology, Engineering and Mathematics (STEM) are seen as valuable and key to driving national innovation and competitiveness (U.S. Department of Commerce, 2014). These sectors of the economy are a key source of technological development allowing for economic growth. A current area of major concern for governments and businesses is the existence and persistence of a shortage of STEM skilled workers. The Social Market Foundation (2013) estimates that the UK has an annual shortfall in domestic supply of around 40,000 new STEM skilled workers and EngineeringUK (2013) calculated a need to double the number of graduates and apprentices in the engineering discipline alone by 2020 to meet demand. A recent report from the UK Commission for Employment and Skills (2015) found Jobs vacancies in high level STEM occupations are almost twice as likely to be left unfilled due to a lack of staff with the right skills. BusinessEurope (2011) provides evidence of STEM employment shortages in a number of European Union member states including Germany, Austria, UK, Belgium and Poland.

They state the lack of STEM-skilled labour will be one of the main obstacles to economic growth in the coming years. The European Commission (2014) attributes a lack of applicants with the required qualifications and sufficient experience as a major source of the STEM labour shortages. This includes insufficient numbers of graduates due to gender uptake issues, negative perceptions of STEM occupations and difficulties related to a lack of experienced STEM staff. Compounding the problem are high numbers of STEM workers approaching retirement age, Caprile *et al.* (2015) estimates around 7 million job openings are forecast until 2025 in the EU, two thirds of which replacing retiring workers.

In response to the shortage, governments are undertaking actions to promote an increase in STEM career uptake. The United Kingdom has eleven 'action programmes' and has opened a National STEM Centre in 2009 to house the UK's largest collection of STEM teaching resources (Dobson, 2013). These initiatives include the British Council's 'STEM Education Programme' and Project Enthuse's 'STEM Learning', which aim to increase the quality of STEM teaching and promote STEM career interest in students. A vast collection of research has been conducted into the causes of the shortage and methods to combat the problem. Academic papers often focus on the lack of students undertaking a STEM related degree. Within the student population, the relative share of STEM students started to decrease in Europe, the US and other developed countries in the 1990s. Rohaan *et al*. (2010) found the decline of pupils' interest in STEM subjects is most prominent at the secondary school level.

STEM AND EDUCATION

To enter a STEM related occupation a high level of education is often required. Caprile *et al.* (2015) states demand for STEM skills requires both upper-secondary and university graduates. Statistics from the EU show in the STEM labour market more than 80% of workers hold high level qualifications, with 16% holding medium and 3.5% low (Caprile *et al.*, 2015). The STEM related degrees required to advance into the industries are seen as some of the most challenging to complete. The results from a study undertaken by Stinebrickner & Stinebrickner (2011) indicate mathematics and science are believed to be the most difficult degrees by students starting university and this belief strengthens over time. The difficulty of a degree can be reflected by the frequency of students ending the course before completion. Observing the Higher Educational Statistics Agency's (2015) statistics on the non-continuation rates for UK bachelor degrees, it appears STEM related subjects generally have higher rates. Computer sciences have the highest rate at 9.8% while engineering and technology are a close third with 7.2%.

The difficulty and time/opportunity cost is thought to be offset by STEM employment being associated with pay premiums and shorter periods of joblessness compared to other sectors. On average those working in STEM occupations earn 20% more than those working in other fields in the UK according to Greenwood *et al.* (2011). Caprile *et al*. (2015) state the unemployment rate for STEM labour in the EU was well below the total unemployment rate since the beginning of the 2000s, this holds true even for countries effected worst by the recent financial crisis, such as Greece and Spain. Past analysis of private returns to education identify STEM subjects as very worthwhile and returns for the effort are justified. Despite these apparent benefits STEM uptake remains low, in response a number of papers critically analyse the claims of high returns.

Becker (2010) conducted an investigation into the causes for the shortage of engineering graduates, a number of factors which diminish the attractiveness of engineering were found. One important finding was the improvement in prospects in other subjects and careers, notably insurance and consulting, where the potential rewards can be higher. The increase of offshoring lower level/entry-level technology jobs to countries such as China and India, where cheaper labour costs for engineers are found, was an off-putting phenomenon. Due to the labour market shortage it would be expected that salaries would rise due to the demand surplus, Becker (2010) instead found entry-level salaries for German engineers have dropped in real terms when adjusted for inflation. The high level of specialisation found in STEM occupations, especially engineering, is found to have a negative impact on corporate mobility. It was observed that managers and other specialisations can have better mobility, even in a technologically oriented company such as Siemens. Training as an engineer or scientist is far from being the best career track to a top position. He concludes capable students are able to calculate and judge which type of education will lead them to the top positions in companies, causing overly specialised jobs to become less attractive.

Beblavý *et al.* (2013) investigates the private returns on education for STEM related studies whilst considering the different cost of studying to students in terms of time, namely study hours and years in education. Study hours are utilised as they differ among subjects, as some are more demanding in terms of personal study time and class attendance than others. To receive a competitive STEM education additional years may have to be studied. For example, Becker (2010) quoted Minks (2007) and stated 83% of German university professors did not consider the BA to be a standalone degree but 'rather an intermediate step on the way to an MA'. This had the effect of lowering the perceived value of the engineering bachelor's degree, causing employers to increase their preference for master's students. Beblavý *et al.* (2013) finds in the short and medium term after graduation STEM careers do not provide as much benefit as previous studies have suggested, with this particularly true for women. Within their study education is approached as an investment choice in one's future, which can be influenced by an individual's level of risk aversion. This appears to be one of the few occurrences where risk aversion has been applied to the choice to undertake STEM education. They find those who enter STEM programmes are notably risk averse given that they anticipate positive labour market outcomes despite the high cost. In their results this holds true for those who have better knowledge of their ability and believe they can cope with the challenge.

The relationship between degree choice and individual levels of risk aversion is a topic of some attention in the past. Past studies in the area have shown the financial risk associated with different fields (Saks & Shore, 2005) and perceived probability of success (Buonanno & Pozzoli, 2009) influences university degree choice. Paola & Gioia (2012) conduct an analysis directly estimating the relationship between degree choice and risk aversion. Their estimates are based on a sample of undergraduate students enrolled on different degree courses at an Italian university, using levels of willingness to invest in a hypothetical risky asset. They explain the choice of academic study is a risk, due to a high levels of uncertainty in a number of dimensions. Such dimensions include an individual generally not able to fully assess whether they will be able to complete the course and so must face the risk of dropping-out. Once the qualification has been obtained there is also no guarantee of finding an adequate job, creating uncertainty for the benefits of a subject choice in terms of wages. Technological changes or changes in supply and demand may impact the market value of a qualification over time, further contributing to the uncertainty. In the study students can choose among four different fields: Engineering, Sciences, Humanities, and Social Sciences. The estimates suggest the more risk averse students are significantly more likely to undertake a Humanities or Engineering study than Social Sciences, whilst controlling for a large number of individual characteristics. Paola & Gioia explain these preferences are the result of these subjects allowing students the choice to minimize the risk of dropping out or minimise the risk faced in the labour market. Humanities students enjoy the lowest risk of academic failure, but the highest risk of unemployment and low wages after graduation. Students undertaking Engineering have better labour market prospects compared with graduates in most fields, but face a higher chance of dropping out. To explain the choice of students to prioritise the avoidance of one kind of risk over the other, a measure of student ability was introduced. They found risk averse students of higher abilities are more concerned about risks faced in the labour market and prefer fields which allow the best protection against these types of risks. Contrastingly students with lower ability are more likely to choose majors that reduce the risk of dropping out from an academic study. The findings refer to just one university meaning it is not possible to derive general conclusions, however it is suggested an individual's level of risk aversion has a significant effect on the choice of academic study.

STEM GENDER GAP

National labour statistics and studies have conveyed a significant disproportion in the number of males to females employed within STEM related careers. It is reported that women make up only 14.4% of the STEM work force in the UK (WISE, 2015), this gender gap is also found in the US with a 24% proportion of the workers being female (U.S. Department of Commerce, 2011). Numerous explanations have been explored in academic circles including: differences in ability, education, gender discrimination in hiring, societal and biological factors. A simple explanation for the gap would be active gender discrimination in the STEM labour market, reducing the likelihood of a women being hired due to beliefs about their ability or productivity. Past studies have found evidence of such discrimination taking place, including the work of Wenneras & Wold (1997) and Steinpreis *et al*. (1999). However, a more recent investigation by Ginther & Kahn (2006) concluded this effect had been diminishing over time and has now become negligible.

A recent study by Hill *et al*. (2010) evaluates the current literature on the STEM gap and concludes societal beliefs and the learning environment are major contributors to gender differences in career choice. Negative stereotypes about female abilities in mathematics and science persist despite considerable improvements in these areas, two main stereotypes are identified: boys perform better in maths and men are better suited for scientific work. Low *et al*. (2005) and Andreescu *et al*. (2008) find the representation of women in science and mathematical fields and culturally prescribed gender roles influence occupational interest. It appears society fails to provide sufficient visible 'role models' of people who have succeeded in STEM (Becker, 2010). Sáinz *et al.* (2012) identifies parents and family as playing a key role, as they often bring up their children to conform to traditional gender roles, while the education system and peers tend to reinforce these stereotypes. A number of researchers have identified that the divergence of career path begins at an early age. Lapan *et al*. (2000) Turner *et al*. (2008) found girls express less interest in math or science careers than boys starting in early adolescence. Pajares (2005) found that gender differences in self-confidence in STEM subjects begin in secondary school and increase in college and university. A similar gender gap has been observed in students obtaining STEM related degrees. Although women have become the majority of university students, they are far less likely than their male counterparts to undertake a major in a STEM field (National Science Foundation, 2009). Caprile *et al.* (2015) showed graduates in STEM-related subjects account for 12.6 % of total female graduates as compared with a share of 37.5 % among total male graduates on average in the EU in 2012. The overall proportion of STEM bachelor's degrees awarded to women has increased significantly over the past four decades, however they remain a relatively small percentage. In an attempt to understand the lack of female STEM students Ceci & Williams (2010) studied gender differences in maths-intensive fields. Mathematical skills are considered essential to success in STEM fields, so a difference in mathematical ability could provide a reason for the gap. However, no systematic gender differences in mean mathematics scores were found. Sáinz *et al*. (2012) reviewed past International Student Assessments and found there was no statistically significant difference between the performance of girls and boys in science in a 2010 study. These findings indicate a difference in ability between the genders is not responsible.

A number of organisations have been established in an effort to increase the participation of women in STEM sectors including the Campaign for Science and Engineering (CaSE). CaSE (2014) states a more diverse STEM workforce is not simply desirable in terms of equality, but necessary to maximise individual opportunity and meet economic need. Such organisations also focus on improving diversity for other demographics including ethnic minorities and disabled individuals. Increasing participation by all demographics would contribute to reducing labour shortfalls.

STEM ETHNICITY AND DISABILITY GAP

Statistics show variations in the participation of minority ethnic groups within the STEM labour market, relative to their population size in the UK. Findings from CaSE (2014) indicate certain Black and Minority Ethnic (BME) groups are more active in STEM subjects than white groups, while individuals from other ethnic groups are still far less likely to study or work in STEM. Their study concludes ethnicity is unlikely to be the sole reason for the differences between the selections of STEM courses by BME groups, due to the complex interaction of cultural, socioeconomic, and other factors. Despite not being considered the sole reason, difference in ethnicity and culture may impact an individual's career choices through a number of ways.

Studies have identified the lack disabled individuals within the STEM labour force a concern, such as those conducted by White & Massiha (2015) and the National Science Foundation (2015). Golshani (2005) found the training and employment gap for disabled individuals is even wider in STEM fields than the already significant gap in the wider US labour market. CaSE (2014) identifies in the UK disabled STEM students are 57% less likely to take up postgraduate STEM study than non-disabled students, suggesting educational difficulties for those who are disabled.

RISK AVERSION AND EDUCATION

From the literature, it is clear that the uptake and choice of a degree is a crucial component of entering a STEM career. Papers have indicated an individual's choice of degree can be significantly impacted by their level of risk aversion. Previous findings suggest individuals who are risk averse may have preference for STEM related study, dependent on being of a high level of academic ability. Apart from an indication that the preference for uptake is less evident for females, the role of risk aversion on selection into STEM between other demographic groups has not been analysed in great depth. The author observes a lack of discussion of the role of risk aversion in explanation of the STEM diversity gaps. Differing levels of risk aversion may play a role in the diversity of genders, ethnicities and disability in the STEM labour market. The literature on the topic of risk aversion is explored to investigate whether risk preference differences are observed within these socio-economic characteristics.

RISK AVERSION AND GENDER

Within the literature there is little mention of the role of risk preferences in a women's choice in undertaking a STEM related career. This is surprising as there is a large body of literature on gender differences in risk preference. Studies based on the general or student populations by Eckel & Grossman (2008) and Croson & Gneezy (2009) found on average women have lower risk preferences than men. There has also been a focus on observing risk preferences within certain sub-populations. When comparing risk preferences between particular groups of women and the larger population differences have been found, such as Johnson & Powell's (1994) study on student betting which observed female students with a background in management having lower risk aversion than the overall population. Adams & Ragunathan (2015) conducted an investigation addressing the 'Lehmans Sister' hypothesis by regressing a bank's risk and risky behaviour against the gender diversity of its board. They find women who are employed within the financial industry women need not be more risk averse than men and differ in risk preferences with the general population of women.

The effect of gender differences in competitiveness on the choice of academic track was investigated by Buser *et al*. (2014). Midway into the six years of secondary school education Dutch students choose one of four study tracks of ranked mathematical and scientific difficulty. Despite no difference in average academic performance, males are observed to be more likely to choose the more academically intense tracks, being almost twice as likely to choose the most science-oriented track compared to females. A strong correlation was found to exist between the study track chosen and the choice of major in further education, with most graduates of the most difficult track continuing to study a subject in science and engineering. This suggests choice of academic direction in these early years have potentially important future outcomes in educational specialisation, such as entering STEM related higher education. Within the analysis on the impact of competitiveness, risk aversion and confidence were used as control variables. They found the gender difference in competitiveness accounts for a substantial portion of the gender difference in track choice, while gender differences in risk aversion pay a generally significant but minor role. The impact of risk attitudes on the gender gap in study track choices was variable and not always significant in alternative specifications.

The first hypothesis of this paper is risk preferences have a significant impact on a women's choice to enter a STEM related career. Despite the findings of Paola & Gioia (2012) of STEM careers attract those with higher risk aversion, this hypothesis suggests women who have entered a career in STEM have lower risk aversion levels than those who have not. Due to the societal and cultural factors which make these occupations appear to be better suited to male workers, such as stereotyping and the lack of role models, entering a STEM career is perceived as a greater risk to women than to men. This misjudgement on the challenge of perusing a STEM education and career can be observed in the lower levels of confidence females express in their mathematical (Ceci & Williams, 2010) and scientific (Sáinz *et al.*, 2012) academic ability compared to males, despite no actual significant difference in grades being found. As no academic performance differences are found it would be expected that a similar amount of each gender would be present in these occupations. However, this overestimation of the risk of succeeding as a female may contribute to the observed gender gap, as only females with lower risk aversion select into the STEM market while the higher risk preferences opt for other occupations.

RISK AVERSION AND ETHNICITY

There are few past academic papers where the effect of ethnicity on risk aversion was the main focus of the study. Within the literature, ethnicity/race is often used a socio-economic control variable often included with others such as age, gender and income. A study commonly cited within the topic of risk and ethnicity was conducted by Hsee & Weber (1999) which investigated differences in risk aversion between individuals of Chinese and American nationality. They discovered the Chinese were significantly more risk-seeking than the Americans, contrary to previous expectations. To explain the finding, they looked to the differences in cultural values and social structures between the two countries, establishing a “cushion hypothesis''. They describe how the Chinese collectivist societal structure encourages interdependence with one's family and community, as opposed to American Individualism which emphasizes personal freedom and independence. This results in the Chinese having closer extended families compared to Americans, meaning if the Chinese individual is in need, they have a greater network to turn to for support and financial assistance. This extended family acting as a safety net or ‘cushion’ might allow the negative outcome of a risky financial option to be perceived as less severe to a Chinese individual than American, allowing larger risks to be taken.

A significant section of the literature explores the effect of race/ethnicity on risky financial decision making. Sung & Hanna (1996) estimated the impacts of financial and demographic factors on risk tolerance, the results relating to race suggest Whites had higher predicted risk tolerance than Hispanics, while Blacks had the lowest actual risk tolerance level. Brown’s (2007) analysis in the US found Blacks and Hispanics are less likely to invest their money in the stock market than are whites, concluding employee decision making is influenced by race and ethnicity. Similarly, Gutter & Fontes’s (2006) examination of the impact of race on investment behaviour found Black households were less willing to take financial risk than the White households.

There are a number of papers which discuss the relationship between migration and risk aversion, this is relevant to ethnicity as minority groups living in the UK are likely to be migrants or the descendants of migrants. Barsky *et al.*’s (1997) study found foreign born Americans were more risk tolerant than the native-born Americans. They reasoned the immigrants were somewhat self-selected to be more risk tolerant than the native-born Americans, because of their willingness to leave their native countries and acceptance of the uncertainties of migrating to a new country. Halek & Eisenhauer (2001) analysed risk aversion across a number of US demographics using relative risk aversion estimates based on life insurance data and results from an income gamble survey. Their findings suggest race membership significantly affects risk aversion, as both blacks and Hispanics are consistently significantly less risk averse than whites and other races, while blacks are slightly more risk averse than Hispanics. They observed a significant difference in aversion between natives and migrants to the country, with natives far less likely to accept the speculative income gamble than immigrants, unfortunately there is no consideration of the differences among the migrants' countries of origin. The results from Fang *et al*.'s (2013) investigation suggest that Blacks were more risk averse than Whites. Members of the 'Hispanic' and 'other' racial group that were born in the United states were found not to be significantly different in terms of risk aversion from whites, while members of the two groups who were immigrants were more risk averse. They concluded the ethnic differences found in other risk aversion studies may be partly due to differences in immigrant status.

Dohmen *et al.* (2006) showed that risk attitudes are correlated across generations meaning children keep, to a large extent, the original risk attitudes of their parents. This was found true while controlling for a wide variety of background characteristics, including permanent income and characteristics of the region of childhood. In the same year Bonin *et al.* (2006) conducted a study into native-migrant differences in risk attitudes in Germany and found first-generation migrants have lower risk attitudes than natives, a result contrary to the expected. They explore a number of explanations including Germany's 'guest worker' generation, who were generally provided with a job when entering Germany, meaning their migration decision involved less risk. They also find a strong intergenerational adjustment of risk attitudes, with second generation immigrants equalising risk attitudes with the natives.

A paper by Bartke & Schwarze (2008) investigates the role of nationality and religion as possible determinants of the willingness to take risk. In the analysis nationality was initially a significant predictor of risk aversion. However, its explanatory power diminishes as a number of socio-economic characteristics are included and finally loses its significance when religion is added. They also found religious individuals are less risk tolerant than those who do not identify as religious and religious affiliation appears to matter, with Muslims less risk-tolerant than Christians. The researchers suggest people with a strong religious faith generally limit risky behaviour to act in accordance with their faith's rules. Islam, Catholicism, and other religions were found to exhibit the same effect without being connected to a national subgroup.

In a later extension into Eastern religions, Miller (2000) finds a relation between active participation in religious faith and risk aversion in monotheistic societies, but he could not identify such a relation among Buddhists or Hinduists. Batista & Umblijs (2014) also find strong evidence that religious people are more risk averse with regard to financial risks. Their findings also suggest that the link between risk aversion and religion is driven by social aspects of religious membership, rather than by religious beliefs themselves. A similar study by Hilary & Hui (2009) find evidence of this induvial level association between risk and religion, while also observing religion influencing organizational behaviour. Their results suggest firms located in counties with increased levels of religiosity undertake lower degrees of risk exposure. If the influence of religion can effect businesses it is possible such behaviour is ingrained within in the society.

Unfortunately, none of the literature on the topic of race and risk aversion was conducted within the UK. It is not known how effectively the previous findings would generalise to the country, as the makeup of ethnic minorities differs greatly between nations. Despite a large number of contrasting findings, some suggesting those of a white ethnicity have higher risk aversion than members of different ethnicities and others indicating the opposite, there is a consensus that significant differences between some ethnicities exist. The second hypothesis for the paper is differences in risk aversion levels between ethnic group's plays a role in the difference between their STEM participation rates. A third hypothesis is any significant effect found relating STEM participation, ethnicity and risk would have its explanatory power diminished when controlling for religion. The size of this dampening impact would be expected to be greater for ethnic groups which are observed to be more religious.

The possible observation of low participation in the UK STEM labour market by Chinese individuals could be directly related to Paola and Gioia's (2012) finding that STEM degrees such as engineering were the preference for the risk adverse as opposed to risk seeking. A lower risk aversion of the Chinese could be due to the 'cushion hypothesis' put forward by Hsee and Weber's (1999).

RISK AVERSION AND DISABILITY

There is an apparent lack of an academic study focused on the impact of having a disability on an individual's risk aversion. This could be due to the difficulty of collecting data on a respondent's level of risk aversion before and after having a disability for obvious reasons. The affliction of a physical disability has previously been included in risk aversion studies as one of many social-demographic characteristics, such as the work by Hartog *et al*. (2002). They found respondent's characterised as disabled had no significant difference in their preference to risk aversion to those who were not disabled. Unfortunately, the author could find no other mention of disability within the topic of risk attitudes. A few papers analysed the role of health on risk aversion, though disability was not mentioned. Gandelman & Hernández-Murillo's (2013) investigation suggests that the marginal utility of income increases when satisfaction of health deteriorates, however the findings of Finkelstein *et al*.'s (2013) similar analysis concluded the opposite.

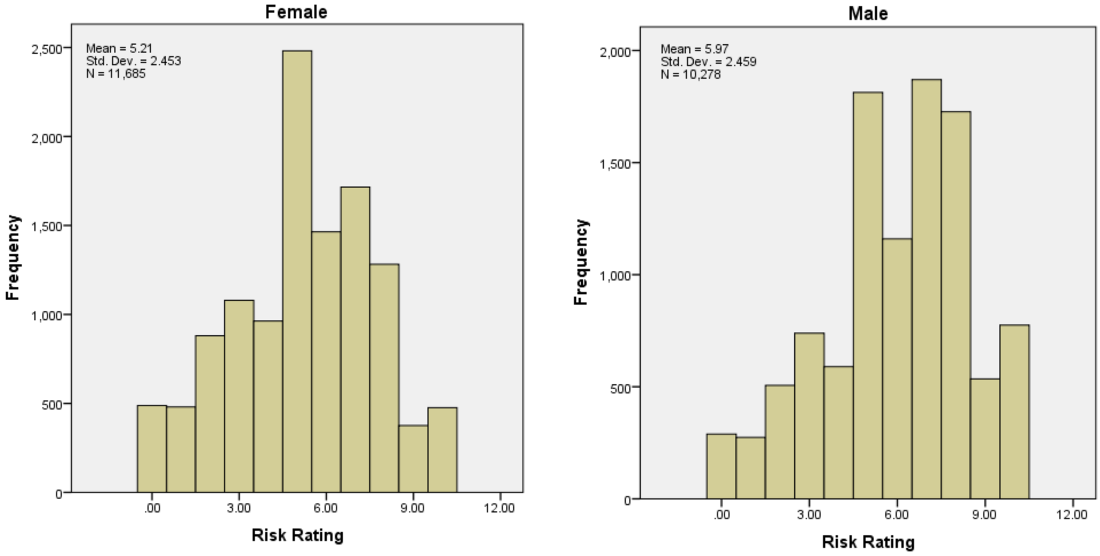
The fourth and final hypothesis of this paper states differences in risk preferences between those with and without physical disabilities do not play a significant contributory role in the reported gap between the two in STEM labour market participation. The impact of wellbeing on risk aversion is more likely to be captured by a measure of an individual's health satisfaction.

DATA

The dataset utilised in this investigation was taken from the 'Understanding Society: the UK Household Longitudinal Study', the continuation of the widely recognised British Household Panel Survey. The survey can be retrieved either as a whole in a panel dataset form or a singular 'wave'. Periods of waves overlap with data collection taking place over a 24-month period, individual respondents are interviewed around the same time each year (Understanding Society, 2016). Each wave of the survey includes additional questions to allow focus on a particular topic of interest, usually on a rotating schedule. The first wave of the survey, the years 2009 to 2010, included a focus on risk taking behaviour and so included a number of questions related to risk preference. Unfortunately, the topic has not been revisited in the survey since the time of writing, meaning a comparison between years is not possible. The survey contains numerous useful variables including a focus on employment and life satisfaction. Due to the large scope of the survey and the wide variety of topics explored, many areas are covered with simple questions with limited depth. The dataset of the survey used in the main analysis 'a_indresp' contains data for responding adults, from the ages of sixteen and upward. This means the dataset includes a vast number of retired individuals and full time students. For the majority of the analysis, with the greater focus on career self-selection, the dataset will be restricted to those currently in the workforce. This is determined as those who identify as 'In paid employment (full or part time)' under the current economic activity variable. When this restriction is applied the sample sized reduces from the original 50994 down to 27103, a smaller but still workable size.

The focus of the analysis is on the risk aversion measure labelled 'Risk_Rating'. The measure of risk aversion is derived from the survey question: Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks? The response was on an eleven-point scale with zero indicating complete risk adversity and ten indicating the highest willingness to take risk. The full eleven-point scale was retained in the creation of the workable variable. The use of such a question to elicit risk attitudes has been validated through past incentivized experiments such as the work of Becker *et al.* (2012). The German counterpart to the British Understanding Society Study, the German Socio-Economic Panel, includes the same risk taking question. This measure has been utilised in numerous risk aversion focused studies, including Bartke & Schwarze (2008), Jaeger *et al.* (2010), Bonin *et al.* (2006) and Dohmen *et al*. (2006). The popularity of this measure could be explained partly by Dohmen *et al*.'s (2005) experimental validation of the question. They undertook incentive compatible lottery experiments with real money utilising a representative sample of 450 German adults to show the risk question can reliably predict individuals' actual risk-taking behaviour. The German Socio-Economic Panel also includes six additional scale questions about the willingness to take risks in specific contexts of life: driving, financial portfolio, sports and leisure, career, health, and trusting strangers. Unfortunately, these were not utilised by the Understanding Society survey. Below, **Figure One** displays the frequency and distribution of risk ratings for both genders. A tendency to provide higher ratings can be observed for men, as suggested in earlier work on the topic.

Figure One: Histograms of the 'Risk Rating' Variable for Males and Females



The dataset contains a wide variety of employment related variables. This includes a number of Standard Occupational Coding classifications which breaks down employment into a number of coding structures. The coding deemed most suitable for this analysis was a condensed variation of the 'Standard Occupational Classification 1990' which provided a breakdown of around eighty occupations. The categorisation of an occupation as STEM related can be difficult due to the variety of jobs and aspects a single job can entail. Categorization as STEM is imperfect and may differ between agencies. For an occupational classification to be considered STEM in this paper it must appear on the 'List of occupations used in OES STEM definition' from the US Bureau of Labour Statistics (2015), the occupation's used can be found under **Appendix A**. The dummy variable 'STEM_Career' is created from these classifications, along with dummy variables for 'Science&Technology_Career' and 'Engineer_Career' to allow a greater breakdown and focus of the occupations that make up STEM.

Table One and **Table Two:** Summary Statistics for the Control Variables

Population Percentage Within the Sample		Total	STEM	Non-STEM
Female		50.4	18.6	54.6
Degree of higher		29.4	44.8	27.4
Private Sector		62.7	78.6	60.6
Health	1	2	1.2	2.1
	2	10.2	8.6	10.4
	3	28.2	27.6	28.2
	4	37.2	38.5	37
	5	22.4	24.2	22.2
Risk Rating	0	3.5	2.1	3.7
	1	3.4	2.2	3.6
	2	6.3	5.6	6.4
	3	8.3	8.6	8.2
	4	7.1	5.6	7.3
	5	19.6	15.3	20.1
	6	11.9	13.6	11.7
	7	16.3	19.6	15.9
	8	13.7	17.1	13.3
	9	4.1	5	4
	10	5.7	5.4	5.7

Comparison of Means with 'Risk Rating'			STEM	Non-STEM
Female		Mean	**5.4592**	**5.2018**
		SD	*2.25506*	*2.46173*
Males		Mean	**6.0381**	**5.9533**
		SD	*2.35985*	*2.48288*
Degree or higher		Mean	**5.933**	**5.861**
		SD	*2.24063*	*2.34909*
No Degree		Mean	**5.9194**	**5.3899**
		SD	*2.44552*	*2.54118*
Private Sector		Mean	**5.8757**	**5.5484**
		SD	2.37177	2.5119
Public Sector		mean	**5.5323**	**5.2675**
		SD	*2.28629*	*2.41156*
Health	1	Mean	**5.5**	**5.0719**
		SD	*2.91548*	*2.80314*
	2	Mean	**5.7069**	**5.2392**
		SD	*2.39775*	*2.5416*
	3	Mean	**5.7706**	**5.2893**
		SD	*2.34644*	*2.48047*
	4	Mean	**5.9227**	**5.6067**
		SD	*2.306*	*2.41633*
	5	Mean	**6.2224**	**5.8787**
		SD	*2.36863*	*2.55358*

The tables above show the population percentages of the variables included in the analysis, as well as the comparison of means of these variables with 'Risk_Rating'. Despite females making up 50.4% of the total workforce, in this sample only 18.6% of the STEM workforce were women. This participation gap between the genders is similar to that by estimated by WISE (2015), of a 14.4% STEM uptake by females. These close figures suggest the findings of this paper focused in this area may generalise to the real STEM labour market. The attainment of a degree or higher level of qualification appears more common within the STEM group compared to the larger workforce. This supports the idea that high level qualifications are generally required to enter these occupations. A noticeably higher proportion rate their willingness to undertake risk in the top half of the scale in the of the STEM group compared to the Non-STEM.

The comparison of means between the risk rating variable and others provides an indication of average willingness to undertake risks between these groups. Observing the table above, for all variables the mean risk rating is a higher value for those in the STEM group compared to non-STEM. This trend of higher willingness to take risk for those in STEM occupations is present throughout all the variables examined within the paper, possibly indicating a positive correlation between occupation choice and risk preferences exists. Throughout the variables the standard deviations of the risk ratings appear to maintain relatively constant, with a values of around 2.5.

Interestingly females in STEM employment have a higher average risk rating than non-STEM, by one fifth of a rating unit. These values alone would provide support for the first hypothesis. However, these differences may not be statically significant, meaning further analysis is warranted before conclusions can be drawn. The average willingness to undertake risk also appears to steadily increase with each higher average health rating, this may indicate a positive correlation between an individual's health or health satisfaction with risk preferences, as briefly mentioned in the work of Finkelstein *et al*. (2013).

Table Three: Summary Statistics for the Ethnicity and Religion Variables

Population Percentage Within the Sample			
	Total	**STEM**	**Non-STEM**
White	81.2	82.9	81
Black	5.1	3.3	5.3
Chinese	0.7	1.2	0.6
Indian	4.3	6	4.1
Arab	0.2	0.3	0.2
Pakistani	2.3	1.8	2.4
Born Abroad	18.4	17.1	18.6
Belong to Religion	51.5	48	51.9
Weekly Religious attendance	13.9	10.8	14.3
At least Monthly Religious Attendance	21.6	18	22
Religion Great Difference to life	18.5	13.9	19.1
Religion Some Difference to Life	20.4	21.3	20.3
Religion Little or No Difference to life	61.1	64.8	60.6

For the second hypothesis, the role of ethnicity and risk aversion on STEM uptake, a number of ethnicity variables were utilised. The dataset allows the breakdown of multiple ethnic minority groups. Ethnicities which are often included in an analysis of this type were utilised, namely ‘white’, ‘Black’ and ‘Chinese’. Due to the history of the Britain, a sizable proportion of individuals in the population are of Indian and Pakistani descent. As members of one of the largest minority groups in the country they were included in the analysis. Despite being a small part of the ethnic make-up of the UK, a variable indicating an individual of Chinese ethnicity was included to allow comparison to past research on race and risk aversion focused on the Chinese. Within the STEM groupings Indians and the Chinese have a greater representation than their overall population size. Similarly, Pakistani and Black ethnicities appear to have smaller STEM participation rate relative to their population size.

To allow for the extension of the second hypothesis and explore whether any significant relationships maintain after an individual’s religion in controlled for, a number of suitable variables related to religion were found. Unfortunately, difficulties arose in utilising the identification of specific religious affiliations, however variables indicating the importance and influence of religion on an individual were available. Importance of religion may be more useful than simple identification of affiliation, as an individual can identify as a certain religion without practicing its values. A simple identification of belonging to a religion shows close to half of all individuals identify as such, while the number of those who participate in weekly attendance drops to close to a tenth. For this analysis it is assumed more frequent religious attendance will imply closer adhering to the rules of the faith. The characteristics which identify religious belief have a greater presence in the Non-STEM workforce than STEM.

The importance of religious belief to the respondent was examined using the survey question ‘Religion makes a difference to life’, which had four possible answers. Two of these answers were maintained and formatted into dummy variables, Religion makes a Great Difference to Life (Religion_GDTL) and Religion makes Some Difference to Life (Religion_SDTL). The two remaining answers create the benchmark, allowing comparison between the dummies and when religion makes ‘little difference to life’ and when religion makes ‘no difference to life’. This benchmark is indicated in **Table Three** and **Table Four** as ‘Religion Little or No Difference to Life’.

Table Four: Summary Statistics for the Ethnicity and Religion Variables

Comparison of Means with 'Risk Rating'			
		STEM	**Non-STEM**
White	Mean	**5.9291**	**5.5142**
	SD	*2.326*	*2.47114*
Black	Mean	**6.1333**	**5.7016**
	SD	*2.32107*	*2.66167*
Chinese	Mean	**6.25**	**5.7547**
	SD	*1.87824*	*2.01807*
Indian	Mean	**5.6831**	**5.2536**
	SD	*2.61575*	*2.73383*
Arab	Mean	**6.3333**	**5.1842**
	SD	*2.54951*	*2.65956*
Pakistani	Mean	**5.725**	**5.2933**
	SD	*2.63105*	*2.54495*
Belong to Religion	Mean	**5.8259**	**5.3414**
	SD	*2.38254*	*2.52982*
Weekly Religious attendance	Mean	**5.8271**	**5.3164**
	SD	2.27376	2.64102
At least Monthly Religious Attendance	Mean	**5.7728**	**5.3818**
	SD	*2.33989*	*2.58441*
Religion Great Difference to life	Mean	**5.8431**	**5.4462**
	SD	*2.59495*	*2.65795*
Religion Some Difference to Life	Mean	**5.9906**	**5.4452**
	SD	*2.31468*	*2.46822*
Religion Little or No Difference to life	Mean	**5.9165**	**5.3067**
	SD	*2.31843*	*2.62746*

Along with the variation in relative STEM uptake, differences in average risk rating values can be observed. Individuals of Chinese ethnicity have higher mean risk rating than all others, whether in STEM or Non-STEM, with the expectation of those of Arab heritage. Despite also being over represented in the STEM group, those with an Indian background do not have noticeably higher average risk rating than others. A smaller standard deviation of risk preferences can be found between the Chinese grouping, a possible consequence of the smaller population size or an indicator of greater homogeneity of those of Chinese descent. There is a lack of a clear correlation between average risk ratings of nationalities and STEM uptake, however differences are observed.

In the STEM group, those who signal religion having little or no difference to their lives have a higher willingness to undertake risk on average than when religion has a great difference. The opposite is true for those employed elsewhere in the economy. Interestingly the average risk rating is highest for those who state religion has 'some' difference to their life. A similar contrasting difference is found between the two measures of the frequency of religious participation between STEM and Non-STEM. Overall it is clear those in STEM maintain higher risk ratings, however the differences between the two values of the strength of religious belief doesn't have as clear a direction.

Table Four and **Table Five:** Summary Statistics for the Disability Related Variables

Population Percentage Within the Sample			
	Total	**STEM**	**Non-STEM**
Climbing Stair limited 'a lot'	2.9	1.4	3.1
Climbing Stairs limited 'yes'	12.6	8.2	13.2
Mobility Issues	5	3.6	5.2

Comparison of Means with 'Risk Rating'			
		STEM	**Non-STEM**
Climbing Star limited 'a lot'	Mean	**5.7368**	**5.0032**
	SD	*2.5435*	*2.65184*
Climbing Star limited 'yes'	Mean	**5.6329**	**5.0289**
	SD	*2.38533*	*2.54002*
No Issues Climbing Stairs	Mean	**5.9486**	**5.5977**
	SD	*2.34396*	*2.48339*
Mobility Issues	Mean	**6.0556**	**6.0341**
	SD	*2.4785*	*2.50264*
No Mobility Issues	Mean	**5.9219**	**5.541**
	SD	*2.34251*	*2.49253*

Variables indicating the presence of a physical disability were required for the forth hypothesis. Due to the lack of an official physical disability variable a number of proxies were utilised instead. The first variable indicated when a respondent identified as their health limited the ability to climb stairs 'a lot' and second variable includes the respondents who has their climbing ability 'limited a lot' or 'limited a little'. A final variable was collected in a section of the survey discussing long term illness or impairment, where 5% of the sample population mentioned mobility issues. These proxies would not capture physical disabilities not related to mobility, however other suitable proxies were not available. There is a noticeable reduction of the population of individuals with the aforementioned issues within the STEM grouping compared with non-STEM. This may indicate a negative correlation with STEM participation and physical disability, whether this correlation is statistically significant will discovered in the analysis.

Interestingly for the 'Mobility Issue' variable there is almost no difference in mean risk aversion rating between STEM and Non-STEM. This alone would suggest the choice between STEM and Non-STEM occupations was not effected by risk preferences. A more pronounced difference between STEM and Non-STEM mean risk ratings are found in the stair climbing variables. Statistical significance for this hypothesis is likely to differ between the choice of physical disability used in the main analysis.

METHOD

The analysis takes the form of a series of binary logistical regression models, with inferences drawn from the resulting coefficients and marginal effects. The first hypothesis states differences in risk preferences between the two genders play a role in the STEM gender gap. This is tested through regressing a 'female' dummy variable and a number of control variables against the binary variable 'STEM_Career', the model taking the following form:

$$\boldsymbol{STEM\ Career} = \beta_1 \boldsymbol{Age} + \beta_2\ \boldsymbol{Age\ Squared} + \beta_3 \boldsymbol{Female} + \beta_4 \boldsymbol{Degree} + \beta_5 \boldsymbol{Health} + \beta_6 \boldsymbol{White} + \boldsymbol{\varepsilon_i}$$

A second model is then conducted using the same specification as the initial regression, this time with the inclusion of the 'risk rating' variable. This second regression is modelled:

$$\boldsymbol{STEM\ Career} = \beta_1 \boldsymbol{Age} + \beta_2\ \boldsymbol{Age\ Squared} + \beta_3 \boldsymbol{Female} + \beta_4 \boldsymbol{Degree} + \beta_5 \boldsymbol{Health} + \beta_6 \boldsymbol{White} + \beta_7 \boldsymbol{Risk\ Rating} + \boldsymbol{\varepsilon_i}$$

The magnitudes of the marginal effects for the female variable of both regressions are compared in an attempt to identify an effect. In this investigation the marginal effects are calculated as the slope at mean, the effect of a unit increase when all other variables are set at their mean value. A reduction in the marginal effects between the first and second models would imply part of the gender effect is being captured by the risk rating variable. This would provide support for the differences in risk preferences impacting the STEM gender gap. This two model process is then repeated with the 'Engineer career' and 'Science & Technology career' as the dependent variable, to allow comparison between the some of the occupations that comprise STEM. The impact of risk preferences may be more prevalent in certain occupations, for example as engineering has a reputation as one of the hardest subjects it could be the case that only those of the lowest levels of risk aversion may be willing to undertake it.

The second hypothesis explores whether differences in risk aversion preferences between ethnic groups play a role in the ethnic STEM participation gaps. Structurally similar to the first hypothesis, an initial regression excluding the risk rating variable is conducted and followed by a model with its inclusion. The initial regression takes the following form:

$$\boldsymbol{STEM\ Career} = \beta_1 \boldsymbol{Age} + \beta_2\ \boldsymbol{Age\ Squared} + \beta_3 \boldsymbol{Female} + \beta_4 \boldsymbol{Degree} + \beta_5 \boldsymbol{Health} + \beta_6 \boldsymbol{Black} + \beta_7 \boldsymbol{Chinese} + \beta_8 \boldsymbol{Indian} + \beta_9 \boldsymbol{Pakistani} + \beta_{10} \boldsymbol{Arab} + \boldsymbol{\varepsilon_i}$$

The second regression is structured as follows:

$$\boldsymbol{STEM\ Career} = \beta_1 \boldsymbol{Age} + \beta_2\ \boldsymbol{Age\ Squared} + \beta_3 \boldsymbol{Female} + \beta_4 \boldsymbol{Degree} + \beta_5 \boldsymbol{Health} + \beta_6 \boldsymbol{Black} + \beta_7 \boldsymbol{Chinese} + \beta_8 \boldsymbol{Indian} + \beta_9 \boldsymbol{Pakistani} + \beta_{10} \boldsymbol{Arab} + \beta_{11} \boldsymbol{Risk\ Rating} + \boldsymbol{\varepsilon_i}$$

The coefficient of each ethnic group between the models is compared to identify whether risk preferences impact the probability of STEM occupation uptake. The benchmark was respondents of a white, mixed and the ethnic groups not included as variables in the model, meaning the coefficients would indicate each ethnic group’s likelihood of STEM participation in relation to this benchmark. This is repeated for Engineering and Science & Technology to allow comparisons.

As an expansion on the topic of ethnicity, the third hypothesis explores whether controlling for religion significantly diminishing the explanatory power of the ethnic group variables. The two regression analysis format is used again, expanding on the second hypothesis’s model specification. The three religious variables will be separately added to the model and impact of each on the ethnic group variables will be observed. A reduction in an ethnic variable’s coefficient or marginal effects would imply part of the explanatory power is captured by the religious variable. An example of the comparative regression output model can be found below:

$$\boldsymbol{STEM\ Career = \beta_1 Age +\ \beta_2\ Age\ Squared +\ \beta_3 Female +\ \beta_4 Degree +\ \beta_5 Health +\ \beta_6 Black + \beta_7 Chinese +\ \beta_8 Indian + \beta_9 Pakistani + \beta_{10} Arab + \beta_{11} Risk\ Rating + \beta_{12}\ Religion\ Weekly\ Attendence\ + \varepsilon_i}$$

The two dummy variables indicating the difference religion makes to the respondent's life are included in the same model, as they are sourced from the same question in the survey. The structure of this model is as follows:

$$\boldsymbol{STEM\ Career = \beta_1 Age +\ \beta_2\ Age\ Squared +\ \beta_3 Female +\ \beta_4 Degree +\ \beta_5 Health +\ \beta_6 Black + \beta_7 Chinese +\ \beta_8 Indian + \beta_9 Pakistani + \beta_{10} Arab + \beta_{11} Risk\ Rating +\ \beta_{12} Religion\ GDTL + \beta_{13}\ Religion\ SDTL + \varepsilon_i}$$

The final hypothesis will be testing using the same regression structure, with the inclusion of one of the physically disabled proxy variables. This coefficient will then by observed as the risk aversion measure is later included, any changes the coefficient will undertake will provide an indication of the role of risk aversion on a physically disabled individual's likelihood of entering a STEM career. The initial regressions are structured as follows:

$$\boldsymbol{STEM\ Career = \beta_1 Age +\ \beta_2\ Age\ Squared +\ \beta_3 Female +\ \beta_4 Degree +\ \beta_6 White + \beta_7 Mobility +\ \varepsilon_i}$$

The second model takes the form:

$$\boldsymbol{STEM\ Career = \beta_1 Age +\ \beta_2\ Age\ Squared +\ \beta_3 Female +\ \beta_4 Degree +\ \beta_6 White + \beta_7 Mobility + \beta_8 Risk\ Rating +\ \varepsilon_i}$$

The potential existence of reverse causality is explored in an additional set of regressions, as a form of robustness check. Reverse causality in this case would imply an individual's risk preference shifting as an outcome of entering into the STEM occupation. For example, entering a secure or high paying STEM job could induce an individual to become generally more risk taking as their financial security is improved. Conversely after undertaking the risk to enter such employment an individual may be less willing to endure further uncertainty and become more averse. The research by Buser *et al.* (2014) mentioned earlier in this paper addresses this problem by analysing choices in career direction in secondary school students, far before any influence of employment can take effect. The results of this paper found even in this early stage of education, differences in risk preferences between gender is seen to impact career choice. The reverse causality regressions of this paper will hopefully support these findings, to increase confidence in the rejection of reverse causality problems.

The set first of regressions aim to limit the potential risk preference change of career uptake, by analysing individuals at the beginning of their career. The three regressions of the first hypothesis will be repeated while restricting the ages in the sample between 20 and 24 in an attempt to isolate individuals who are in their first or second place of employment. If the results from these additional regressions are similar to the initial findings this would suggest the reverse causality of occupation on risk preference is not present. However, if there are significant disparities between results this could indicate Individual risk preferences are being influenced by their career in the longer term. The results from the age restricted models will be presented alongside the first hypothesis results to allow for comparison.

Appendix B presents four histograms that allow the comparison of the risk ratings of STEM and Non-STEM workers between this age restricted sample and the sample of the main analysis. Between the two samples the histograms indicate the same general trend, with a higher average risk rating in STEM occupations found for both. The average ratings are around one rating point unit higher in the age restricted sample compared to their counterparts in the unrestricted sample, at face value suggesting younger respondents have higher willingness to undertake risk. The differences in shape which do occur are likely explained by the different size of each sample. In the specified age range only 2078 individuals were employed, of which only 140 were in a STEM related occupation.

The second robustness check will focus on the career self-selection of full time students, related to their risk preference. The individuals identified as full time students in the first wave (2009 to 2010) of the understanding society dataset will be tracked into the later fifth wave five of the dataset (2013 to 2014), to observe which occupations the students selected into. The three or four-year time difference should allow most of the full time students to complete their studies and enter the workforce and for the interview process to capture their career direction. A variable indicating their risk rating in the first wave will be utilised and the relationship between the risk rating and occupation sector selection will be observed, focusing whether those of with low levels of risk aversion were significantly more likely to enter a STEM job. The occupation classification code used in the main analysis was not available in the later wave dataset, so ‘Current job: SOC 2000, condensed’ was utilised instead. These new groupings for STEM, Engineering and Science and Technology can be found under **Appendix C**. The results from the second robustness check will appear after the main analysis in the results section.

RESULTS

Before the main analysis is undertaken two tests were conducted to explore whether the dataset could reproduce a number of established relationships from past risk related literature. A number of studies including Bellante & Link (1981) and Pfeifer (2008) found individuals who enter a career in the public sector are more risk averse than those who enter the private, having preference of job security at the cost of higher but riskier wages. Using the German Socioeconomic Panel Survey Pfeifer (2008) estimated the probability of being employed in the public sector conditional on individual risk aversion while controlling for age, gender and education. Risk aversion was included as two eleven-point scale ratings for willingness to undertake risk, one indicating career risk and the other general risk. Career risk was found to be significantly correlated to entering the public sector significant to the 1% level, while General risk taking was found to be statistically insignificant.

Table Six: Public Sector Regression Results

Dependent: Public Sector Employment			
	B Coefficient	**Marginal Effect**	**Std. Error**
Intercept	-4.66029		0.194***
Age	0.13327	0.02579	0.008***
Age Squared	-0.00135	-0.00026	0.000***
Female	0.92590	0.17567	0.033***
Degree	0.74273	0.15269	0.034***
Health	0.03704	0.00717	0.016**
Ethnic White	0.01743	0.00336	0.044
Risk Rating	-0.04055	-0.00785	0.006***
McFadden R-squared	0.069392	* Significant at the 10% level	
Schwarz criterion	24363.17	** Significant at the 5% Level	
		*** Significant at the 1% Level	

The public sector variable used in this regression excludes those in the armed forces. It is assumed the risk preferences of those enlisted in the forces differ from the typical local government job, due to the extreme contrast of the dangers involved. Emergency services would also have been removed if possible for the same reason, as these occupations have unique aspects with no real counterpart in the private sector. Career risk was not available within the understanding society dataset, so the model was reproduced with only a risk variable comparable to Pfeifer's (2008) general risk. The risk rating coefficient was significant to the one percent level with a negative coefficient. The marginal effect implies the probability of entering the public sector falls by less than a percent as the willingness to undertake risk rating increases by a unit, holding all other variables at their average. It is likely the risk rating variable in this model is capturing both the effects of career risk and general risk, meaning if the effects were separated general risk may also become insignificant as seen in Pfeifer's (2008) work. Another result highlighted by Pfeifer was a significant and positive effect on the probability of entering the public sector for females, which is also supported in this model.

Table Seven: Female Financial Sector Regression Results

Dependent: Financial Sector Employment			
	B Coefficient	**Marginal Effect**	**Std. Error**
Intercept	-4.96259		0.467***
Age	0.08454	0.00495	0.022***
Age Squared	-0.00105	-0.00006	0.000***
Degree	0.37423	0.02346	0.081***
Health	0.12204	0.00714	0.039***
Ethnic White	0.09847	0.00559	0.111
Risk Rating	0.01113	0.00065	0.015
McFadden R-squared	0.011142	* Significant at the 10% level	
Schwarz criterion	5464.126	** Significant at the 5% Level	
		*** Significant at the 1% Level	

The finding from Adams & Ragunathan (2015) that women who enter a career in finance differ in their risk preferences to those who do not is also explored. This is achieved by restricting the sample to females only and regressing a dummy variable for employment in the financial sector against the risk rating measure. The resulting coefficient implies the probability of entering a financial occupation increases the higher an individual rates their willingness to undertake risk. The coefficient is insignificant; however, the direction of the effect follows the expectation. The previous relationships of economic interest were able to be identified within the sample, though with varying statistical significance. This may indicate the sample is somewhat representational of the wider economy.

HYPOTHESIS ONE

The first set of regressions of the main analysis aim to explore whether risk aversion plays a role in explaining the gender gap in STEM uptake. The hypothesised effect is a reduction in magnitude of the female variables once risk is included, signifying that differences in risk aversion between males and females contribute to the gap in STEM uptake probability between the genders.

Table Seven: Hypothesis One STEM Career Regression Results

Dependent Variable: STEM Career Employment						
	Initial Model			**Second Model**		
	B Coefficient	**Marginal Effect**	**Std. Error**	**B Coefficient**	**Marginal Effect**	**Std. Error**
Intercept	-3.94405		0.236***	-4.02294		0.262***
Age	0.09238	0.00707	0.011***	0.09664	0.00755	0.012***
Age Squared	-0.00110	-0.00008	0.000***	-0.00115	-0.00009	0.000***
Female	-1.71262	-0.14412	0.048***	-1.70677	-0.14780	0.052***
Degree	0.82079	0.07292	0.042***	0.78207	0.07025	0.045***
Health	0.02295	0.00176	0.021	0.03619	0.00283	0.023
Ethnic White	0.42791	0.02939	0.054***	0.32895	0.02346	0.062***
Risk Rating				0.01286	0.00101	0.009
McFadden R-squared	0.108581	* Significant at the 10% level		0.108594	* Significant at the 10% level	
Schwarz criterion	16263.6	** Significant at the 5% Level		14062.28	** Significant at the 5% Level	
		*** Significant at the 1% Level			*** Significant at the 1% Level	

Above is the tabled results for the STEM career model regression, the full results for the Engineering and Science & Technology regressions can be found under **Appendix D.** The 'age' and 'age squared' coefficients indicate the probability of entering a STEM related job increases with age, with a diminishing effect. The same effects were found by Albert & Duffy (2012) in their investigation of risk preferences and age. Due to the establishment of importance of higher education found in the literature, it is unsurprising that the attainment of a degree level education or higher increases the probability of employment within the STEM industry, maintaining a one percent level of significance throughout all regressions.

The sign of the coefficient for the health rating variable is changeable between occupational groups, with higher health rating correlating with a higher chance of employment in STEM as a whole and engineering. A higher health rating appears to decrease the probability of employment in Science & Technology, however the effect is shown to be highly statically insignificant. The final control variable, signalling an individual is of white ethnicity, is significant and positive for STEM as whole and engineering. This 'Ethnic White' variable has no statistical significance within Science & Technology, suggesting differences in ethnicity have a less prominent role in selection in such occupations.

The tables below show the coefficients, marginal effects and standard errors for the female variable in the initial and second models for the three career specification models. **Table Nine** shows the results of when the sample has been restricted to the ages of twenty through twenty-four, as part of the investigation into concerns of reverse causality.

Table Eight: Hypothesis One Regression Results Summary

		STEM	Engineer	Science & Tech
Female (Initial)	Coefficient	-1.71262	-2.40328	-0.87792
	M. Effects	-0.14412	-0.11842	-0.01947
	Std.Error	0.048***	0.076***	0.082***
Female (Risk Inclusion)	Coefficient	-1.70677	-2.36088	-0.91044
	M. Effects	-0.14780	-0.12076	-0.02043
	Std.Error	0.052***	0.081***	0.089***
Risk Rating	Coefficient	0.01286	0.02235	-0.03424
	M. Effects	0.00101	0.00091	-0.00072
	Std.Error	0.009	0.011**	0.017**

Table Nine: Hypothesis One Regression Results Summary - Age Restricted Specification

Age Restricted: 20 to 24				
		STEM	**Engineer**	**Science & Tech**
Female (Initial)	Coefficient	-1.89690	-3.18581	-0.83979
	M. Effects	-0.08674	-0.07298	-0.01216
	Std.Error	0.252***	0.514***	0.383**
Female (Risk Inclusion)	Coefficient	-1.80278	-3.05755	-0.73429
	M. Effects	-0.08977	-0.07880	-0.01160
	Std.Error	0.261***	0.508***	0.403*
Risk Rating	Coefficient	0.01723	-0.00531	0.02326
	M. Effects	0.00074	-0.00009	0.00035
	Std.Error	0.046	0.056	0.086

The impact of an individual's risk preferences appears sporadic within this first collection of regressions. The probability of employment in engineering is implied to increase as the willingness to undertake risk rises, significant to at least the five percent level. Contrastingly the risk rating coefficient for Science & Technology suggests decreasing risk aversion negatively impacts the probability of selection into these occupations. For the grouping of all STEM occupations combined, risk rating does not appear to have a statistically significant correlation. Looking at the two contrasting effects from two of STEM's sub groupings, the lack of significance could be the result of positive and negative effects of individual occupations within STEM negating each other out, to reduce the observed overall impact. The marginal effects of risk preference appear small, with unit increases in the risk rating changing the probabilities of career uptake by values of a tenth of a percent. When accounting for the eleven-point scale construction of the variable, the size of these effects would be barely noticeable compared to other factors such as gender. This could be interpreted as an individual's risk aversion having an occasionally statistically significant, although minor, impact on career self-selection in these sectors.

Observing the results from the initial models for each specification in **Table Eight**, marginal effect for STEM indicates being female reduces the probability of uptake by around fourteen percent, when holding all other variables at their mean. Engineering had a lower negative impact at an estimated eleven percent while Science & Technology's marginal effect was close to two percent. These results support the claim females are less likely to enter into STEM careers, with coefficients statistically significant to at least the one percent.

When comparing the female variable outputs between the initial and second models there is little evidence to support the hypothesised effect. The STEM and engineering models see a fall in the size of the coefficient, however this reduction is not found in the marginal effects which in fact increase by a small amount. Within Engineering the marginal effect of being female grows from an estimated probability decrease of 11.84% up to 12.07%, holding all other variables at their mean. Similar sized increases are found for STEM and Science & Technology. These changes do not indicate that the effect of the gender gap is being captured by the inclusion of risk preferences. Even if a reduction in the marginal effect was found in the STEM specification model, the lack of significance for the risk rating variable itself would not allow support for the hypothesis to be accepted with confidence. From these estimations, the practical implications of gender differences in risk aversion on the STEM labour market are unlikely to be of a noteworthy size. The changes in career uptake probabilities are of values of in the magnitudes of only tenths of a percentage.

AGE RESTRICTED MODEL

The age restricted results provided above in **Table Nine** allow comparison between entire sample and a smaller subset, aimed to capture individuals at the beginning of their career. For the results to indicate a lack of a reverse causality effect, the direction and magnitude of effects and the significance of variables should be similar. Due to the restrictions in place, the two age related control variables were excluded from these models. The full results tables can be found under **Appendix E**.

When comparing the two tables, the coefficients and marginal effects of the female variable are of similar magnitude and significance. The negative impact on the probability of entering these occupations holds within the smaller age range, although with a lower degree of significance for Science & Technology. The impact of the inclusion of risk on these values also falls in line with the original findings, with reductions in the coefficients but increases in the marginal effects. However, discrepancies are found when looking at the output from the risk rating variable. The STEM specification results are almost identical between the two samples. For both Engineering and Science & Technology, statistical significance is lost and the directions of effects reversed. As the willingness to undertake risk increases for an individual, the probability they enter an engineering occupation falls, contrary to expectations. As STEM as a whole sees no major differences, while the subgroups exhibit a minor reversal of the impact of risk, the findings of these regressions are inconclusive. Neither the existence or lack of reverse causality is strongly indicated. The topic is revisited later in the paper.

HYPOTHESIS TWO

The second hypothesis aims to examine whether risk preferences play a role in the differences in ethnic group STEM participation. Between the three dependent variables some significant correlations between career selection ethnicities do occur.

Table Ten: Hypothesis Two Regression Results Summary

		STEM	Engineer	Science &Tech
Ethnic Black (Initial)	Coefficient	-0.56425	-0.68563	-0.24331
	M. Effects	-0.03516	-0.02092	-0.00460
	Std.Error	0.111***	0.147***	0.194
Ethnic Black (Risk Inclusion)	Coefficient	-0.53337	-0.64867	-0.28334
	M. Effects	-0.03414	-0.02049	-0.00528
	Std.Error	0.126***	0.168***	0.225
Ethnic Chinese (Initial)	Coefficient	0.21789	-0.95022	0.87497
	M. Effects	0.01827	-0.02531	0.02833
	Std.Error	0.211	0.400**	0.265***
Ethnic Chinese (Risk Inclusion)	Coefficient	0.32212	-0.98418	0.90730
	M. Effects	0.02870	-0.02650	0.03000
	Std.Error	0.235	0.464**	0.296***
Ethnic Indian (Initial)	Coefficient	0.02762	-0.20899	0.24670
	M. Effects	0.00214	-0.00766	0.00577
	Std.Error	0.089	0.117*	0.148*
Ethnic Indian (Risk Inclusion)	Coefficient	0.10297	-0.09333	0.22424
	M. Effects	0.00836	-0.00368	0.00522
	Std.Error	0.101	0.131	0.169
Ethnic Pakistani (Initial)	Coefficient	-0.70379	-0.84097	-0.54679
	M. Effects	-0.04102	-0.02371	-0.00902
	Std.Error	0.145***	0.190***	0.284*
Ethnic Pakistani (Risk Inclusion)	Coefficient	-0.68122	-0.86149	-0.40598
	M. Effects	-0.04070	-0.02460	-0.00713
	Std.Error	0.175***	0.235***	0.311
Ethnic Arab (Initial)	Coefficient	-0.21511	-0.98752	0.31514
	M. Effects	-0.01509	-0.02581	0.00770
	Std.Error	0.358	0.591*	0.519
Ethnic Arab (Risk Inclusion)	Coefficient	-0.04993	-0.71655	0.55668
	M. Effects	-0.00382	-0.02145	0.01542
	Std.Error	0.389	0.606	0.526
Risk Rating	Coefficient	0.01475	0.02462	-0.03322
	M. Effects	0.00115	0.00101	-0.00070
	Std.Error	0.009	0.011**	0.017**

Identifying as a member of the Black or Pakistani ethnicity appears to have a significant and negative impact on the probability of selection into STEM a whole. The number of significant ethnicities increases to include Chinese, Indian and Arab within the Engineering career model, all with lower levels of statistical significance and a negative coefficient. In the Science & Technology specification those of a Chinese background have a significant and positive coefficient, those of Indian descent also have a positive coefficient at a lower level of significance. The marginal effects for all significant ethnicities varies between around five and one percent, when all other variables are held at their mean. As also seen in the first hypothesis, the risk rating variable lacks statistical significance in the STEM grouping model, while having a significant positive and negative correlation for Engineering and Science & Technology respectively.

When risk is controlled for in the STEM model, a reduction in the magnitude of the marginal effects is found in the two significant ethnicities, Black and Pakistani. When risk is included the estimated marginal effect of being of Black ethnicity drops from -3.516% down to -3.414%, holding all over variables at their mean. Being of Pakistani descent sees a similar minor reduction. However, as the risk variable itself lacks significance in this model, the identification of the hypothesised risk capturing effect cannot be claimed with confidence.

In the Engineering models a reduction in marginal effects is found for three ethnicities. The introduction of risk causes the marginal effect of being Indian is cut in half from -0.00766 to -0.00368 and the loss of its statistical significance. Similarly, being of Black or Arab heritage sees a slight reduction in the marginal effects. Taken alone these results would support the hypothesis. However, this trend is not consistent throughout the significant ethnicities, as the Pakistani variable sees a small increase in its marginal effect when risk is included. Science & Technology sees small reductions in the marginal effects for its Indian and Pakistani variables, however an increase in the Chinese ethnic impact once risk has been introduced to the model.

The results from this second hypothesis imply the role of risk in differences in career selections between ethnic groups cannot be generalised. Differing directions, magnitudes and significances of effects are found even in the limited selection of ethnicities used in this sample. When risk is found to have an impact, the change in values are a matter of tenth of percentages in the probability of career uptake. These results provide some evidence of risk potentially capturing some of the effects of ethnicity, but the impacts of which are negligible and unlikely to be of practical economic relevance. These findings suggest risk preferences do not underpin the STEM ethnicity gap as strongly as other factors. Differences in ethnicity participation may be better explained through differences in other factors such as education. The complete results tables for hypothesis two can be found under **Appendix F**.

HYPOTHESIS THREE

The third hypothesis aims to explore whether career self-selection effects attributed to an individual's ethnicity is reduced when religious faith is controlled. As seen on the full results table found under **Appendix G**, three variables indicating religious faith have a negative impact on the probability of entering STEM employment, significant to the one percent level. When religion has a 'great difference to life' the difference in STEM participation is significantly different from the benchmark of religion having little or no difference to life. In the same model indicating that religion has 'some' difference was found not significantly different from the benchmark. This suggests individuals who identify as having strong religious belief are less likely to enter all the specified occupations by a value between one and three percent, when all other variables are at their mean.

Table Eleven: Hypothesis Three Regression Results Summary

		Initial	Weekly R. Attend	Monthly R. Attend	Religion Difference to Life
Ethnic Black	Coefficient	-0.53337	-0.41038	-0.413	-0.37440
	M. Effects	-0.03414	-0.02736	-0.028	-0.02529
	Std.Error	0.126***	0.127***	0.128***	0.129***
Ethnic Chinese	Coefficient	0.32212	0.31883	0.307	0.28954
	M. Effects	0.02870	0.02825	0.027	0.02535
	Std.Error	0.235	0.235	0.235	0.238
Ethnic Indian	Coefficient	0.10297	0.17316	0.196	0.19057
	M. Effects	0.00836	0.01439	0.016	0.01594
	Std.Error	0.101	0.102*	0.104*	0.103*
Ethnic Pakistani	Coefficient	-0.68122	-0.48831	-0.521	-0.48714
	M. Effects	-0.04070	-0.03129	-0.033	-0.03123
	Std.Error	0.175***	0.178***	0.178***	0.179***
Ethnic Arab	Coefficient	-0.04993	0.07938	0.053	0.06844
	M. Effects	-0.00382	0.00638	0.004	0.00547
	Std.Error	0.389	0.384	0.385	0.387

In the table above the 'Initial' column states the model output before any religious variables are included. The dependent variable in all regressions was 'STEM_Career'. A repeat of the analysis for Engineering and Science & Technology was judged to be unnecessary, as the hypothesis does not directly link to the risk preference focus of the paper.

When religious belief is controlled, the Indian variable becomes statically significant to the ten percent level, while almost doubling the initial positive marginal effect of 0.8%. This may suggest those of strong religious faith in the Indian community were reducing the average Indian STEM participation rate. The inclusion of the religious variables makes little difference to the ethnicities repeatedly observed to have no statistical significance in STEM career uptake. Black and Pakistani variables see reductions in their estimated marginal effects by around a percent in all three models inclusive of faith. As the variables themselves are significant these findings may indicate support for the hypothesized capturing effect, implying the STEM gap for these two ethnicities can be partly explained by their religious characteristics.

These findings support Bartke & Schwarze's (2008) conclusion that the explanatory power of nationality, as opposed to the similar characteristic of ethnicity in this paper, on risk preferences diminishes as a number of socio-economic characteristics are included. They identified religion as having the greatest negative impact on nationality's explanatory power.

HYPOTHESIS FOUR

The fourth and final hypothesis explored the interaction between physical disability and individual's risk preferences on career self-selection. Based on a general consensus in the literature that differences in risk preferences between physically disabled and non-disabled were not significant enough to be of interest, it was hypothesis no interaction would be found in the sample. Those who identify as being afflicted with a physical disability issues are unlikely to be severely beset, as the sample is restricted to those in employment. Cases of severe disability may prevent the undertaking of work. There may be correlation between severity of disability and risk preferences, however it cannot be measured robustly in this analysis.

Table Twelve: Hypothesis Four Regression Results Summary

		STEM	Engineer	Science & Tech
Mobility Issues (Initial)	Coefficient	-0.20483	-0.38598	0.31455
	M. Effects	-0.01451	-0.01304	0.00761
	Std.Error	0.108*	0.139***	0.182*
Mobility Issues (Risk Inclusion)	Coefficient	-0.27350	-0.44829	0.22048
	M. Effects	-0.01930	-0.01526	0.00514
	Std.Error	0.118**	0.152***	0.201
Risk Rating	Coefficient	0.01359	0.02319	-0.03566
	M. Effects	0.00106	0.00094	-0.00075
	Std.Error	0.009	0.011**	0.017**
Stairs_Limited_A_lot (Initial)	Coefficient	-0.44081	-0.52904	0.17552
	M. Effects	-0.02840	-0.01675	0.00401
	Std.Error	0.169***	0.217**	0.269
Stairs_Limited_A_lot (Risk Inclusion)	Coefficient	-0.43352	-0.57972	0.31138
	M. Effects	-0.02863	-0.01856	0.00761
	Std.Error	0.180**	0.236**	0.271
Risk Rating	Coefficient	0.01376	0.02363	-0.03587
	M. Effects	0.00107	0.00096	-0.00076
	Std.Error	0.009	0.011**	0.017**
Stairs_Limited_Yes (Initial)	Coefficient	-0.18115	-0.21247	-0.02105
	M. Effects	-0.01310	-0.00782	-0.00044
	Std.Error	0.074**	0.093**	0.139
Stairs_Limited_Yes (Risk Inclusion)	Coefficient	-0.23191	-0.25122	-0.04299
	M. Effects	-0.01686	-0.00941	-0.00090
	Std.Error	0.081***	0.101**	0.149
Risk Rating	Coefficient	0.01293	0.02272	-0.03623
	M. Effects	0.00101	0.00093	-0.00077
	Std.Error	0.009	0.011**	0.017**

The table above provides a summary of the findings; the full results tables can be found under **Appendix H**. Continuing the trend found in the earlier hypothesises, the STEM career risk rating variable was not found statistically significant, while a small positive effect was found for Engineering and a small negative in Science & Technology.

For the STEM and Engineering model specifications all three disability variables had significant and negative impacts on the probability of uptake, to at least the ten percent level. The interpretation of the estimated marginal effects reveal the affliction of a physical disability reduces the likelihood of career selection by an estimated one to three percent, holding all other variables at their mean. Under the Science and Technology model only one regression of the six provided a significant correlation between disability and selection into such occupations. This regression had a positive marginal effect which suggests the impact of mobility issues reduces the likelihood of entering these jobs by 0.02 percent, when all other variables are held at their mean. This implies having a physical disability does not impact the probability of working in Science and Technology compared to no disability, with the small significant effect found to be relatively inconsequential.

The impact on the marginal effects when the risk rating variable was introduced into the model was a small increase in magnitude for all regressions, regardless of occupation specification. From these results the hypothesis that risk aversion plays little or no role on a disabled individual's selection into a STEM career is supported.

REVERSE CAUSALITY

The previous set of regressions aimed to address concerns regarding reverse causality, by limiting the dataset to those between the ages twenty and twenty-four, was inconclusive. The following three regressions aimed to capture the direction of career choice of students and whether an individual's risk rating played a significant role.

Table Thirteen: Student's Career Direction Results

Dependent Variable: STEM Career Employment						
	Initial Model			Second Model		
	B Coefficient	Marginal Effect	Std. Error	B Coefficient	Marginal Effect	Std. Error
Intercept	-3.15621		0.223***	-2.79362		0.366***
Female	-1.82829	-0.04775	0.281***	-1.72339	-0.04685	0.290***
Ethnic White	0.57898	0.01213	0.251**	0.74982	0.01571	0.295**
Religion GDTL	0.06812	0.00150	0.274	0.16986	0.00400	0.305
Risk Rating				-0.08173	-0.00184	0.043*
McFadden R-squared	0.074927	* Significant at the 10% level		0.0749	* Significant at the 10% level	
Schwarz criterion	792.6078	** Significant at the 5% Level *** Significant at the 1% Level		690.248	** Significant at the 5% Level *** Significant at the 1% Level	

Table Fourteen: Student's Career Direction Results

Dependent Variable: Engineer Career Employment						
	Initial Model			**Second Model**		
	B Coefficient	**Marginal Effect**	**Std. Error**	**B Coefficient**	**Marginal Effect**	**Std. Error**
Intercept	-4.11274		0.333***	-3.36907		0.584***
Female	-2.19078	-0.01789	0.538***	-2.17968	-0.02021	0.546***
Ethnic White	0.59167	0.00356	0.368	0.42403	0.00280	0.388
Religion GDTL	-0.45356	-0.00256	0.457	-0.64756	-0.00388	0.516
Risk Rating				-0.07864	-0.00054	0.064
McFadden R-squared	0.082881	* Significant at the 10% level		0.086078	* Significant at the 10% level	
Schwarz criterion	354.6333	** Significant at the 5% Level		334.6177	** Significant at the 5% Level	
		*** Significant at the 1% Level			*** Significant at the 1% Level	

Table Fifteen: Student's Career Direction Results

Dependent Variable: Science and Technology Career Employment						
	Initial Model			**Second Model**		
	B Coefficient	**Marginal Effect**	**Std. Error**	**B Coefficient**	**Marginal Effect**	**Std. Error**
Intercept	-3.92059		0.330***	-3.83625		0.545***
Female	-2.60351	-0.02929	0.525***	-2.40484	-0.02467	0.542***
Ethnic White	0.66693	0.00507	0.343*	1.12626	0.00748	0.421***
Religion GDTL	0.41950	0.00369	0.359	0.75625	0.00683	0.393*
Risk Rating				-0.10114	-0.00074	0.067
McFadden R-squared	0.101329	* Significant at the 10% level		0.107801	* Significant at the 10% level	
Schwarz criterion	463.6942	** Significant at the 5% Level		373.5189	** Significant at the 5% Level	
		*** Significant at the 1% Level			*** Significant at the 1% Level	

Due to the restrictions of the model a number of control variables used in previous regressions are unusable, namely the attainment of a degree and the two age related measures. As religious belief was found to have an impact of career selection earlier in the analysis it was introduced into these models. Within the 2009 to 2010 wave of the dataset only 3824 respondents are identified as full time students. When the sample is restricted to those employed at the later wave and the inclusion of the other variables the final sample size is 2437, a reduction of over tenfold from the main analysis.

Interestingly the hypothesised effect from the first hypothesis is visible in **Table Thirteen**. Once the risk rating variable is included the impact of the female variable falls from 4.78% to 4.69%, while the risk rating variable holds small statistical significance. However, due to the significantly smaller sample size and reduction in control variables this result shouldn't take priority over the main analysis.

For an indication that reverse causality to not be present, the coefficients and marginal effects of the risk rating variables should conform to unrestricted sample results, ideally having the same sign and similar significance. In these regressions the risk rating variable appears only significant for STEM specification. Contrastingly in the previous models risk was not significant for STEM and only for the other two career specifications. For Science & Technology, risk has a negative coefficient and marginal effect, similar to the main analysis. However, the effect of risk has changed from a positive effect on the probability to enter STEM and engineering occupations to negative. Taken together noticeable differences in the impact of risk preference exist within this subsample compared to the main analysis. The change in the sign and significance between the models suggests the impact of risk preferences may change over time, possibly over the duration of an individual's career. Based on the results from the two restricted analysis's in this investigation reverse causality cannot be dismissed with confidence.

The attempts to address the possibility of reverse causality in this paper were used in conjunction with the findings from Buser *et al*. (2014). The model specification from Buser *et al*. allowed for the natural exclusion of the potential reverse causality of employment, the findings indicated reverse causality is not of major concern. This provides a stronger and more compelling indication than the regressions of this paper and should be held with higher regard.

CONCLUSION

The initial comparison of means conducted in this paper indicated higher levels of willingness to undertake risks for those employed in STEM related careers, compared to those employed elsewhere in the economy. Throughout the main analysis the correlations between risk preference and selection into STEM related occupations have been changeable, with fluctuating levels of statistical significance, however some reliable patterns have emerged. A positive correlation between the willingness to undertake risk and the probability of entering a career in Engineering can be found. The difficulty and reputation for difficulty of engineering degrees is a likely possible explanation. An unexpected correlation found was a negative association between the willingness to undertake risk and the uptake of careers classified as Science & Technology, no obvious explanations come to mind. When these two occupation classifications were combined with a few other professions to make the STEM career specification, a slight positive marginal effect of career uptake and risk was repeatedly observed. However, the risk rating variable utilised failed to achieve statistical significance throughout the testing. As speculated earlier in the paper, this finding could be a consequence of opposing positive and negative effects of risk combining to a smaller overall impact. It could also simply signify an overall lack of the importance of risk preference in an individual's choice of career within these industries. For the occasions when risk was a significant factor, for example selection into Engineering jobs, the size of the marginal effects on career uptake probability were in the magnitude of tenth of percentages. An effect of such a minor size which may be classed as negligible and not noteworthy in practical terms.

This investigation aimed to identify whether differences in risk preferences within socio-economic groups were a contributory factor for their gaps in participation. To observe whether the explanatory power of these characteristics included risk preference, the impact of the inclusion of a risk preference variable on the marginal effects was examined. A reduction in the marginal effect would indicate risk was partly capturing the explanatory power. Such reductions were only found in two occasions in the analysis. The investigation provides evidence to suggest risk preferences were a contributing factor for a subset of ethnicities namely Black and Pakistani. No evidence is found to support the hypothesis that differences in risk preferences between the two genders play a contributory role in the existence of the STEM participation gap between males and females. The lack of reductions in marginal effects also suggests potential risk preference differences between those with and without physical disability are not responsible for differences in STEM occupation uptake.

Further research on the topic could provide clearer insight into the role of risk. The utilisation of a greater number of risk preference measurements or risk in other contexts, such as those found in the German Socio-Economic Panel Survey, may better isolate the impact of risk aversion on career selection. The opposing correlations of risk between Science & Technology and Engineering found in this paper implies the impact of risk is not uniform within STEM. Further breakdowns of occupations than what was seen in this paper would be beneficial, with a reduced focus on treating STEM as a single group.

However, the results of this paper and the comparable analysis of Buser *et al.* (2014) imply only a minor impact of risk aversion on career uptake exists. Research into other factors responsible for STEM participation gaps may be more fruitful. A continued strong focus on education as well as other less obvious factors would likely make better candidates for future work. Examples include further expanding Buser *et al.*'s (2014) work on the differences in competitiveness on career selection. The gender gap in confidence of STEM subject ability identified by Pajares (2005) may be more deserving of potential research expansions than risk aversion.

The STEM labour shortage remains a growing concern, some form of government or organisational action is likely required to levitate the issue. Research in all relevant areas should contribute to identifying the best courses of action. The findings from this paper suggest the topic of risk aversion should not be a priority in terms of focus, but potentially useful insights could still be found within.

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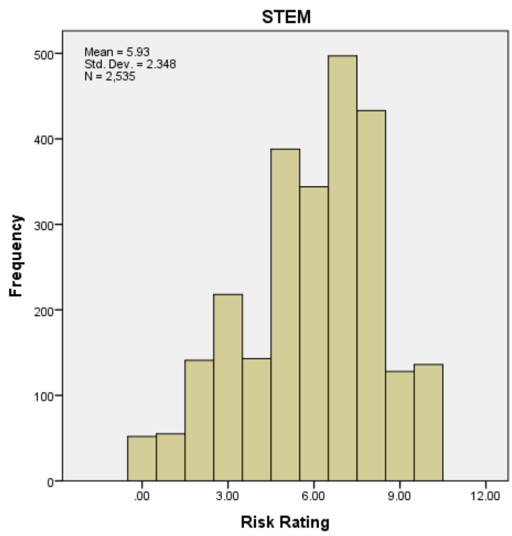
APPENDIX

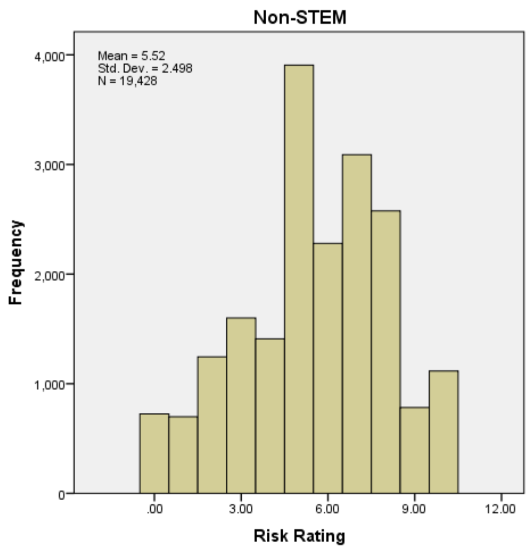
Appendix A: Occupation groupings for the Main Analysis

Science Technology Engineering Mathematics (STEM)	Engineering Career	Production managers in manufacturing, construction, mining and energy industries
		Engineers and technologists
		Architects and surveyors
		Metal machining, fitting and instrument making trades
		Electrical/electronic trades
		Draughtspersons, quantity surveyors and other surveyors
	Science and Technology	Computer analysts /programmers
		Natural scientists
		Scientific technicians
		Business and financial professionals
		Ship and aircraft officers, air traffic planners and controllers

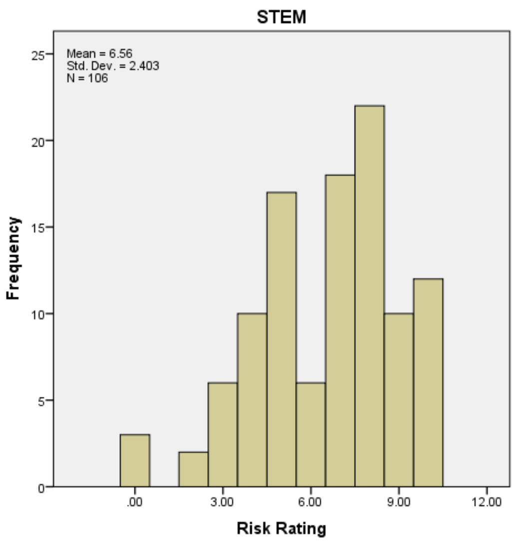
Appendix B: Histograms showing risk rating values between the main analysis sample and the sample restricted between the ages of 20 and 24

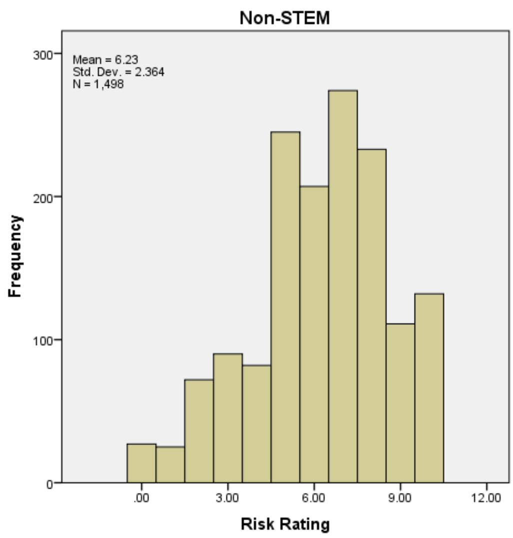
Main Analysis Sample with No Age Restrictions





Main Analysis Sample with Age Restriction between 20 and 24





Appendix C: Occupation Groupings for the Secondary Analysis

Science Technology Engineering Mathematics (STEM)	Engineering Career	Architects, town planners, surveyors Engineering professionals Draughtspersons and building inspectors Metal machining, fitting and instrument making trades Electrical trades
	(In Both)	Science and engineering technicians
	Science and Technology	Research professionals Science professionals It service delivery occupations Information and communication technology professionals Administrative occupations: communications
		Business and finance associate professionals Business and statistical professionals

Appendix D: Full results tables for Hypothesis One

Dependent Variable: Engineering Career Employment

	Initial Model			**Second Model**		
	B Coefficient	**Marginal Effect**	**Std. Error**	**B Coefficient**	**Marginal Effect**	**Std. Error**
Intercept	-4.76272		0.293***	-4.89714		0.325***
Age	0.10791	0.00427	0.013***	0.11092	0.00453	0.014***
Age Squared	-0.00125	-0.00005	0.000***	-0.00129	-0.00005	0.000***
Female	-2.40328	-0.11842	0.076***	-2.36088	-0.12076	0.081***
Degree	0.37876	0.01615	0.053***	0.32231	0.01400	0.057***
Health	0.02447	0.00097	0.025	0.04664	0.00190	0.027*
Ethnic White	0.67890	0.02242	0.072***	0.56455	0.01950	0.082***
Risk Rating				0.02235	0.00091	0.011**
McFadden R-squared Schwarz criterion	0.132644 11635.94	* Significant at the 10% level ** Significant at the 5% Level *** Significant at the 1% Level		0.131571 10083.77	* Significant at the 10% level ** Significant at the 5% Level *** Significant at the 1% Level	

Dependent Variable: Science and Technology Career Employment

	Initial Model			**Second Model**		
	B Coefficient	**Marginal Effect**	**Std. Error**	**B Coefficient**	**Marginal Effect**	**Std. Error**
Intercept	-4.14586		0.437***	-3.73882		0.474***
Age	0.04265	0.00090	0.021**	0.03878	0.00082	0.022*
Age Squared	-0.00068	-0.00001	0.000***	-0.00065	-0.00001	0.000**
Female	-0.87792	-0.01947	0.082***	-0.91044	-0.02043	0.089***
Degree	1.18441	0.03289	0.080***	1.21058	0.03385	0.087***
Health	-0.04332	-0.00091	0.041	-0.06198	-0.00131	0.044
Ethnic White	0.11299	0.00230	0.095	0.07977	0.00164	0.107
Risk Rating				-0.03424	-0.00072	0.017**
McFadden R-squared Schwarz criterion	0.059587 6038.683	* Significant at the 10% level ** Significant at the 5% Level *** Significant at the 1% Level		0.061791 5215.628	* Significant at the 10% level ** Significant at the 5% Level *** Significant at the 1% Level	

Appendix E: Full results tables for the aged restricted Hypothesis One repeat

Dependent Variable: STEM Career Employment						
	Initial Model			Second Model		
	B Coefficient	Marginal Effect	Std. Error	B Coefficient	Marginal Effect	Std. Error
Intercept	-3.48448		0.512***	-3.24246		0.586***
Female	-1.89690	-0.08674	0.252***	-1.80278	-0.08977	0.261***
Degree	1.00055	0.05024	0.207***	0.87973	0.04705	0.219***
Health	0.12895	0.00502	0.116	0.10672	0.00457	0.120
Ethnic White	0.77996	0.02562	0.259***	0.54722	0.02060	0.267**
Risk Rating				0.01723	0.00074	0.046
McFadden R-squared	0.116608	* Significant at the 10% level		0.103567	* Significant at the 10% level	
Schwarz criterion	814.7541	** Significant at the 5% Level		744.2172	** Significant at the 5% Level	
		*** Significant at the 1% Level			*** Significant at the 1% Level	

Dependent Variable: Engineering Career Employment						
	Initial Model			Second Model		
	B Coefficient	Marginal Effect	Std. Error	B Coefficient	Marginal Effect	Std. Error
Intercept	-4.37632		0.630***	-3.79438		0.699***
Female	-3.18581	-0.07298	0.514***	-3.05755	-0.07880	0.508***
Degree	0.75464	0.01363	0.249***	0.61986	0.01245	0.264**
Health	0.24683	0.00364	0.138*	0.19356	0.00330	0.140
Ethnic White	1.00907	0.01196	0.332***	0.70911	0.01018	0.332**
Risk Rating				-0.00531	-0.00009	0.056
McFadden R-squared	0.169659	* Significant at the 10% level		0.155254	* Significant at the 10% level	
Schwarz criterion	575.5458	** Significant at the 5% Level		530.3027	** Significant at the 5% Level	
		*** Significant at the 1% Level			*** Significant at the 1% Level	

Dependent Variable: Science and Technology Career Employment						
	Initial Model			Second Model		
	B Coefficient	Marginal Effect	Std. Error	B Coefficient	Marginal Effect	Std. Error
Intercept	-3.75232		0.892***	-3.72035		1.075***
Female	-0.83979	-0.01216	0.383**	-0.73429	-0.01160	0.403*
Degree	1.30264	0.02601	0.405***	1.31183	0.02896	0.418***
Health	-0.15869	-0.00217	0.223	-0.15594	-0.00234	0.226
Ethnic White	0.27360	0.00349	0.458	0.08371	0.00123	0.460
Risk Rating				0.02326	0.00035	0.086
McFadden R-squared	0.0519	* Significant at the 10% level		0.050238	* Significant at the 10% level	
Schwarz criterion	333.0895	** Significant at the 5% Level		316.5307	** Significant at the 5% Level	
		*** Significant at the 1% Level			*** Significant at the 1% Level	

Appendix F: Full Results Tables for Hypothesis Two

Dependent Variable: STEM Career Employment						
	Initial Model			Second Model		
	B Coefficient	Marginal Effect	Std. Error	B Coefficient	Marginal Effect	Std. Error
Intercept	-3.60845		0.233***	-3.79090		0.259***
Age	0.09324	0.00715	0.011***	0.09818	0.00767	0.012***
Age Squared	-0.00109	-0.00008	0.000***	-0.00116	-0.00009	0.000***
Female	-1.69539	-0.14268	0.048***	-1.69480	-0.14648	0.052***
Degree	0.78418	0.06929	0.042***	0.75054	0.06696	0.046***
Health	0.02665	0.00204	0.021	0.04004	0.00313	0.023*
Ethnic Black	-0.56425	-0.03516	0.111***	-0.53337	-0.03414	0.126***
Ethnic Chinese	0.21789	0.01827	0.211	0.32212	0.02870	0.235
Ethnic Indian	0.02762	0.00214	0.089	0.10297	0.00836	0.101
Ethnic Pakistani	-0.70379	-0.04102	0.145***	-0.68122	-0.04070	0.175***
Ethnic Arab	-0.21511	-0.01509	0.358	-0.04993	-0.00382	0.389
Risk Rating				0.01475	0.00115	0.009
McFadden R-squared	0.108144	* Significant at the 10% level		0.109293	* Significant at the 10% level	
Schwarz criterion	16312.17	** Significant at the 5% Level		14091.29	** Significant at the 5% Level	
		*** Significant at the 1% Level			*** Significant at the 1% Level	

Dependent Variable: Engineering Career Employment						
	Initial Model			Second Model		
	B Coefficient	Marginal Effect	Std. Error	B Coefficient	Marginal Effect	Std. Error
Intercept	-4.15117		0.288***	-4.40802		0.333***
Age	0.10725	0.00429	0.013***	0.11129	0.00456	0.015***
Age Squared	-0.00123	-0.00005	0.000***	-0.00128	-0.00005	0.000***
Female	-2.38462	-0.11823	0.076***	-2.34834	-0.12025	0.081***
Degree	0.34747	0.01486	0.053***	0.29573	0.01282	0.058***
Health	0.02444	0.00098	0.025	0.04647	0.00190	0.028*
Ethnic Black	-0.68563	-0.02092	0.147***	-0.64867	-0.02049	0.168***
Ethnic Chinese	-0.95022	-0.02531	0.400**	-0.98418	-0.02650	0.464**
Ethnic Indian	-0.20899	-0.00766	0.117*	-0.09333	-0.00368	0.131
Ethnic Pakistani	-0.84097	-0.02371	0.190***	-0.86149	-0.02460	0.235***
Ethnic Arab	-0.98752	-0.02581	0.591*	-0.71655	-0.02145	0.606
Risk Rating				0.02462	0.00101	0.011**
McFadden R-squared	0.129791	* Significant at the 10% level		0.130571	* Significant at the 10% level	
Schwarz criterion	11714.59	** Significant at the 5% Level		10135.27	** Significant at the 5% Level	
		*** Significant at the 1% Level			*** Significant at the 1% Level	

Dependent Variable: Science and Technology Career Employment						
	Initial Model			Second Model		
	B Coefficient	Marginal Effect	Std. Error	B Coefficient	Marginal Effect	Std. Error
Intercept	-4.12491		0.427***	-3.75739		0.463***
Age	0.04428	0.00093	0.021**	0.04055	0.00085	0.022*
Age Squared	-0.00068	-0.00001	0.000***	-0.00066	-0.00001	0.000**
Female	-0.86686	-0.01910	0.083***	-0.89838	-0.02005	0.090***
Degree	1.14716	0.03136	0.080***	1.17608	0.03245	0.087***
Health	-0.03568	-0.00075	0.041	-0.05359	-0.00113	0.044
Ethnic Black	-0.24331	-0.00460	0.194	-0.28334	-0.00528	0.225
Ethnic Chinese	0.87497	0.02833	0.265***	0.90730	0.03000	0.296***
Ethnic Indian	0.24670	0.00577	0.148*	0.22424	0.00522	0.169
Ethnic Pakistani	-0.54679	-0.00902	0.284*	-0.40598	-0.00713	0.311
Ethnic Arab	0.31514	0.00770	0.519	0.55668	0.01542	0.526
Risk Rating				-0.03322	-0.00070	0.017**
McFadden R-squared	0.062257	* Significant at the 10% level		0.064294	* Significant at the 10% level	
Schwarz criterion	6062.238	** Significant at the 5% Level		5241.795	** Significant at the 5% Level	
		*** Significant at the 1% Level			*** Significant at the 1% Level	

Appendix G: Full Results Tables for Hypothesis Three

Dependent Variable: STEM Career Employment						
	Weekly Religious Attendance			Monthly Religious Attendance		
	B Coefficient	Marginal Effect	Std. Error	B Coefficient	Marginal Effect	Std. Error
Intercept	-3.76517		0.259***	-3.772		0.259***
Age	0.09777	0.00760	0.012***	0.098	0.008	0.012***
Age Squared	-0.00115	-0.00009	0.000***	-0.001	0.000	0.000***
Female	-1.69886	-0.14631	0.052***	-1.692	-0.146	0.052***
Degree	0.76852	0.06852	0.046***	0.772	0.069	0.046***
Health	0.04460	0.00347	0.023**	0.045	0.003	0.023**
Ethnic Black	-0.41038	-0.02736	0.127***	-0.413	-0.028	0.128***
Ethnic Chinese	0.31883	0.02825	0.235	0.307	0.027	0.235
Ethnic Indian	0.17316	0.01439	0.102*	0.196	0.016	0.104*
Ethnic Pakistani	-0.48831	-0.03129	0.178***	-0.521	-0.033	0.178***
Ethnic Arab	0.07938	0.00638	0.384	0.053	0.004	0.385
Risk Rating	0.01229	0.00096	0.009	0.013	0.001	0.009
Weekly R. Attend	-0.37919	-0.02626	0.075***			
Monthly R. Attend				-0.280	-0.02038	0.062***
McFadden R-squared	0.110963	* Significant at the 10% level		0.11061	* Significant at the 10% level	
Schwarz criterion	14070.16	** Significant at the 5% Level		14075.69	** Significant at the 5% Level	
		*** Significant at the 1% Level			*** significant at the 1% Level	

Dependent Variable: STEM Career Employment			
	Religion Difference to life		
	B Coefficient	Marginal Effect	Std. Error
Intercept	-3.75785		0.259***
Age	0.09726	0.00756	0.012***
Age Squared	-0.00114	-0.00009	0.000***
Female	-1.68722	-0.14514	0.052***
Degree	0.77306	0.06898	0.046***
Health	0.04341	0.00337	0.023*
Ethnic Black	-0.37440	-0.02529	0.129***
Ethnic Chinese	0.28954	0.02535	0.238
Ethnic Indian	0.19057	0.01594	0.103*
Ethnic Pakistani	-0.48714	-0.03123	0.179***
Ethnic Arab	0.06844	0.00547	0.387
Risk Rating	0.01361	0.00106	0.009
Religion GDTL	-0.35868	-0.02534	0.070***
Religion SDTL	-0.01400	-0.00108	0.057
McFadden R-squared	0.110979	* Significant at the 10% level	
Schwarz criterion	14067.85	** Significant at the 5% Level	
		*** Significant at the 1% Level	

Appendix H: Full Results Tables for Hypothesis Four

Dependent Variable: STEM Career Employment						
	Initial Model			Second Model		
	B Coefficient	Marginal Effect	Std. Error	B Coefficient	Marginal Effect	Std. Error
Intercept	-3.85446		0.235***	-3.88241		0.250***
Age	0.09209	0.00704	0.011***	0.09621	0.00751	0.012***
Age Squared	-0.00109	-0.00008	0.000***	-0.00114	-0.00009	0.000***
Female	-1.71033	-0.14372	0.049***	-1.70384	-0.14742	0.052***
Degree	0.82482	0.07327	0.042***	0.78796	0.07082	0.045***
Ethnic White	0.43225	0.02963	0.055***	0.33119	0.02359	0.062***
Mobility Issues	-0.20483	-0.01451	0.108*	-0.27350	-0.01930	0.118**
Risk Rating				0.01359	0.00106	0.009
McFadden R-squared	0.108717	* Significant at the 10% level		0.108799	* Significant at the 10% level	
Schwarz criterion	16264.99	** Significant at the 5% Level		14059.5	** Significant at the 5% Level	
		*** significant at the 1% Level			*** significant at the 1% Level	

Dependent Variable: Engineering Career Employment						
	Initial Model			Second Model		
	B Coefficient	Marginal Effect	Std. Error	B Coefficient	Marginal Effect	Std. Error
Intercept	-4.66275		0.276***	-4.71228		0.310***
Age	0.10743	0.00424	0.013***	0.11030	0.00449	0.014***
Age Squared	-0.00124	-0.00005	0.000***	-0.00128	-0.00005	0.000***
Female	-2.39991	-0.11785	0.076***	-2.35659	-0.12020	0.081***
Degree	0.37986	0.01616	0.052***	0.32823	0.01424	0.056***
Ethnic White	0.68424	0.02251	0.072***	0.56678	0.01952	0.082***
Mobility Issues	-0.38598	-0.01304	0.139***	-0.44829	-0.01526	0.152***
Risk Rating				0.02319	0.00094	0.011**
McFadden R-squared	0.133189	* Significant at the 10% level		0.132168	* Significant at the 10% level	
Schwarz criterion	11631	** Significant at the 5% Level		10077.16	** Significant at the 5% Level	
		*** significant at the 1% Level			*** significant at the 1% Level	

Dependent Variable: Science and Technology Career Employment						
	Initial Model			Second Model		
	B Coefficient	Marginal Effect	Std. Error	B Coefficient	Marginal Effect	Std. Error
Intercept	-4.31784		0.418***	-3.96227		0.457***
Age	0.04307	0.00091	0.021**	0.03887	0.00082	0.022*
Age Squared	-0.00068	-0.00001	0.000***	-0.00065	-0.00001	0.000**
Female	-0.88037	-0.01950	0.082***	-0.91265	-0.02050	0.089***
Degree	1.17857	0.03263	0.079***	1.19656	0.03337	0.086***
Ethnic White	0.10921	0.00223	0.095	0.07523	0.00155	0.107
Mobility Issues	0.31455	0.00761	0.182*	0.22048	0.00514	0.201
Risk Rating				-0.03566	-0.00075	0.017**
McFadden R-squared	0.059842	* Significant at the 10% level		0.061627	* Significant at the 10% level	
Schwarz criterion	6037.071	** Significant at the 5% Level		5216.471	** Significant at the 5% Level	
		*** significant at the 1% Level			*** significant at the 1% Level	

Dependent Variable: STEM Career Employment						
	Initial Model			Second Model		
	B Coefficient	Marginal Effect	Std. Error	B Coefficient	Marginal Effect	Std. Error
Intercept	-3.83776		0.223***	-3.87117		0.2450***
Age	0.09140	0.00699	0.011***	0.09556	0.00746	0.012***
Age Squared	-0.00108	-0.00008	0.000***	-0.00114	-0.00009	0.000***
Female	-1.70666	-0.14336	0.048***	-1.69975	-0.14695	0.052***
Degree	0.82275	0.07303	0.042***	0.78706	0.07069	0.045***
Ethnic White	0.42657	0.02927	0.054***	0.32888	0.02343	0.062***
Stairs Issues A Lot	-0.44081	-0.02840	0.169***	-0.43352	-0.02863	0.180**
Risk Rating				0.01376	0.00107	0.009
McFadden R-squared	0.108946	* Significant at the 10% level		0.108854	* Significant at the 10% level	
Schwarz criterion	16256.13	** Significant at the 5% Level		14057.32	** Significant at the 5% Level	
		*** significant at the 1% Level			*** significant at the 1% Level	

Dependent Variable: Engineering Career Employment						
	Initial Model			Second Model		
	B Coefficient	Marginal Effect	Std. Error	B Coefficient	Marginal Effect	Std. Error
Intercept	-4.64632		0.277***	-4.70055		0.311***
Age	0.10674	0.00422	0.013***	0.10951	0.00446	0.014***
Age Squared	-0.00124	-0.00005	0.000***	-0.00127	-0.00005	0.000***
Female	-2.39629	-0.11770	0.076***	-2.35176	-0.11988	0.081***
Degree	0.38020	0.01618	0.052***	0.32885	0.01427	0.056***
Ethnic White	0.67723	0.02233	0.072***	0.56368	0.01943	0.082***
Stairs Issues A Lot	-0.52904	-0.01675	0.217**	-0.57972	-0.01856	0.236**
Risk Rating				0.02363	0.00096	0.011**
McFadden R-squared	0.1331	* Significant at the 10% level		0.131959	* Significant at the 10% level	
Schwarz criterion	11629.33	** Significant at the 5% Level		10078.77	** Significant at the 5% Level	
		*** significant at the 1% Level			*** significant at the 1% Level	

Dependent Variable: Science and Technology Career Employment						
	Initial Model			**Second Model**		
	B Coefficient	**Marginal Effect**	**Std. Error**	**B Coefficient**	**Marginal Effect**	**Std. Error**
Intercept	-4.31854		0.418***	-3.97460		0.456***
Age	0.04319	0.00091	0.021**	0.03960	0.00084	0.022*
Age Squared	-0.00068	-0.00001	0.000***	-0.00065	-0.00001	0.000**
Female	-0.88039	-0.01954	0.082***	-0.91720	-0.02061	0.089***
Degree	1.17386	0.03252	0.079***	1.19704	0.03338	0.086
Ethnic White	0.11145	0.00228	0.095	0.07747	0.00160	0.107
Stairs Issues A Lot	0.17552	0.00401	0.269	0.31138	0.00761	0.271
Risk Rating				-0.03587	-0.00076	0.017**
McFadden R-squared	0.059452	* Significant at the 10% level		0.061625	* Significant at the 10% level	
Schwarz criterion	6039.326	** Significant at the 5% Level		5216.32	** Significant at the 5% Level	
		*** significant at the 1% Level			*** significant at the 1% Level	

Dependent Variable: STEM Career Employment						
	Initial Model			**Second Model**		
	B Coefficient	**Marginal Effect**	**Std. Error**	**B Coefficient**	**Marginal Effect**	**Std. Error**
Intercept	-3.82816		0.223***	-3.84920		0.250***
Age	0.09126	0.00698	0.011***	0.09515	0.00743	0.012***
Age Squared	-0.00108	-0.00008	0.000***	-0.00113	-0.00009	0.000***
Female	-1.70172	-0.14294	0.049***	-1.69242	-0.14618	0.052***
Degree	0.82087	0.07287	0.042***	0.78451	0.07041	0.045***
Ethnic White	0.42200	0.02900	0.055***	0.32297	0.02304	0.0612***
Stairs Issues Yes	-0.18115	-0.01310	0.074**	-0.23191	-0.01686	0.081***
Risk Rating				0.01293	0.00101	0.009
McFadden R-squared	0.108855	* Significant at the 10% level		0.108986	* Significant at the 10% level	
Schwarz criterion	16257.77	** Significant at the 5% Level		14055.25	** Significant at the 5% Level	
		*** significant at the 1% Level			*** significant at the 1% Level	

Dependent Variable: Engineering Career Employment						
	Initial Model			**Second Model**		
	B Coefficient	**Marginal Effect**	**Std. Error**	**B Coefficient**	**Marginal Effect**	**Std. Error**
Intercept	-4.63477		0.276***	-4.67962		0.311***
Age	0.10654	0.00421	0.013***	0.10918	0.00445	0.014***
Age Squared	-0.00123	-0.00005	0.000***	-0.00127	-0.00005	0.000***
Female	-2.39024	-0.11739	0.076***	-2.34455	-0.11946	0.081***
Degree	0.37852	0.01612	0.052***	0.32747	0.01421	0.057***
Ethnic White	0.67196	0.02220	0.072***	0.55778	0.01927	0.082***
Stairs Issues Yes	-0.21247	-0.00782	0.093**	-0.25122	-0.00941	0.101**
Risk Rating				0.02272	0.00093	0.011**
McFadden R-squared	0.132982	* Significant at the 10% level		0.131903	* Significant at the 10% level	
Schwarz criterion	11630.9	** Significant at the 5% Level		10079.41	** Significant at the 5% Level	
		*** significant at the 1% Level			*** significant at the 1% Level	

Dependent Variable: Science and Technology Career Employment						
	Initial Model			**Second Model**		
	B Coefficient	**Marginal Effect**	**Std. Error**	**B Coefficient**	**Marginal Effect**	**Std. Error**
Intercept	-4.30646		0.418***	-3.94684		0.457***
Age	0.04264	0.00090	0.021**	0.03843	0.00081	0.022*
Age Squared	-0.00067	-0.00001	0.000***	-0.00063	-0.00001	0.000**
Female	-0.87613	-0.01944	0.083***	-0.90889	-0.02043	0.090***
Degree	1.17055	0.03241	0.079***	1.19072	0.03318	0.086***
Ethnic White	0.10988	0.00224	0.095	0.07465	0.00154	0.107
Stairs Issues Yes	-0.02105	-0.00044	0.139	-0.04299	-0.00090	0.149
Risk Rating				-0.03623	-0.00077	0.017**
McFadden R-squared	0.059392	* Significant at the 10% level		0.061417	* Significant at the 10% level	
Schwarz criterion	6039.712	** Significant at the 5% Level		5217.461	** Significant at the 5% Level	
		*** Significant at the 1% Level			*** Significant at the 1% Level	