University of Warwick

Department of Economics

EC331: Research in Applied Economics

Men Vs. Women: Is It Really A Competition?

A Study Into How Women Perform In A Competitive Environment

Student ID
1502822

Word Count
4,940

Abstract

Do women actually compete with men, or is there something about them and their identity that prevents such action? This paper looks at how women perform in competition using the framework of Identity Economics. I investigate whether women do compete against men, or whether they follow the old norms of male superiority in competition. I find that in a competitive workplace environment, women do compete against men, contrary to the literature. There are, however, issues of validity and selection in the methodology, but, it offers a new perspective on gender competition, hopefully encouraging women and motivating them to compete with men.

Acknowledgements

Dr Abby Kendrick - Thank you Abby, for all the 6pm Tuesday Office Hours, 12pm Seminars, and countless emails. Your thoughtful insights and calming influence have definitely carried this project far beyond my capabilities and, hopefully, it is something of which we can both be proud.

Professor Jeremy Smith - Your passion for Econometrics is truly incredible, and I shall never forget the enthusiasm you brought to lectures. I hope this project fully embodies my admiration.

Madeleine Rose Lewis - Thank you for all the library sessions, lifts, and late night calls. This project would not have been half the fun without you there.

Contents

1 Introduction

Men vs. Women: Is It A Competition? In short; no, it's not.

Society has been increasingly interested in the gender wage gap. Equal pay, where employment 'terms and conditions of one sex are not in any respect less favourable than those of the other' (Parliament 1970), has largely been achieved. Closing the gap, however, has not.

The gap remains for two main reasons; hard factors and soft factors. Hard factors, such as education and experience - the observables - have largely been accounted for. The opposite is true for the unobservable soft factors, such as competitive performance. Past laboratory experiments show that female performance fails to improve as a result of competition, therefore, we would expect fewer women in competitive roles. As these roles tend to be the highest paying, this would widen the gender wage gap. But, this is based on laboratory experiments. Would this result hold up in a real world setting?

Laboratory experiments are usually conducted on undergraduate students with small incentives. In this paper, I expand on this by answering the question over greater incentives and more representative data. My aim is to see if female performance changes in a competitive workplace environment. Using the framework of Identity Economics, I form the hypothesis that *female performance will not improve as a result of competition.*

To investigate female performance, I build a model that looks at how competition affects performance. My dataset comes from the General Social Survey (GSS) and uses data from 2002 onwards. These data have some limitations, so I use proxies in place of certain variables. I use eligibility for performance-based pay as a proxy for a competitive environment and earning above average as a proxy for performance.

I find that, under a competitive setting, female performance improves. This contradicts previous literature and my hypothesis, implying that, where incentives are greater, women do compete. This may also represent a shift in gender norms, away from male competitive dominance. Equal competitive performance indicates that effort should be made to encourage women into competition and override the idea that competition is only for men.

In Section 2, I survey the literature on different competitive performance, while creating a foundation for Identity Economics. For Section 3, I describe the data, alterations, and its strengths and weaknesses. Section 4 is about forming my model with Section 5 examining the results. Section 6 relates the results to my hypothesis, analysing differences, while providing a critical analysis of the weaknesses in my model. Finally, Sections 7 and 8, discuss policy implications and potential future research.

2 The Gender Wage Gap, Competition, & Identity Economics

2.1 The Gender Wage Gap and Competition

The causes of the gender wage gap are well-documented, see Blau & Kahn (2017) and Bertrand (2011). There is, however, little research into the effect of differing competitive performance between genders. Literature that does address this often centres on laboratory experiments, not the real world, and there are inconsistencies in theoretical explanations. Nevertheless, as a baseline for further research, it acts as a good starting point.

Previous methodology generally follows a single approach; laboratory experiments. Gneezy et al. (2003) find that, under a competitive setting, female performance does not improve relative to a non-competitive setting. Men's does. This finding is confirmed by Niederle & Vesterlund (2007). But can these results be generalised to the wider population? Levitt & List (2007) discuss the significance of 'the particular context' and in some 'instances...the lab might exaggerate their importance.' Laboratory experiments using undergraduate students and low stakes differ from a workplace environment. Bertrand (2011) also discusses how current research in this area is 'in its infancy and far from conclusive.' This brings the external validity of the experiments into question, so to address this, I use real world data.

Good methodology, using real world data, is challenging as variables are often unavailable. Manning & Saidi (2010) look at gender selection into competition in the labour market, using performance-based pay as an indicator of competition. I will follow their methodology, also using this to represent competition. However, I shall be looking at how it affects performance rather than selection.

Most studies use data on undergraduates, which are not representative of the wider population. Antonovics et al. (2009), therefore, investigate real world competitive behaviour using data from the game show, *The Weakest Link*. They find no effect of competition on gender, contradicting the laboratory experiments. The show's producers, however, select people based on 'who they believe television audiences will enjoy watching,' with subjects being 'attractive and charismatic,' and so unrepresentative. This limits conclusions about everyday interactions. Studies also use sports data to measure competitive performance. Paserman (2010) looks at competitive performance of professional tennis players, arguing 'that the men's game deteriorates at least as much as the women's game' in competitive situations. However, professional players are trained to deal with such environments, hence, results may not be applicable to the outside population. Random survey data from across the US is more representative and allows my conclusions to be extrapolated to the wider population.

2.2 Identity Economics

Past research fails to establish a single theory for different competitive performance. Gneezy et al. (2003) mention how differences in competitive attitudes have foundations in evolutionary psychology (see Daly & Wilson (1988)), while Antonovics et al. (2009) focus on constructing ‘a theoretical model that formalizes the relationship between outcomes in the field and those in the lab.’ This paper will use Identity Economics as the theoretical underpinning to help explain and predict competitive behaviour.

What people care about and how much they care depends, in part, on their identity; this comes from the groups with which they associate. Tied to these groups are certain ideals describing how members *should* behave. Following this behaviour will make them feel better about themselves as they are ‘fitting in’ with society. Otherwise, they will feel bad, like an outcast on the fringes of popular society (Akerlof & Kranton 2010).

Akerlof & Kranton (2000) propose the following utility function and explanation:

$$U_i = U_i(a_i, a_{-i}, I_i) \tag{1}$$

Here, utility depends on i’s identity, I_i, their actions, a_i, and the actions of others, a_{-i}. a_i and a_{-i} determine i’s consumption of goods and services. They are sufficient in capturing the standard economics of own actions and externalities. Identity is given by the following:

$$I_i = I_i(a_i, a_{-i}; c_i, \epsilon_i, P) \tag{2}$$

Person i’s identity depends on their actions, a_i, others’ actions, a_{-i}, and i’s assigned social category, c_i. Within a category, the social status is given by the function I_i, and people assigned to a category with a higher social status generally enjoy an improved self-image. Identity also depends on the degree to which i’s own characteristics, ϵ_i, conform to the ideal of i’s assigned category, shown by the prescription, P. Finally, identity can be influenced by how well i’s own and others’ actions correspond to the ideal as indicated by P. An increase in utility derived from I_i is called a gain in identity, and a decrease is called a loss. Individuals act to maximise utility (1) by choosing their actions, taking c_i, ϵ_i, P, and the actions of others as given.

The gender norm that I will be testing is whether women perform better in competition. This comes from the laboratory experiments of Gneezy et al. (2003) and Niederle & Vesterlund (2007).

Women will attempt to maximise (1) by choosing actions based on the actions of others and their own identity, as in (2). Their assigned social category, c_i, is women, and their ideal, P, is lower performance in competitive environments à la Gneezy et al. (2003). The difference between their behaviour and characteristics, ϵ_i, and this ideal determines whether they gain or lose identity and, hence, utility as a result. Conforming should increase a woman’s utility, whilst not conforming should decrease it. Therefore, my hypothesis is *female performance should not increase as a result of competition.*

3 Data

My data is from the General Social Survey (GSS), a repeated cross-sectional survey conducted 'to monitor and explain trends and constants in attitudes, behaviours, and attributes' (General Social Survey 2018). Participants are randomly selected from 'a scientific sample designed to represent a cross-section of the country' and subjected to ninety minute interviews based on a questionnaire.

The data contain 62,466 observations on 5,897 variables; however, not all of these are included as my chosen variables are only available from 2002 onwards. Additionally, as this research focuses on women, men are removed. These are the main changes that I make to perform my analysis. For further discussion see Appendix A.

Using data from the real world, the conclusions I draw will be more applicable to policy and the wider population. Random sampling makes the results more representative than Antonovics et al. (2009). Additionally, these data contain many more observations, increasing the reliability of results.

Unfortunately, this dataset has some drawbacks. Firstly, it does not contain the exact variables that I would like to use, therefore, I must use proxies instead. Secondly, confining my sample to women from 2002 onwards reduces my observations to 1,447 (see Female row, Table 1). Consequently, my results are less reliable than initially expected with such a large dataset.

Table 1 presents a comparison, by gender, of those eligible for performance-based pay. Men are more likely to be eligible than women, 573 compared to 493, which would agree with Niederle & Vesterlund (2007) and Manning & Saidi (2010) in that women select into competitive environments less frequently. Matching past literature indicates reliability. Additionally, the split of men and women in this sample of the population is roughly fifty-fifty, see the Total column of Table 1. Therefore, no bias should exist from a disproportionate population.

Table 1
Performance-Based Pay by Gender.

		Performance-Based Pay		
		Yes	No	Total
Gender	Male	573	828	1,401
	Female	493	954	1,447

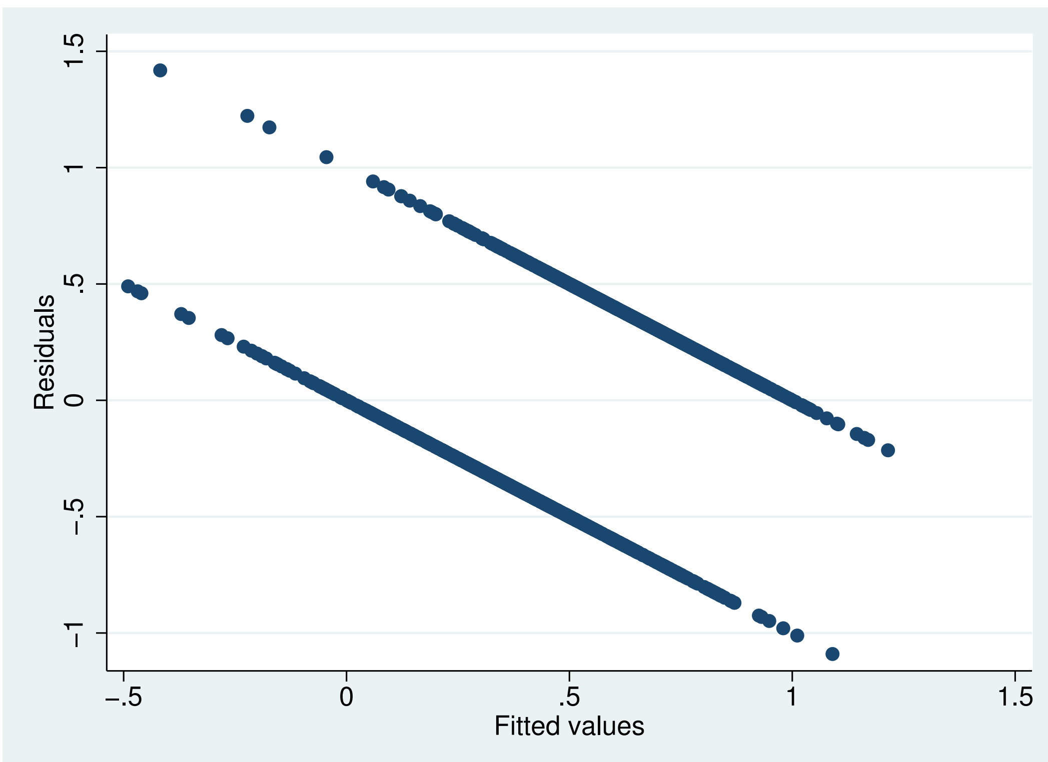
4 Methodology

Output per worker data is limited and the competitiveness of a workplace is subjective. Therefore, I use proxies. I proxy performance with a dummy variable for earning above average female pay using logarithms, where average is defined as median since it is not skewed by extreme values (ONS 2017). For competition, I use a dummy variable indicating eligibility for performance-based pay, à la Manning & Saidi (2010).

My binary dependent variable indicates whether the individual earns above median female earnings (1 if yes, 0 otherwise) because a continuous earnings variable would not accurately measure performance. My main independent variable is also a binary variable (1 if someone is eligible for performance-based pay, 0 if not). This will represent a competitive environment as wages depend on performance over a fixed fee (Manning & Saidi 2010).

Since I have a binary dependent variable, I use a binary response model. Testing a Linear Probability Model (LPM), many results lie outside the 0-1 range of a probability (see Figure 1), which are impossible to interpret. Appendix B further discusses the limitations of an LPM. Running a Logit model solves this problem as the values are bounded between 0 and 1. The parameters are estimated using maximum likelihood estimation, which, in simple terms, finds the parameter value that makes the observed result most likely. I use robust standard errors to account for heteroscedasticity.

Figure 1
Scatter Plot of LPM Predicted Probabilities.



Blau & Kahn (2017) detail the determinants of the gender wage gap. Using their model will account for most of the variation in wages and, therefore, allow me to accurately estimate the effect of competition. But, this accuracy might be counteracted by a lack of variables. A variable they include is unionisation, which is not in my dataset. Despite this, excluding unionisation should not largely affect my other coefficient estimates, as in today's economy, unions have much less effect than previously. Further description of my variables is provided in Appendix C.

My regression equation is:

$$\Lambda(averageearnings_i) = \alpha_i + \beta_1 perfpay_i + \beta_2 education_i + \beta_3 region_i + \beta_4 race_i + \beta_5 industry_i \\ + \beta_6 occupation_i + \beta_7 age_i + \beta_8 age_i^2 + \beta_9 hours_i + \beta_{10} hours_i^2 + \epsilon_i$$

This model is based on one central assumption:

Women have similar ability under competition.

Niederle & Vesterlund (2007) justify this assumption, finding 'no significant difference in performance between those who do and do not enter the tournament.' This allows me to directly compare the treatment group, those eligible for performance-based pay, to the non-treatment group, those not eligible for performance-based pay.

To test my hypothesis, I run a significance test on the performance-based pay coefficient, $\beta_1 = 0$. This will show whether being in a competitive environment affects earning above average income, and, therefore, performance.

5 Results

Table 2 presents the Logit regression of eligibility for performance-based pay on the likelihood of earning above average. It gives coefficient estimates, standard errors, and p-values for the regression. Two control variables, region and race, are insignificant so have no effect on earning above average. Being illegal to pay someone based on their ethnicity likely makes race insignificant. People are, however, often paid based on their location, since different regions have different living costs; therefore, region does affect earnings. Being included in past literature, both remain in my model.

Table 2
Logit Regression for Average Earnings.

	Coefficient	Standard Error	P-Value
Performance-based pay	0.649	0.137	0.000*
Education	0.281	0.032	0.000*
Region	−0.021	0.026	0.426
Race	−0.037	0.104	0.722
Industry	0.444	0.227	0.050*
Occupation	−0.117	0.031	0.000*
Age	0.218	0.037	0.000*
Age^2	−0.002	0.0004	0.000*
Hours	−0.115	0.028	0.000*
Hours^2	−0.001	0.0002	0.002*

*Significant at 5% level

Looking again at the p-values from Table 2 we see eligibility for performance-based pay is significant, therefore, affecting whether an individual earns above average. This suggests that women do actually compete in a competitive environment, contradicting my hypothesis and past literature.

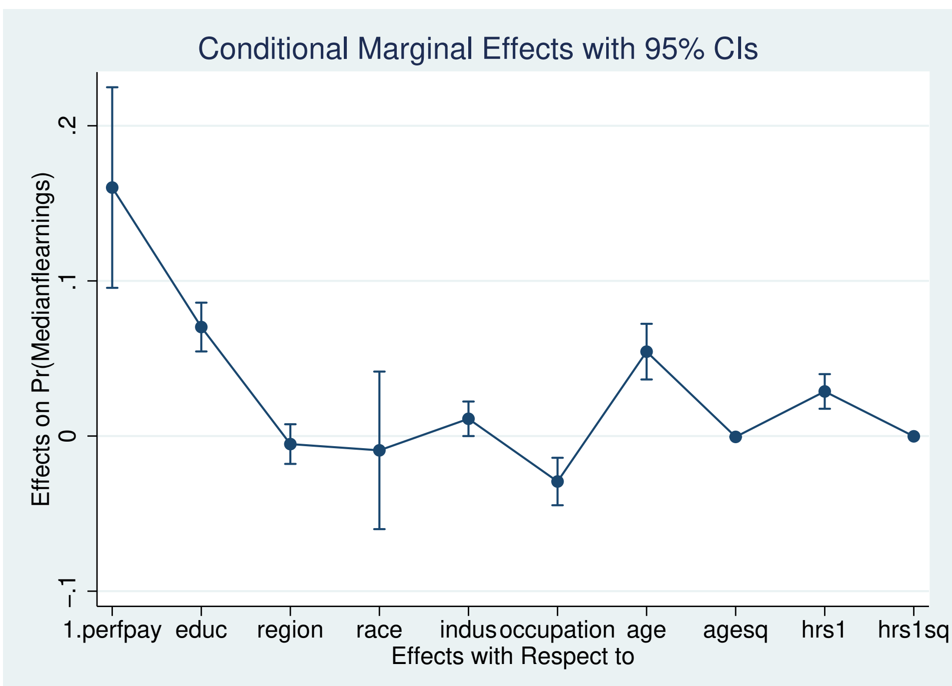
Table 3 gives the marginal effects of all the variables. For categorical variables the full vectors are provided in Appendix D. For performance-based pay, the marginal effects column shows it is 0.160, therefore, being eligible increases the probability that you earn above average earnings by 16 percentage points compared to not being eligible. This is a large increase, and is clearest in a marginal effects plot (Figure 2). This figure shows that being eligible for performance-based pay has the largest effect. If this is true, it would be expected that much more literature would cover the topic. As it does not, my model might be inaccurate. This could potentially be due to a factor being concealed, such as having a higher income job. There are also precision issues, seen by the wide confidence intervals of my estimate. This suggests the sample size was too small.

Table 3
Marginal Effects for Logit Regression.

	Marginal Effect	Standard Error	P-Value
Performance-based pay	0.160	0.033	0.000*
Education	0.070	0.080	0.000*
Region	−0.005	0.007	0.426
Race	−0.009	0.026	0.722
Industry	0.111	0.006	0.050*
Occupation	−0.029	0.008	0.000*
Age	0.054	0.009	0.000*
Age^2	−0.001	0.0001	0.000*
Hours	−0.029	0.006	0.000*
Hours^2	−0.0001	0.0006	0.002*

*Significant at 5% level

Figure 2
Marginal Effect Estimates from Logit Regression.



5.1 Predictive Ability

The classification table below shows the predictive ability of the model. Roughly 74% of observations were correctly predicted, with positive (73%) and negative (75%) predictions also high. This accuracy implies correct specification and no obvious omitted variables. However, this level of accuracy also suggests multicollinearity. Counting the impact of one overriding variable multiple times gives unstable and biased marginal effects estimates, as well as high standard errors. Perhaps performance-based pay only occurs in higher income jobs, giving the model almost perfect predictions. However, looking at Table 3, none of the standard errors seem overly high, signalling no multicollinearity.

		Actual Outcome		
		Above	Below	**Total**
Predicted Outcome	$\widehat{Above}$	582 (73.12%)	214 (26.88%)	796
	$\widehat{Below}$	162 (24.96%)	487 (75.04%)	649
	Total	744	701	

Correct percentage classification in parentheses.

5.2 Changing Specification

Table 4 compares an LPM, Logit, and Probit model. It presents the coefficient values for each of the variables in each of the models. Other than race and region, all variables are significant in all models. The coefficient estimates are similar, which is expected for a reliable model. This robustness check indicates that the model is correctly specified, increasing confidence in my conclusions.

Table 4
LPM, Logit, & Probit Comparison Table.

	Model		
	LPM	Logit	Probit
Performance-based pay	0.127*	0.649*	0.396*
	(5.130)	(4.740)	(5.040)
Education	0.0503*	0.281*	0.157*
	(11.0200)	(8.750)	(10.270)
Region	−0.003	−0.021	−0.012
	(−0.610)	(−0.800)	(−0.750)
Race	−0.007	−0.037	−0.035
	(−0.370)	(−0.360)	(−0.580)
Industry	0.008*	0.044*	−0.0296*
	(1.910)	(1.960)	(2.280)
Occupation	−0.0121*	−0.117*	−0.0677*
	(−3.6400)	(−3.760)	(−3.650)
Age	0.0342*	0.218*	0.130*
	(6.3700)	(5.950)	(6.600)
Age^2	−0.0003*	−0.002*	−0.0013*
	(−5.5100)	(−5.110)	(−5.8400)
Hours	0.018*	0.115*	0.062*
	(6.310)	(5.050)	(6.116)
$Hours^2$	−0.0001*	−0.0001*	−0.0004*
	(−3.3600)	(−3.1500)	(−3.4800)

t statistics in parentheses.
*Significant at 5% level

6 Implications & Discussion

My results suggest that female performance does increase as a result of competition. But why?

6.1 Adapting Theory

One possible reason is changing gender norms throughout an individual's life. Past laboratory experiments focus on young college students (Antonovics et al. 2009). As students get older, they receive more messages of empowerment and equality with men. They no longer identify with the norm of not competing and, entering the workplace, they are more willing to compete, hence, performance improves. Another reason may be increased incentives. The utility they lose from not conforming to their identity may be compensated for by the increasing utility from higher wages. This would still fit with Identity Economics and explain past experiments.

6.2 Validity

A key issue with my research is validity: is what I am trying to measure actually being measured?

6.2.1 Performance-Based Pay

Does being eligible for performance-based pay actually create a competitive environment? In certain cases; no, it would not. For example, if performance was measured for departments instead of individuals. Unfortunately, a variable indicating this is not in my dataset, and if it is the case, the conclusions I draw about female performance in competitive environments may be invalidated. However, use in past literature (Manning & Saidi 2010) gives it credibility as a valid measure.

Another problem is the composition of the competition. Competition in a female dominated environment is an issue, as, according to theory and literature, competition with other women would increase performance. Table 1 and Appendix E show that the data is roughly evenly split between men and women, yet, I am unable to look at the gender composition of each workplace. Given the split of genders, however, this should not cause too much upward bias in my results.

A better alternative would give a clear indication of a competitive environment, for example, comparing a mixed tournament-based pay scheme to a piece-rate scheme. In the tournament-based scheme individuals would be set against each other, with only top performers rewarded, indicating a competitive environment. Then, being a mixed gender scheme, we could directly see the effect of competition between genders. Potential scenarios for further study could be found in sports. For example, chess, as often there is competition between different genders, although payment schemes may not vary.

6.2.2 Average Median Earnings

Performance is not the same as pay. Observing that a competitive environment increases earnings, does not mean it also increases performance. Pay is determined by multiple factors, often unrelated to performance, such as negotiation skills. Controlling for those factors helps, however, removing all outside effects is not possible, potentially invalidating my conclusions. Using performance pay as my independent variable slightly mitigates this as it links performance to pay.

An ideal alternative would be actual output per worker or the level of performance-based pay. This would give a measurable indication of how an individual's performance changes when moving from a non-competitive to a competitive environment, increasing the validity of my estimates and conclusions.

6.3 Endogeneity

An endogenous variable is one which is influenced by another set of variables making it non-stochastic. As a result, the endogenous variable will be correlated with the error term, making the coefficient estimate biased and not represent its true value. There are two main sources of endogeneity in this paper; selection bias and omitted relevant variables.

6.3.1 Selection Bias

Selection bias occurs when an individual selects into a treatment based on unobservable characteristics or their personal expected gains from the treatment. Those aware they perform better under competition will select in. To investigate, I split the regression by industry, giving a similar effect to adding interactive terms between the industry and performance pay variables. Table 5 shows performance pay is significant in half, suggesting that my sample is not random. Therefore, my estimates would be upward biased as those who choose to be eligible are those who are confident that such an environment would maximise their wage and, thus, utility. There could be, however, other reasons for this (see Appendix F); therefore, I look at how performance pay affects the probability of being employed in a particular industry (see Appendix G). In half of the industries, a competitive environment was a factor in the decision to work there. This was the case for both selecting in and selecting out, suggesting both groups differ in their competitive ability, resulting in an upward bias in my marginal effect estimate.

Table 5
Performance-Based Pay By Industry.

	Coefficient	Std Error	P-Value
Agriculture, energy, transport & storage	0.226	0.694	0.707
Manufacturing & construction	1.593*	0.651	0.014
Wholesale, retail & repair of motor vehicles	−0.204	0.385	0.596
Accommodation & food services	0.916*	0.496	0.065
Financial, insurance, & real estate activities	0.517	0.431	0.230
Professional, communication, scientific & technological activities	1.509*	0.555	0.007
Administrative, support service & defence; social security	0.813*	0.463	0.079
Education	−0.028	0.596	0.963
Human health & social work activities	0.548*	0.297	0.065
Other services	3.394	2.175	0.119

*Significant at 10% level

Additionally, there might be a lack of common support (Appendix H) as not enough similar individuals would be part of both groups to make sufficient comparisons, meaning I would be comparing incomparable individuals, those who can compete against those who can not. This would cause significant upward bias in my marginal effects estimates, as those currently in competition will perform better than those who have selected out. Furthermore, I would be measuring the effect of different competitive attitudes rather than different competitive environments.

Zero-inflation and Heckman correction models are potential solutions to selection bias. Unfortunately, they solve selection bias in the dependent variable, whereas the selection bias comes from the independent variable. However, this might not be necessary. Niederle & Vesterlund (2007) find that even women who select into competitive environments still underperform in that setting relative to men. Therefore, the effect of selection bias may be small. Despite potentially overestimating the effect of a competitive environment on performance, my results could still be significant, indicating women do compete in competitive work environments.

6.3.2 Omitted Relevant Variables

Many factors affect earnings, unfortunately, due to limitations in my dataset and their unobservable nature, I am not able to include them all. These factors include characteristics such as competitive attitudes, risk aversion, and ability to negotiate. In omitting these, the effects are included in the current marginal effects of the model, hence, they will be systematically different from the true value (biased).

For performance-based pay, potential omitted variables include competitive attitudes and competitive experience. More experience in competitive environments increases an individual's performance under competition and, therefore, earnings. The effect of this goes into the performance-based pay variable and results in upward bias, potentially causing it to be significant. This weakens the conclusion that a competitive environment increases female performance.

I introduce new variables into the model that might affect performance (see Appendix I). The marginal effect of performance pay on performance remains similar, suggesting that the model is well specified and increases confidence that any variables I have omitted would not affect my conclusions.

6.3.3 Reverse Causality

Often, we hear news stories of CEOs being awarded six-figure bonuses, similar stories about cleaners, however, are non-existent. This suggests that those who earn more are the ones more likely to earn performance-based pay. Being eligible would, therefore, almost perfectly predict whether an individual was a high-income earner or not, additionally, making my model highly collinear. This would explain the high ability of the model to classify individuals correctly, resulting in significant upward bias on the competition measure, reducing the accuracy of conclusions. To compensate, I add controls for the determinants of income, to ensure comparison of similar individuals, however, due to a lack of support inhibiting this, upward bias may persist.

6.3.4 Endogeneity Solutions

The main solution to endogeneity is to use instrumental variables (IVs). A description of IVs is given in Appendix J. Here, the endogenous variable is eligibility for performance-based pay and an IV would give a much more accurate estimation of the effect of competition on performance. The marginal effect estimate would likely decrease, as much of the upward bias introduced from endogeneity would be removed.

A potential IV could be a variable indicating how competitive the market is for the individual's job. This would be relevant as more competitive jobs tend to have more competitive workplaces, and so individuals would be more likely to be paid based on performance. It would also be exogenous as people rarely choose jobs based on how competitive the application process is. They often decide on the job first, then face the associated competition. However, individuals often choose jobs based on income. Higher income jobs will attract more and higher-skilled applicants, creating a more competitive pool. As a result, jobs with more competitive application processes will naturally have higher wages, making the IV less exogenous. Unfortunately, due to limitations in my dataset, I am not able to conduct an IV estimation. This keeps upward bias in my results meaning performance pay might not have a significant impact on performance.

6.4 Overall Impact

Due to the upward bias discussed above, it is not conclusive that a competitive environment results in increased performance for women. There is evidence above, however, to indicate that the upward bias is small, so, female performance does improve. Further research would help.

7 Future Research & Policy Implications

7.1 Extensions

It would be useful to repeat the work with more specific data, for example, using the alternative variables mentioned in Section 6. This would give less biased estimates of the effect of competition on performance among women in the workplace. From this, it would be possible to draw better conclusions and provide a stronger argument for potential policy suggestions.

A second area of investigation might be into why competition only has significant effects in certain sectors. One explanation for this might be different competitive attitudes between individuals. Understanding this difference might make it clear why there are so few women in seniors roles and research might help determine policies to stop this, further closing the gender pay gap.

7.2 Policy Implications

According to firms, the main reason behind the gender pay gap is a lack of female representation in senior roles. One potential cause of this is fewer women selecting into competitive environments. It has been shown, however, that when in competitive environments, women do compete and performance improves. Therefore, a useful policy might be to encourage self-selection into these environments, which are often higher paying. If women can be moved into these environments, we might be able to reduce the gender pay gap. The impact of such a policy, however, is unclear. The issues with selection mean that competition might not improve the performance of every woman. Therefore, it might be useful to screen individuals to understand their competitive capabilities before encouraging them to compete.

Another interesting area is changing gender norms. One possible explanations for the change in performance from college to the workplace is that as women get older, they might no longer identify with old competitive norms. New research could look at how and why such norms and individual's identities change. With information like this, it would be possible to not only change perceptions in many other areas, but also encourage women to select into more competitive environments. While the gender norm of women not competing may change over time, it might now be necessary to look into how we can change the idea that competition is still only meant for men.

This all depends on the amount of upward bias, as a result of endogeneity and questionable validity. Therefore, repeating this paper with more precise data is key. Large upward bias would invalidate my conclusions and policy implications. Due to this, it is necessary to run confirmation studies about my results before we can look specifically at how to influence policy.

8 Conclusion

Men vs. Women: Is It Really A Competition?

In one sense; yes, it is. Women have been shown to be able to effectively compete with men when placed into a competitive real-world environment. Yet this is not without error. The research problems with this paper indicate more detailed work is necessary before we can be certain of this conclusion. The updated theory and results, however, suggest women do, indeed, compete.

In a different sense; no, it is not. It is not in the respect that, while they can compete with men, they are not doing so. Women are simply not in the necessary environments to compete with men, so there is simply no competition. This is a problem. Hopefully, this paper has given encouragement to the idea that women can compete, and that, now, creating the competition is the next challenge waiting.

Appendix

A Industry & Occupation Categories

The dataset contains both a variable for industry and occupation. One issue, however, is that the variable for industry has 270 unique values and occupation has 445. For categorical variables this is too many, especially given that most will only occur with a frequency of one. This lack of variation will likely cause them to be insignificant. Most datasets contain more broad industry and occupation categories. Therefore, to solve the issue I reclassified my data according to the ONS specifications for both industry and occupation (ONS 2018*a*,*b*). This naturally included some subjective judgement, but, as the categories were largely obvious, this should not have an effect on my results.

B Linear Probability Models

Figure 1 shows a scatter plot of the predicted probabilities of an LPM regression. The fitted values show many lie outside of the 0-1 range of a probability. These values are impossible to interpret which is a major drawback of running an LPM. Logit regressions solve this as the predicted probabilities are bounded by 0-1.

An additional limitation of an LPM is that the error term will be heteroscedastic. Homoscedastic residuals against fitted values plot would look like a random scatter of points. Figure 1 does not look like this. Heteroscedasticity will cause the standard errors to be incorrect so any hypothesis tests will also be wrong.

Horrace & Oaxaca (2006) give a more detailed description about the bias and inconsistency in results for LPMs and why using one may be suboptimal.

C Description of Variables

Averageearnings is a dummy variable indicating whether an individual earns above average female logarithmic earnings. Logarithms are used to make the variable normally distributed and avoid positive skew.

The occupation categories are;

1. Process, Plant, and Machine Operatives (Default)
2. Managers & Senior Officials
3. Professional Occupations
4. Administrative & Secretarial
5. Personal Services
6. Skilled Trades

7. Sales & Customer Services

These are adapted from the ONS (2018*a*) definitions.

The industry categories are;

1. Other services (Default)
2. Agriculture, energy, transport & storage
3. Manufacturing & construction
4. Wholesale, retail & repair of motor vehicles
5. Accommodation & food services
6. Financial, insurance, & real estate activities
7. Professional, communication, scientific & technological activities
8. Administrative, support services & defence; social security
9. Education
10. Human health & social work activities

These are adapted from the ONS (2018*b*) definitions.

In my regression I also include covariates on hours and age as more experience and working longer increases wages. For both, I include squared terms. Squared terms cause the relationship to be non-linear; their effect on earning above average wears off over time. As an individual gets older, they are more likely to earn above average, but, the effect decreases as most that age will already be earning above average. The same is true for hours worked.

Table 6
Description of Variables

Variable	Description	Why Included	Method of Formation
Performance-based Pay	Dummy variable indicating if an individual is eligible for performance-based pay or not. 1 if yes, 0 otherwise	Indicates a competitive environment	Adapted from categorical variable about the method of payment in the individual's job
Education	Years of education	From Blau & Kahn (2017)	From dataset
Region	Region where individual lives	From Blau & Kahn (2017)	From dataset
Race	Race of individual	From Blau & Kahn (2017)	From dataset
Industry	Industry individual works in	From Blau & Kahn (2017)	Adapted from dataset. Original variable had around 270 unique values, so each was categorised into a broader set of 10 industries
Occupation	Occupation of individual	From Blau & Kahn (2017)	Original variable had around 445 unique values, so each was categorised into a broader set of 7 occupations
Age	Age of individual	As age increases so will earnings	From dataset
Age^2	*Age*x*Age*	Effect of age on earning above average decreases over time	Multiplied *Age* by itself
Hours	Hours worked	As hours worked increases so will earnings	From dataset
$Hours^2$	*Hours*x*Hours*	Effect of increasing hours worked on earning above average decreases over time	Multiplied *Hours* by itself

D Full Specification Model

Table 7 gives the marginal effects from the full specification, with all of the individual categorical variables.

Table 7
Full Marginal Effects for Logit Regression.

	Coefficient	Standard Error	P-Value
Performance-based pay	0.649	0.137	0.000*
Education	0.281	0.032	0.000*
Region - Mid Atlantic	−0.066	0.091	0.426
Region - NE Central	−0.082	0.088	0.352
Region - NW Central	−0.282	0.098	0.004*
Region - South Atlantic	−0.168	0.088	0.058
Region - SE Central	−0.244	0.103	0.018*
Region - SW Central	−0.107	0.096	0.268
Region - Mountain	−0.178	0.099	0.070
Region - Pacific	−0.050	0.096	0.602
Race - Black	−0.047	0.047	0.310
Race - Other	−0.003	0.066	0.961
Industry - Agriculture	0.369	0.102	0.000*
Industry - Manufacturing	0.340	0.098	0.000*
Industry - Wholesale	0.110	0.098	0.229
Industry - Accommodation	0.109	0.097	0.262
Industry - Financial	0.224	0.092	0.015*
Industry - Professional	0.306	0.101	0.409
Industry - Administrative	0.276	0.098	0.005*
Industry - Education	0.077	0.094	0.409
Industry - Health & Social	0.152	0.084	0.071
Occupation - Managers & Senior	0.321	0.071	0.000*
Occupation - Professional	0.273	0.068	0.000*
Occupation - Secretarial	0.283	0.069	0.000*
Occupation - Personal Services	0.374	0.072	0.000*
Occupation - Skilled Traders	0.247	0.080	0.002*
Occupation - Sales & PR	0.040	0.058	0.492
Age	0.218	0.037	0.000*
Age^2	−0.002	0.0004	0.000*
Hours	−0.115	0.028	0.000*
Hours^2	−0.001	0.0002	0.002*

*Significant at 5% level

For each categorical variable, we need a default variable for comparison. For Region, the default is New England. For Race, the default is White. For Industry, the default is Other Services. For Occupation, the default is Process, Plant, and Machine operatives. As an example, looking at the 'Industry - Agriculture' row from Table 7, we get the following interpretation. Working in agriculture increases the probability of earning above average by 36.9% points for women, compared to working in Other Services.

E Gender Breakdown From Dataset

Table 8 shows the split between men and women in different occupations. In most industries it is an approximately even split, sometimes with men dominating. In *Administration and Secretarial*, however, there seems to be a strong female dominance. This is largely expected as described by Akerlof & Kranton (2010), who discuss about how such roles are predominately female.

Table 8
Gender By Occupations.

	Gender	
	Male	Female
Process, Plant, & Machine Operatives	202	110
Managers & Senior Officials	141	140
Professional Occupations	263	223
Administration and Secretarial	30	160
Personal Services	170	286
Skilled Trades	355	115
Sales and Customer Services	240	431

One interesting point is that *Sales and Customer Services* looks to be female dominated. This goes against popular culture as sales roles tend to be highly competitive so, according to Niederle & Vesterlund (2007), should be predominately male. One reason for this might be human error in dividing occupation into wider categories. In this case, I may have misinterpreted which occupational category an individual truly belonged to. This is likely to bias my marginal effects estimates on my categorical variable for occupation as individuals are not classified correctly. As this is not my key independent variable, however, this should not have too much of an effect on my final conclusions.

F Regressions by Industry

Industries have varying income levels, some paying much more than others. Therefore, to remove this effect, I run separate regressions for each industry, using the median income in that field. Table 5 (page 14) shows the coefficient, standard error, and p-value for the performance-based pay variable in each of those regressions. Looking at the p-value column, out of the ten industries, five are significant at the 10% level. This indicates that only some women perform under competitive environments, violating the assumption that all women share the same competitive attitudes. Although, it could also be due to some industries being less competitive than others, such as education. Hence, being eligible for performance-based pay would not represent a competitive atmosphere. Sectioning into ten groups, however, substantially reduced the sample sizes, in some cases below 100 observations. This will affect the reliability of results and could contribute to the insignificant values.

G Effect of Performance Pay on Industry Choice

Selection bias is a key problem in my research so it is good to investigate whether a competitive environment is a factor when individuals are selecting their job. To do this, I run regressions on the likelihood of selecting into a given industry. In each industry, I see whether being eligible for performance-based pay is significant to work out if being in a competitive environment is a factor influencing the decision of where to work. Table 9 shows the results of the Logit regression. The model I use is;

$$\Lambda(Industry_i) = \alpha_i + \beta_1 perfpay_i + \beta_2 education_i + \beta_3 fathersocc_i + \beta_4 mothersocc_i + \beta_5 hours_i + \beta_6 hours_i^2 + \beta_7 children_i + \beta_8 marital_i + \epsilon_i$$

Reported are the coefficients of the performance pay variable. They show whether being eligible for performance pay makes a woman more likely to work in a given industry. For example, in the first row, we can see that being eligible for performance pay is not significant and so is not a factor in women deciding to work in agriculture, energy, transport, or storage.

Table 9
Logit Regression of Performance Pay on Industry.

	Coefficient	Std Error	P-Value
Agriculture, energy, transport & storage	0.007	0.334	0.985
Manufacturing & construction	1.123*	0.336	0.001
Wholesale, retail & repair of motor vehicles	0.198	0.254	0.435
Accommodation & food services	−0.224	0.303	0.458
Financial, insurance, & real estate activities	0.927*	0.249	0.000
Professional, communication, scientific & technological activities	0.731*	0.278	0.009
Administrative, support service & defence; social security	−0.216	0.292	0.459
Education	−1.411*	0.292	0.000
Human health & social work activities	−0.043*	0.189	0.818
Other services	−0.779	0.415	0.060

*Significant at 5% level

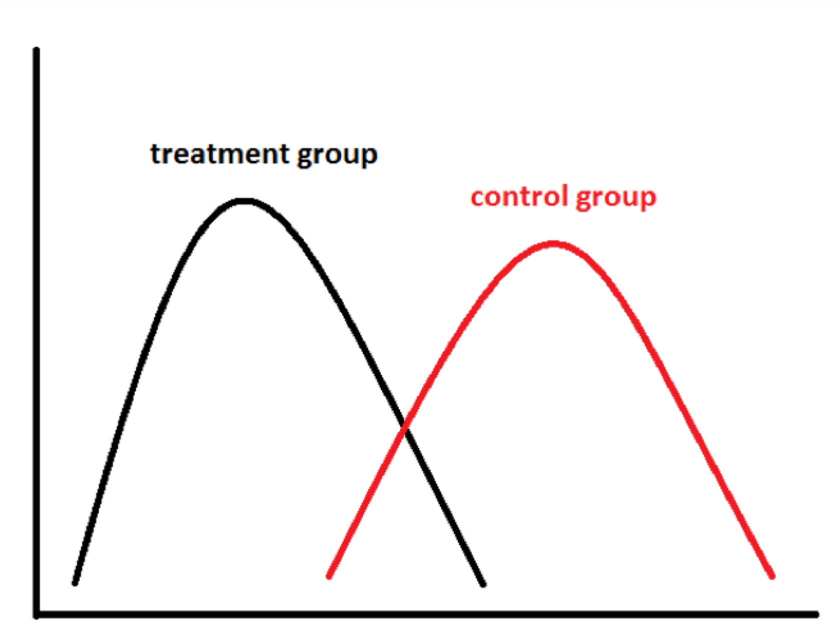
As we can see, performance pay is a significant influence on the probability of working in a given industry in five out of the ten. As this affects both selection in and out of a given industry, shown by the positive or negative coefficient, this indicates that, some of the time, women are selecting their chosen industry based on how competitive the environment is. This potentially shows that not all women have the same competitive attitudes, therefore, women would not all be comparable.

While there was some overlap in the significant industries between selection into and performance under competition (see Table 5, page 14), they are not identical. This suggests that while women may select in based on the environment being competitive, they are not able to accurately predict how they will perform, and so, do not act optimally. This is most clearly demonstrated for 'Human health & social work activities' where performance pay is likely to make someone select in less, yet, it has a positive impact on pay. Nevertheless, their beliefs about their competitive performance and their actual competitive performance are likely to be correlated, leaving some selection (and therefore upward) bias in the model.

H Lack of Common Support

A lack of common support occurs when individuals with a certain characteristic (or combination of characteristics) are almost always in either the treatment or the non-treatment group. As a result, we can almost perfectly predict which group they are in. In the context of this model, the characteristic corresponds to different competitive attitudes. If individuals with higher competitive attitudes always select in and those with lower competitive attitudes always select out, they are incomparable. Figure 3 shows this. The overlapping area is called the support.

Figure 3
Diagram of a Lack of Common Support.



There is little overlap across the two groups when an individual could be in either one. This means that there is little room for equal comparison and we would compare individuals who are inherently incomparable. For this paper, this would mean there are few individuals with the necessary competitive attitude to be part of either group. Therefore, in attempting to equate individuals this will lead to some problems and bias in the model. This bias is likely an upward bias on the coefficient estimator as those with higher competitive attitudes who select in are more likely to perform better under competition.

One potential solution to this problem would be matching. This is where an individual or group of individuals from the control group are paired with an individual from the treatment group. The control group individuals are then given weights to make them look as similar as possible to the treated unit. Then the outcome of that treated unit is compared to that of the re-weighted control unit. However, the main problem with this solution is that it can require a lot of data to do correctly, and since my dataset has already been substantially reduced, this method would not be practical.

I Adding Variables

It is important to see how omitted relevant variables may affect the marginal effect estimates of interest. Table 10 gives the marginal effects of the performance pay variable in various regressions that include extra variables, that are potentially omitted.

Table 10
Performance Pay Marginal Effect with Additional Variables.

	Marginal Effect	Std Error	P-Value
None	0.160*	0.033	0.000
Number of Children	0.155*	0.033	0.000
Marital Status	1.160*	0.033	0.000
Job Satisfaction	0.132*	0.040	0.001

*Significant at 5% level

None of the additional three variables seem to cause the marginal effect of the performance pay variable to change that much. The largest change comes from adding a covariate describing job satisfaction. Even this change, however, is not that large. This gives confidence that the model is well specified and adding new variables will not affect the key independent variable and so will not affect my conclusions.

Nevertheless, there are many other potentially omitted variables, which are unobserved, that may have a much greater effect than the observed and testable ones in Table 10. Unfortunately, there is little to do in this situation other than acknowledge their possibility and how it will affect my results. As discussed above, the most obvious variables, such as competitive attitude, will generally create an upward bias on the marginal effect of performance-based pay.

J Instrumental Variables

An instrumental variable is an arguably exogenous variable that causes or is associated with the endogenous regressor of interest. They are useful because they allow us to replace endogenous variables with exogenous ones, removing bias in our estimates. Additionally, they can allow us to isolate variation in the endogenous variable that is driven by exogenous factors only, and use just this part in our model. For instruments to be valid they must be *relevant* and *exogenous*.

A variable is relevant if it can predict the endogenous regressor. This means that it must have some influence over determining it. A variable is exogenous if it is only correlated with the dependent variable through the endogenous variable. Hence, the only way it can affect the dependent variable is from its influence on the endogenous variable, not in any other way.

The IV is regressed on the endogenous variable, with all of the original covariates from the initial model. The predicted or fitted values from the regression are then used in place of the endogenous variable in the original model. This will remove the endogenous variation in the variable, and so reduce the bias in our estimate.

For eligibility for performance-based pay, an IV would most likely reduce the value of our marginal effect estimate as there is significant upward bias from endogeneity. Due to the limited dataset, however, one can not be included, leaving upward bias in my results.

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