

Schwerter, Jakob

Conference Paper

Impact of universities in a flat hierarchy: Do degrees from top universities lead to a higher wage?

Beiträge zur Jahrestagung des Vereins für Socialpolitik 2020: Gender Economics

Provided in Cooperation with:

Verein für Socialpolitik / German Economic Association

Suggested Citation: Schwerter, Jakob (2020) : Impact of universities in a flat hierarchy: Do degrees from top universities lead to a higher wage?, Beiträge zur Jahrestagung des Vereins für Socialpolitik 2020: Gender Economics, ZBW - Leibniz Information Centre for Economics, Kiel, Hamburg

This Version is available at:

<https://hdl.handle.net/10419/224583>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

Impact of universities in a flat hierarchy: Do degrees from top universities lead to a higher wage?

Work in Progress*

Jakob Schwerter[†]

February 28, 2020

Abstract

The literature shows a wage premium for graduates from high quality, elite, or more selective universities. The results, however, exist for countries with a clear hierarchy of top universities, such as the US, England, and Australia. I evaluate if such an effect also exists in Germany, a country in which universities are top-performing in some but not all fields, and the general differences between universities are smaller compared to, e.g., the USA. I use the University Ranking of the Quacquarelli Symonds and a revealed preference and acceptance ranking to measure the quality of a university. Both rankings show a wage premium in IV regression in-between five and 13 percent. This effect is specially prevalent for women.

JEL-Classification: I23, I24, I26, J31

Keywords: wage premium, ranking, revealed preferences, Germany

*I thank Martin Biewen, Steffen Hilmert, Simon Jäger, Frederik Schwerter, Herman van de Werfhorst and participants of the Inequality Workshop in Tübingen as well as various seminar audiences for many helpful comments and discussions. This paper uses data from the Centre for Higher Education Research and Science Studies (DZHW), Hannover.

[†][University of Tübingen](#), [LEAD Tübingen](#), jakob.schwerter@uni-tuebingen.de

1 Introduction

For several countries, there is a rich set of results showing that the decision to enroll to which university matters for the wage. The literature almost unambiguously finds a positive wage premium for (subgroups of) graduates from universities with an elite-status (e.g. Brewer et al., 1999; Brand and Halaby, 2006; Birch et al., 2009; Hoekstra, 2009; Carroll, 2014; Andrews et al., 2016; Anelli, 2016; Carroll et al., 2018), a higher quality (e.g. Black and Smith, 2004; Thomas and Zhang, 2005; Black and Smith, 2006; Long, 2008; Hussain et al., 2009; Jung and Lee, 2016; Weinstein, 2017) or a high student selectivity (e.g. Monks, 2000; Dale and Krueger, 2002; Thomas, 2003; Lindahl and Regnér, 2005; Chen et al., 2012; Dale and Krueger, 2014; Walker and Zhu, 2017; Milla, 2017). Most of the literature, however, relies on findings from the United States, England, or Australia, which have a publicly known hierarchy of universities. It is, however, unclear if this wage premium is also present in countries with a rather flat university hierarchy in which top universities are field-specific. To answer this question, I exploit graduate survey data from Germany. Compared to the U.S. or England, German universities meet the flat hierarchy. There is, to the best of my knowledge, no other paper analyzing this wage premium for Germany so far.

To measure the quality of a university, I rely on two different rankings. The first one is the [Quacquarelli Symonds World University \(QS\) Ranking](#). The QS is an international top-university ranking starting in 2014. The ranking is subject-specific and includes 50 to 500 universities, depending on the year and the subject. Similar to other university rankings, they use standard quality measures used in the literature. I extracted the German universities which were listed by these rankings to get a measure for top (or at least high-ranked) universities in Germany.

Another measure for *better* universities follows Avery et al. (2013). They calculated a revealed preference ranking based on top students' university decisions. Top students can decide which university to go to and thus collectively decide which universities are the best. This selection of the best students should thereby result in a ranking of top universities

by the revealed preferences of the students and the acceptance of the universities of these students. Thus, I construct one ranking based on the mean High School GPA of (top) students per cohort, university, and subject to get a second subject-specific university ranking for Germany.

To overcome the selection problem possible in simple OLS regression, I use an IV-approach. The instruments is the number of top universities per state, cohort and area of study. IV-regression results show a wage premium of 11 to 13 percent for the QS ranking and five to eight percent for the RPA ranking. One difference between the two rankings is, that when I split the regressions into first and second wave. Then, the QS ranking effect is mainly prevalent in the first wave, while the RPA ranking effect is stable over both waves. Running gender specific regression, one sees that women are the main profiteer of a degree from a top university for both rankings.

The paper continues as follows. Section 2 reviews the literature and section 3 gives an insight into the data. Then, the econometric model is presented in section 4. After that, I present the estimation results in section 5 and conclude in section 6.

2 Literature

There are only a few studies that used university rankings to identify top universities wage premium. Hartog et al. (2010) is one of the few ever using a ranking to find a university wage premium. They use Chinese graduates and find a premium of graduates of the top 100 universities of 28 percent compared to those of the ranks 401-500. They use the ranking from the China University Alumni Association, which includes measures for research quality, quality of education, and reputation. Birch et al. (2009), Carroll (2014), and Carroll et al. (2018) use the ShanghaiRanking to identify the so-called *Group of Eight*¹ universities in Australia. While Birch et al. (2009) could not find any wage premium, Carroll (2014) and Carroll et al. (2018) found a small but significant wage

¹Australian universities ranked in the top 100 in the world in 2012 according to the ARWU Ranking (later called ShanghaiRanking) are coded as 1 and 0 otherwise.

premium of around 3 to 5 percent. For Milan, Italy, Anelli (2016) find a wage premium of the elite universities of 52 percent higher yearly income.

Apart from these studies, the literature relies on elite status, the selectivity of universities, and single quality measures. Brewer et al. (1999) reports a substantial wage premium of up to 40% for graduates of elite private colleges in the US relative to public colleges. Brand and Halaby (2006) find that graduates from an elite college have an advantage in educational achievement and occupational status. Results for wages are mixed and thus cannot confirm the results mentioned above.

Similar to the idea of identifying elite universities, Hoekstra (2009) analyze the effect of so-called flagship universities of the US. Using regression discontinuity, they find a wage premium of around 24 percent only for white men. Using an official hierarchical classification of Korean universities, Jung and Lee (2016) find that university prestige is vital for the wage of graduates. They further prove a gender difference, i.e., results are more pronounced for males than for females.

The next branch relies on quality measures of a university rather than a status. A typical measure of quality is, for example, the mean test score, faculty-student ratio, retention rate, total tariff score, mean faculty salary, or expenditure per pupil. McGuinness (2003) finds that, for the UK, proxies for university quality do not affect labor market outcomes. Long (2008) use the average quality of universities within a certain radius of the student's location during high school. Across methods of estimation, they find robust evidence of the positive effects of college quality on college graduation and household income and weaker evidence of effects on hourly wages. Hussain et al. (2009) emphasize the positive relationship between university quality and earnings by around six percent for a one standard deviation increase in university quality. They further add that the relationship is highly non-linear and that the top students benefit the most. They also find a higher wage growth for graduates from high-qualified universities, which is also a results in Thomas and Zhang (2005). Weinstein (2017) find a positive effect of relative and absolute university quality on earnings one year after graduation, but cannot confirm the higher

wage growth for high-quality universities, because the results are insignificant ten years after graduation.

Another branch of the literature focuses on the selectivity of universities only, i.e., compare more selective universities to less selective ones. Monks (2000) shows that graduates from highly selective universities earn more than from less selective institutes. They further note that the results vary for gender and race. Dale and Krueger (2002) estimate the payoff to attending more selective universities and thereby match students who applied to the same colleges but got accepted differently to reduce the selection bias. Using this matching method, they find a wage premium only for the more selective universities for children from low-income families, but no general effect for everyone. Those results are, however, restricted to highly elite schools. Dale and Krueger (2014) expanded the earlier study using administrative data, increasing the number of universities and still find only subgroup effects of university characteristics for blacks and Hispanics. They use average SAT score, Basson's index of college selectivity, and net tuition as quality measures (and not the selectivity anymore). Chen et al. (2012) follows the matching method in Dale and Krueger (2002) and find substantial results for more selective MBA programs, which are not just for subgroups. Ge et al. (2018) follow Dale and Krueger (2002) as well and confirm the missing significance for a wage premium only for males after controlling for the selection into highly selective universities. They expand the literature by showing that for women, there are indeed significant results. A high selective university increases women's probability of an advanced degree, earnings and reduces their likelihood of marriage, and the earnings increase is higher for married women than for singles.

Walker and Zhu (2017) match mean standardized admission scores for each field of study off an institution per cohort and further include the selectivity of each subject of the institute. They find that a considerable portion of the wage premium is due to the abilities of students who are selected by the universities.

3 Data

3.1 Ranking

The main interest of this paper is to analyze the impact of top universities in a flat university hierarchy on wages. For that, I measure the university quality of the area of study level. Thus, more specifically, I measure the effect of top programs within universities compared to the rest of the area of study. I use two different rankings to identify a university as better than others. The first relies on the international, subject-specific Quacquarelli Symonds World University Rankings (QS). Then, I also calculate a revealed preferences and acceptance (RPA) ranking based on the mean High School GPA of graduates.

The QS ranks universities since 2014 for several areas of study. The number of universities in the sub-rankings which are listed, differ from area to area and by year. Table 1 summarizes the areas of study and the number of universities that were ranked in that year. The ranking includes information of (i) academic reputation, (ii) employer reputation, (iii) faculty/student ratio, (iv) citations per faculty, (v) the international faculty ratio and (vi) international student ratio. Depending on the specific areas, they weight this information to end up with one ranking. The QS, however, does not report the specific weighting formulas.

The (customized) German QS ranking for the analysis is calculated as followed: At first, I subtract all German universities from the rankings and then calculate the mean from 2014 to 2017 to get a more robust result for each area of study. I then convert the means into percentiles per area of study because the number of universities offering an area of study differs.

Because of data confidentiality I am not allowed to identify the universities of each individual, I then had to group universities. I did so, taking means of the percentiles of the two universities next to each, beginning from the top.² The identification of one particu-

²In case two universities have the same mean value, they also have the same ranking. The next best

lar university is thereby not possible anymore, but because the groups are based on the ranking, the signal should not change much in the regression. In the group of two, the better university is downgraded a little bit, and the worst one is upgraded. Assuming that the signal, coming from a high-quality university, decreases with the percentile-ranking, estimates should be downward biased. It is forbidden to compare universities with each other, which is why the DZHW cannot provide data linking graduates with the university they graduated. If universities are not listed, they are not good enough to be in the ranking. Thereby, I can also alternate the ranking to a dummy separating universities into being ranked by the QS and not being ranked.

For the revealed preferences and acceptance (RPA) ranking, I calculated the mean of the High School GPA per university, area of study, and cohort. I then rank the universities based on the mean and calculated a ranking in percentiles based on the number of universities providing the area of study. The idea behind the RPA ranking is the following: Students can decide in which university they want to enroll and thereby reveal what the best (possible) university is for them. If students do not have the best grades, they are bounded to the acceptance of universities that can select students. Thus, the data shows not only the revealed preferences of students but the best possible preference. The combination of the collective decision of all students and the acceptance of the universities then results in a ranking of universities.

3.2 Sample

For the data analysis, I exploit the Graduate Panel of the German Centre for Higher Education Research and Science Studies (DZHW). Due to the unique sample and survey design, the DZHW Graduate Panel offers the best opportunities to comprehensively ex-

university gets the very next number in line, not overstepping any number. Thereby, the ranking is somewhat condensed. The reason for this is that the difference might become too big. The grouping, however, does not take similar ranks into account. This means that there are only groups of two. Thereby universities with the same ranking can have a different percentage in the end if they are not in the same group. Which one is chosen to be better was done randomly. Differences that occurred because of this are rather small. In most of the analysis, I use a simplification of the ranking. The QS-dummy is equal to one if the university was ever ranked in the QS ranking for the specific area of study and zero otherwise.

amine research questions about German university graduates (Baillet et al., 2017; Baillet et al., 2019). The data is based on individuals graduating in 2005 and 2009, observed in two waves each. The first wave is conducted about a year after graduation, and the second is after 4 to 5 years. Thus, I observe individuals in 2005 and 2009 in their first wave and in 2010 and 2014 in their respective second wave. I include only individuals full-time employed individuals.

The complete set of variables used in the analysis is shown in table 2 for three different (sub-)samples. The first shows general sample information, containing up to 16,453 full-time employed individuals. When relying on the RPA ranking, 10,218 individuals are left in the sample. For the analysis, all individuals with more than one degree are dropped because of an unclear matching of rankings. Additionally, in all variables, there are some missing, as can be seen in the number of observations in the first column for the whole sample. For the QS ranking, the number drops to 6,573 because the QS ranks only a subset of areas. Because both subgroups suffer a loss of individuals, table 2 shows the number of observations, the means and the standard deviations for each variable of the three subgroups.

For the basic set of variables for a wage regression, I have the gender, age, age squared, cohort, and period. Cohort refers to the cohort 2005 and 2009 and period to the first and second waves. Period, therefore, is a measure for the possible increase in experience individuals got from wave one to wave two. Then, I include dummies for the different areas of study. Grouping those by subjects, most of the students in Germany go for subject group Language and Cultural Science, Legal, economics and social sciences, mathematics and natural sciences as well as engineering sciences. I further include variables to account for the state of High School graduation, educational background, university information, work experience before graduation, family information, state variables, and NUTS-2 variables.

Comparing the three subgroups shows that the loss of information should be rather random. Only for the areas of study, since the QS ranking does not rank all of them, I find

certain changes. The share of females is also lightly affected by the QS ranking. The main reason is that very popular fields among women, such as German studies, are not within the QS ranking. The complete sample has a share of 0.59 women, the RPA subsample of 0.58, and the QS-subsample of 0.52. This should difference in the share is driven by the different areas of study decisions and should be kept in mind in the interpretation. Apart from this, for example, the age (29.04; 29.41; 29.45), a dummy for the first and second wave (0.33; 0.36; 0.36), a cohort dummy (0.49), the High School GPA (0.49; 0.43; 0.44), High School graduation from a vocational school (0.05; 0.05; 0.05), going to an applied University (0.32; 0.33; 0.31), being employed before university (0.29; 0.31; 0.31) and a dummy for having children (0.15; 0.16; 0.15) have very similar means.

4 Econometric Model

I conduct a general OLS framework for the estimations to acquire baseline results. Our regression model is

$$y_{it} = \alpha_{OLS} + \rho_{OLS} \cdot ranking_{it} + X_{it}\beta_{OLS} + \epsilon_{it}$$

where i stands for the individual and t for the specific period. The outcome variable y is the current wage of the first wave and the second wave. The primary variable of interest is *ranking*, which will be either the QS ranking or the RPA ranking or a dummy for the top universities based on these rankings. The coefficients ρ , therefore, measure the effect of a graduate from a top university. Within X , I include the variables listed in table 2. I control for basic wage regression variables, such as the gender, age and age squared, the cohort and the period, area of study, educational background, university decision information and the final GPA, (work) experience before and during the studies and family information. The vector of coefficients β captures the effects of the respective variables. The general intercept is included with α and ϵ is the idiosyncratic error term

Though I employ a rich set of control variables, there might still be omitted variables

leading to a selection bias. In case this selection variable is not covered by the set of control variables, results are expected to be biased. To solve the selection problem, I run an instrumental variables regression with the following two-step procedure:

$$ranking_{it} = \alpha_{FS} + \lambda \cdot Instruments_{it} + X_{it}\beta_{FS} + \nu_{it}$$

$$y_{it} = \alpha_{IV} + \rho_{IV} \cdot \widehat{ranking}_{it} + X_{it}\beta_{IV} + \eta_{it}$$

First, I estimate the ranking using the general model and add the instruments to it. Next, I calculate the fitted values $\widehat{ranking}_{it}$ and plug these into the wage regression. The main instrument for both rankings is the number of top universities in the state of the individuals higher education entrance qualification. Thereby, I assume that students first choose an area of study and then the location.³

5 Results

The regression results for the QS-ranking are summarised in table 3. In the first four columns, I present the OLS results and, in the next four, the IV results. The first for both the OLS and the IV uses the general QS ranking, column (2) and (6) show the estimates for the dummy if the QS ranked a university for this area or not, column (3) and (7) apply a indicator for the top quartile of universities per area of study of the QS ranking. Since the cut-off value of the 75. percentile is subjectively chosen, column (4) and (8) show additionally zöregression results for an indicator of the top decile.

The QS ranking in column (1) has a coefficient of -0.0000 and is both economical and statistically insignificant. Simplifying the ranking into the QS-dummy in column (2) even decreases the estimator but is still statistically insignificant. In column (3), when the dummy includes only the top quartile of QS-ranked universities, the coefficient increases

³I also include (relative) distances to the next top universities and include neighbour states, but those instruments did not show an improvement of the first stage f-statistic.

to 0.0186, i.e., an estimates monthly gross wage increase by 1.86 percent. The change in the coefficient would suggest that the effect is not linear and driven by some of better universities. The literature already showed this nonlinearity. Though the effect would be of economic interest, it is not statistically significant unequal from zero. Using a more selective definition of top universities, column (4) shows a 2.34 percent wage premium for the top decile, which is still statistically insignificant.

The coefficients for all four specifications increase when running the IV regressions. An increase of the coefficient in the IV regression is typical in the literature. The QS ranking coefficient increases only marginally and is now equal to 0.0010 and statistically significant at the 5 percent level. The coefficient of the three dummies is equal to 0.0822, 0.1036, and 0.1337, with the last two even statistically highly significant. The coefficient results are within the boundaries of effects found in the literature and would predict a wage premium of around 10 percent. This effect, though found in the literature in other countries as well, seems high, which is why I further look at the RPA ranking in table 4.

Within this ranking, students decide what a top university is and not a company. Column (1) includes the mean High School GPA without converting it into a ranking. The coefficient is equal to -0.0384 and is significant at the 5% significance level. Thus, a better mean GPA by one (i.e., is lower), is associated with a 3.84 percent increase in the gross wage for the observed graduates. Using the RPA ranking leads to a coefficient equal to 0.0003 significant at the 5 percent level.⁴ The small coefficient should be seen in perspective: The ranking ranges from 0 to 100, and if a university improves, the increase in percentile would be more than one. An increase of 10 percent in the ranking would lead to a 0.3 increase in the wage. To simplify the RPA ranking, the third column shows an estimate for a dummy for the top quartile of universities per area of study. Here, I get an increased wage of 1.32 percent, while missing a statistical significance. When comparing the bottom 90 to the top ten, the coefficient is equal to 0.0307, with a statistical significance at the 1 percent level. Thus, graduating from a university of the top decile of the RPA ranking

⁴Results are similar if the ranking is based only on those with a GPA higher than 2.0 or on the top 10 percent High School students (per area of study).

would predict a higher wage of 3 percent.

To overcome the selection problem, I again use the number of top universities within the state of the higher education entrance qualification. As for the QS ranking, the coefficients increase and are all statistically significant. The wage premium for the top quartile is equal to 4.85 percent and for the top decile 8.25 percent. Thus, the RPA ranking suggests a smaller but still substantial wage premium than the QS ranking.

The dataset includes wage information of two waves: One year after graduation and five years after graduation. The question naturally arises if the estimated wage premium is carried on from wave one to wave two or just found in one of them. Table 5 and 6 show the wave specific estimation results for the IV regressions. This wave separation shows an interesting insight: For the QS ranking, the four different measures are only significant for the first wave (column 1 to 4) but not for the second (column 5 to 8). This difference between the waves would suggest that graduates from a top university benefit with a higher starting salary, which equalizes at some later point of the career. This could suggest that the QS wage premium is a signal effect. Employers know the QS ranking and thus give these graduates higher wages. Graduates from other universities, however, can catch up.

For the RPA ranking, the case differs. Here, the coefficient for top decile is significant in both waves, and the point estimate of the wage premium is 8.33 percent (wave 1) and 8.93 percent (wave 2), so basically the same. This stable estimation would suggest that students graduating from the top decile of the RPA ranking experience a wage premium early on and keep that advantage. For the top quartile, only the second wave is statistically significant and with a premium of 6.63 percent more prominent than the first wave of 2.51. This could mean that graduates acquired a higher human capital at the better universities, which is not known to the employer right away but after some time leads to a wage premium. Graduates from the top decile of the RPA ranking, however, might combine both the signal and the hum capital acquisition.

Next, I check the sensitivity and robustness of the estimated wage premium. Table 9 and

10 drop smaller areas of study, and the estimation is not robust for the top decile of the RPA ranking when less than half of the observations are left in the sample. Dropping smaller universities, as shown in tables 11 and 12 does not lead substantial different estimation results.

Given that both cut-offs of the top quartile and top decile are somewhat arbitrary, figure 1 and 2 show the dummy coefficient with a rolling cut-off and its 90% confidence interval for the IV specification. Only for the RPA, when the top percentile is above 93, the coefficient drops and is insignificant.

5.1 Gender specific regressions

Labor participation and aspiration (among others) usually lead to a difference in the wage distribution of males and females. Table 7 and 8 thus shows IV-regression results for the QS and the RPA rankings for men and women. For the QS ranking, the coefficients for men in column (1) to (4) are all positive but not statistically significant. The coefficients are also smaller in magnitude compared to the gender-unspecific regressions in table 3. Consequently, the coefficients for the female regression specifications in column (5) to (8) are larger and statistically significant. Female graduates with a degree from the top decile experience a wage premium of 22.73 percent.

For the RPA ranking, the case is less extreme but similar. The top decile leads to a wage premium of 5.45 percent for men while statistically significant; the premium for women is equal to 9.20 percent significant at the 1 percent level. Thus, the top university wage premium of the RPA ranking increase only by around one percentage point from 8.25 up to 9.20. In general, the wage premium for females and not males is not necessarily surprising. Women face a gender wage gap due to several reasons. One reason is lowered competition seeking. Graduating from more competitive universities could be seen as a signal by the employer.

– to be completed –

6 Conclusion

The literature shows a wage premium for graduates from elite universities, especially for the USA, England, and Australia. I analyzed the same question for Germany, a country with a rather flat hierarchy of the universities. To identify universities as *better* than others, I use two different approaches. At first, the QS ranking, which relies on typical university quality measures and secondly a revealed preference and acceptance ranking based on the mean High School GPA of students. I find a significant positive effect using both the QS and the RPA ranking. One striking difference between the two rankings is revealed when regressing the first and second waves separately. Then, the QS-ranking gives a wage premium only in the first wave. The RPA ranking gives a wage premium in both waves. Additionally, the main profiteer appear to be females and not males.

– to be completed –

References

- Andrews, Rodney J, Jing Li, and Michael F Lovenheim (2016). “Quantile Treatment Effects of College Quality on Earnings”. In: *Journal of Human Resources* 51, pp. 200–238.
- Anelli, Massimo (2016). “The Returns to Elite College Education: A Quasi-Experimental Analysis”. In: *IZA Discussion Papers*.
- Avery, Christopher N, Mark E Glickman, and Caroline M Hoxby (2013). “A revealed preference ranking of U.S. colleges and Universities”. In: *Quarterly Journal of Economics* 128, pp. 425–467.
- Baillet, Florence et al. (2017). “DZHW-Absolventenpanel 2009: Daten-und Methodenbericht zu den Erhebungen der Absolvent(inn)enkohorte 2009 (1. und 2. Befragungswelle)”. In: *dfz.DZHW*, pp. 1–42.
- (2019). “DZHW-Absolventenpanel 2005: Daten-und Methodenbericht zu den Erhebungen der Absolvent(inn)enkohorte 2005 (1., 2. und 3. Befragungswelle)”. In: *dfz.DZHW*, pp. 1–49.

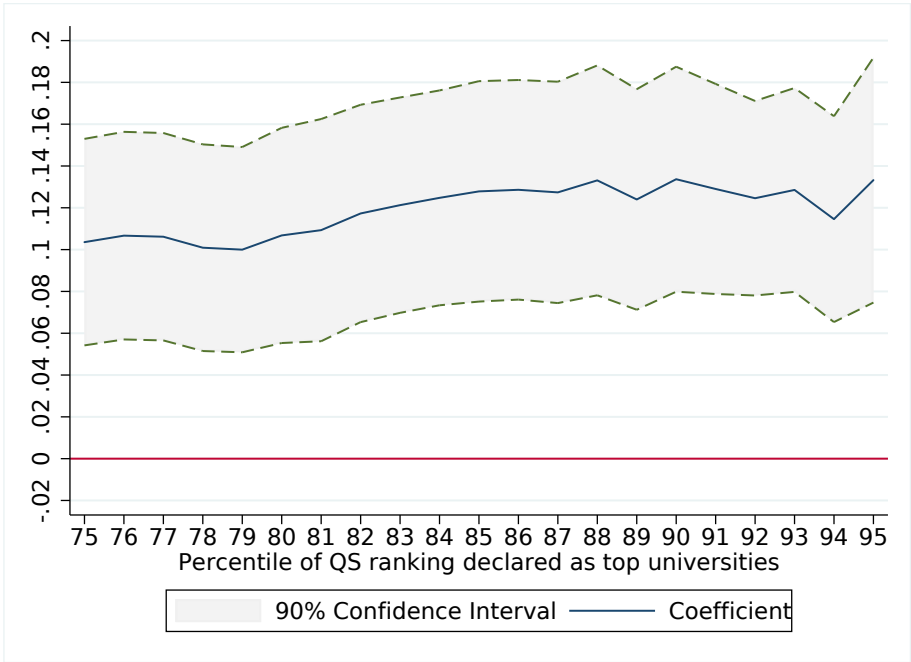
- Birch, Elisa Rose, Ian Li, and Paul W. Miller (2009). “The influences of institution attended and field of study on graduates’ starting salaries”. In: *Australian Economic Review* 42, pp. 42–63.
- Black, Dan A. and Jeffrey A. Smith (2004). “How robust is the evidence on the effects of college quality? Evidence from matching”. In: *Journal of Econometrics* 121, pp. 99–124.
- (2006). “Estimating the Returns to College Quality with Multiple Proxies for Quality”. In: *Journal of Labor Economics* 24, pp. 701–728.
- Brand, Jennie E. and Charles N. Halaby (2006). “Regression and matching estimates of the effects of elite college attendance on educational and career achievement”. In: *Social Science Research* 35, pp. 749–770.
- Brewer, Dominic J, Eric R Eide, and Ronald G Ehrenberg (1999). “Does It Pay to Attend an Elite Private College? Cross-Cohort Evidence on the Effects of College Type on Earnings College”. In: *Journal of Human Resources* 34, pp. 104–123.
- Carroll, David (2014). “An Investigation of the Relationship Between University Rankings and Graduate Starting Wages”. In: *Journal of Institutional Research* 19, pp. 46–54.
- Carroll, David, Chris Heaton, and Massimiliano Tani (2018). “Does It Pay to Graduate from an ‘Elite’ University in Australia?” In: *IZA Discussion Paper Series*.
- Chen, Weiwei, Wayne A. Grove, and Andrew Hussey (2012). “The payoff to school selectivity: An application of Dale and Krueger’s method to MBA programs”. In: *Economics Letters* 116, pp. 247–249.
- Dale, Stacy and Alan Krueger (2014). “Estimating the Effects of College Characteristics over the Career Using Administrative Earnings Data”. In: *Journal of Human Resources* 49, pp. 323–358.
- Dale, Stacy Berg and Alan B. Krueger (2002). “Estimating the Payoff to Attending a More Selective College: An Application of Selection on Observables and Unobservables”. In: *Quarterly Journal of Economics* 117, pp. 1491–1527.
- Ge, Suqin, Elliott Isaac, and Amalia Miller (2018). “Elite Schools and opting-in: Effects of college selectivity on career and family outcomes”. In: *NBER Working Papers*, pp. 1–42.

- Hartog, Joop, Yuze Sun, and Xiaohao Ding (2010). “University rank and bachelor’s labour market positions in China”. In: *Economics of Education Review* 29, pp. 971–979.
- Hoekstra, Mark (2009). “The effect of attending the flagship state university on earnings: A discontinuity-based approach”. In: *Review of Economics and Statistics* 91, pp. 717–724.
- Hussain, Iftikhar, Sandra McNally, and Shqiponja Telhaj (2009). “University Quality and Graduate Wages in the UK”. In: *CEE Discussion Papers* 0099, pp. 1–29.
- Jung, Jisun and Soo Jeung Lee (2016). “Influence of university prestige on graduate wage and job satisfaction: the case of South Korea”. In: *Journal of Higher Education Policy and Management* 38, pp. 297–315.
- Lindahl, Lena and Håkan Regnér (2005). “College choice and subsequent earnings: Results using Swedish sibling data”. In: *Scandinavian Journal of Economics* 107, pp. 437–457.
- Long, Mark C. (2008). “College quality and early adult outcomes”. In: *Economics of Education Review* 27, pp. 588–602.
- McGuinness, Séamus (2003). “University of quality and labour market outcomes”. In: *Applied Economics* 35, pp. 1943–1955.
- Milla, Joniada (2017). “The context-bound university selectivity premium”. In: *IZA Discussion Paper*.
- Monks, James (2000). “The returns to individual and college characteristics: Evidence from the National Longitudinal Survey of Youth”. In: *Economics of Education Review* 19, pp. 279–289.
- Thomas, Scott L. (2003). “Longer-term economic effects of college selectivity and control”. In: *Research in Higher Education* 44, pp. 263–299.
- Thomas, Scott L. and Liang Zhang (2005). “Post-baccalaureate wage growth within four years of graduation: The effects of college quality and college major”. In: *Research in Higher Education* 46, pp. 437–459.
- Walker, Ian and Yu Zhu (2017). “University Selectivity and the Graduate Wage Premium: Evidence from the UK”. In: *IZA Discussion Papers*.

Weinstein, Russell (2017). “University Selectivity, Initial Job Quality, and Longer-Run Salary”. In: *IZA Discussion Paper Series*, pp. 1 –38.

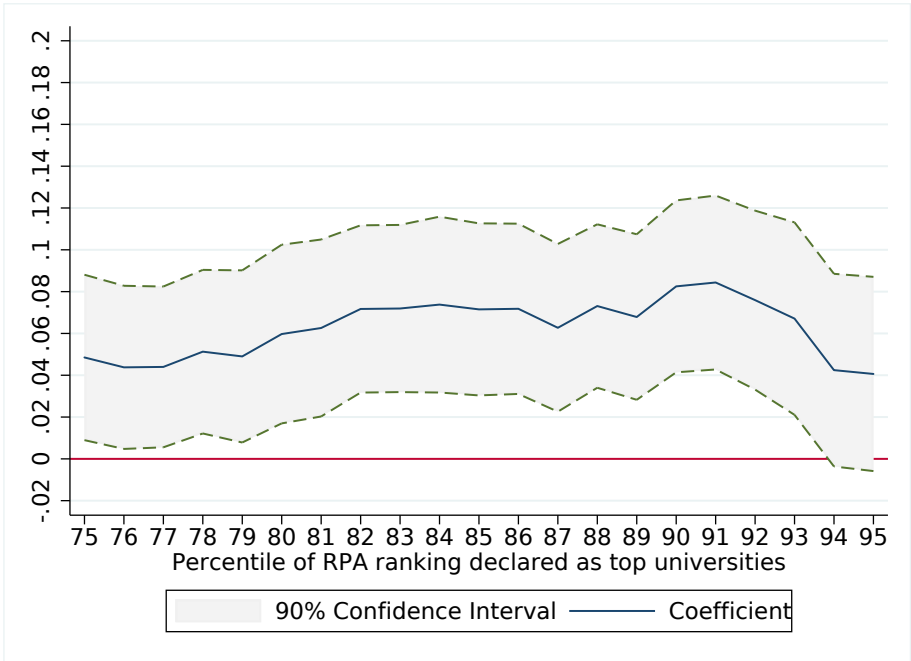
Figures

Figure 1: Rolling cut-off value for indicator of top universities - QS ranking



Notes: The graphs shows the regressions results for the IV regressions of the top percentile of the QS ranking, starting from the top 25 to the top 5 percentile. The blue solid line shows the coefficient and the green dashed line shows border of the 90% confidence interval.

Figure 2: Rolling cut-off value for indicator of top universities - RPA ranking



Notes: The graphs shows the regressions results for the IV regressions of the top percentile of the QS ranking, starting from the top 25 to the top 5 percentile. The blue solid line shows the coefficient and the green dashed line shows border of the 90% confidence interval.

Tables

Table 1: QS ranking

Subject of study	Area of study	Universities ranked per year			
Language and cultural sciences	English studies	200	300	300	300
	Media studies	200	200	200	200
Sports	Sport studies	0	0	0	100
Legal, economic and social sciences	Business administration	0	200	200	300
	Education science	200	200	300	300
	Law	200	200	200	300
	Politics and Sociology	200	200	200	300
	Psychology	200	200	200	300
	Economics	200	200	300	400
	Public management and governance	0	0	100	100
Mathematics, natural sciences	Biology	200	400	500	500
	Chemistry	200	200	200	300
	Geography	200	200	200	200
	Computer sciences	200	400	500	500
	Mathematics	200	400	400	400
	Pharmacy	200	200	200	300
	Physics	200	500	400	500
Medicine, health care sciences	Medicine	200	400	500	500
Veterinary medicine	No area of study from this subject is included in the QS ranking				
Agricultural forestry and nutritional sciences	No area of study from this subject is included in the QS ranking				
Engineering sciences	Architecture	0	100	100	200
	Building and environmental engineering	200	200	200	200
	Electrical engineering	200	300	400	400
	Engineering	200	300	300	400
Art, aesthetics	No area of study from this subject is included in the QS ranking				

Notes: The table shows the areas of study which are ranked by the QS. There are no areas of the subject groups Veterinary medicine, agricultural forestry and nutritional sciences, and art and aesthetics. Sports is not included in the QS-analysis, because not a single German university was included.

Table 2: Summary statistics of variables

	Obs	Mean	SD	Obs	Mean	SD	Obs	Mean	SD
<i>Outcome</i>									
log monthly gross wage	15076	7.86	0.52	10218	7.87	0.50	6573	7.95	0.46
<i>QS rankings</i>									
Customized QS ranking	10745	24.46	37.98				6573	24.41	37.94
Indikator for QS ranked University	10745	0.30	0.46				6573	0.30	0.46
Indikator for QS ranked and above 75. percentile	10709	0.23	0.42				6573	0.23	0.42
Indikator for QS ranked and above 90. percentile	10709	0.15	0.36				6573	0.15	0.36

Number of qs-ranked universities per state, cohort and area	16412	0.62	0.94				6573	0.95	1.01
Number of qs-ranked universities above 75 percentile	16412	0.52	0.82				6573	0.81	0.90
Number of qs-ranked universities above 90 percentile	16412	0.40	0.72				6573	0.60	0.83
<i>RPA rankings</i>									
Mean HS GPA per university, field of study and cohort	16448	2.28	0.33	10218	2.28	0.33			
Revealed preferences and acceptance ranking	16448	56.74	29.08	10218	56.57	29.15			
Indikator for RPA ranking above 75. percentile	16405	0.33	0.47	10218	0.32	0.47			
Indikator for RPA ranking above 90. percentile	16405	0.15	0.35	10218	0.14	0.35			
Number of RPA universities per state, area and cohort above 75. percentile	16405	1.24	1.23	10218	1.24	1.24			
Number of RPA universities per state, area and cohort above 90. percentile	16405	0.63	0.87	10218	0.63	0.87			
<i>Basic</i>									
Female dummy	16451	0.55	0.50	10218	0.54	0.50	6573	0.49	0.50
Age	16453	29.55	3.31	10218	29.54	3.33	6573	29.66	3.26
Age squared	16453	883.89	201.27	10218	883.75	202.91	6573	890.25	198.77
Wave	16453	0.39	0.49	10218	0.37	0.48	6573	0.37	0.48
Cohort	16453	0.40	0.49	10218	0.38	0.48	6573	0.38	0.48
<i>Area of Study</i>									
Linguistics and cultural sciences	16453	0.01	0.10	10218	0.01	0.11	6573	0.02	0.13
Prot. theology	16453	0.00	0.06	10218	0.00	0.06	6573	0.00	0.00
Cath. theology	16453	0.01	0.08	10218	0.01	0.08	6573	0.00	0.00
Philosophy	16453	0.00	0.05	10218	0.00	0.05	6573	0.00	0.00
History	16453	0.01	0.10	10218	0.01	0.11	6573	0.00	0.00
Library science	16453	0.01	0.12	10218	0.02	0.14	6573	0.00	0.00
General and comparative literature studies	16453	0.01	0.07	10218	0.01	0.07	6573	0.00	0.00
Classical philosophy	16453	0.00	0.02	10218	0.00	0.02	6573	0.00	0.00
German studies	16453	0.04	0.19	10218	0.04	0.19	6573	0.00	0.00
Anglistics	16453	0.02	0.13	10218	0.02	0.13	6573	0.03	0.17
Romanistics	16453	0.01	0.08	10218	0.01	0.08	6573	0.00	0.00
Slavistics	16453	0.00	0.01	10218	0.00	0.01	6573	0.00	0.00
Non-European linguistics and cultural sciences	16453	0.00	0.02	10218	0.00	0.02	6573	0.00	0.00
Cultural studies in a wider sense	16453	0.00	0.04	10218	0.00	0.04	6573	0.00	0.00
Psychology	16453	0.02	0.12	10218	0.02	0.13	6573	0.03	0.16
Educational sciences	16453	0.04	0.21	10218	0.04	0.20	6573	0.04	0.20
Sports	16453	0.01	0.08	10218	0.01	0.08	6573	0.00	0.00
Business and social studies, generally	16453	0.01	0.08	10218	0.01	0.08	6573	0.00	0.00
Regional sciences	16453	0.00	0.01	10218	0.00	0.01	6573	0.00	0.00
Political sciences	16453	0.01	0.10	10218	0.01	0.10	6573	0.02	0.13
Social sciences	16453	0.01	0.11	10218	0.01	0.12	6573	0.02	0.14
Social services	16453	0.05	0.21	10218	0.05	0.21	6573	0.00	0.00
Legal studies	16453	0.04	0.19	10218	0.01	0.08	6573	0.01	0.10
Administrative sciences	16453	0.01	0.08	10218	0.01	0.08	6573	0.00	0.00

Economic sciences	16453	0.15	0.36	10218	0.17	0.37	6573	0.26	0.44
Industrial engineering	16453	0.04	0.20	10218	0.04	0.20	6573	0.00	0.00
Mathmatics, natural sciences, generally	16453	0.00	0.03	10218	0.00	0.02	6573	0.00	0.00
Mathematics	16453	0.03	0.16	10218	0.03	0.17	6573	0.04	0.21
Computer Sciences	16453	0.05	0.23	10218	0.06	0.23	6573	0.09	0.28
Physics, astronomy	16453	0.01	0.09	10218	0.01	0.09	6573	0.01	0.11
Chemistry	16453	0.01	0.11	10218	0.01	0.11	6573	0.02	0.13
Pharmaceutics	16453	0.00	0.02	10218	0.00	0.02	6573	0.00	0.02
Biology	16453	0.02	0.14	10218	0.02	0.13	6573	0.03	0.16
Geosciences	16453	0.00	0.06	10218	0.00	0.06	6573	0.00	0.00
Geography	16453	0.01	0.11	10218	0.01	0.12	6573	0.02	0.15
Health sciences, generally	16453	0.01	0.10	10218	0.01	0.11	6573	0.00	0.00
Human medicine	16453	0.05	0.23	10218	0.06	0.23	6573	0.09	0.28
Veterinary medicine	16453	0.01	0.11	10218	0.01	0.11	6573	0.00	0.00
Landscape management	16453	0.02	0.12	10218	0.02	0.13	6573	0.00	0.00
Agricultural sciences	16453	0.02	0.13	10218	0.02	0.13	6573	0.00	0.00
Forestry, wood industry	16453	0.01	0.07	10218	0.00	0.07	6573	0.00	0.00
Food sciences and home eco- nomics	16453	0.01	0.08	10218	0.01	0.08	6573	0.00	0.00
Engineering, generally	16453	0.00	0.07	10218	0.01	0.07	6573	0.00	0.00
Mining, metallurgy	16453	0.00	0.03	10218	0.00	0.03	6573	0.00	0.04
Mechanical engineering, process engine	16453	0.08	0.28	10218	0.08	0.28	6573	0.13	0.33
Electrical engineering	16453	0.03	0.18	10218	0.04	0.18	6573	0.05	0.23
Traffic engineering, nautical sci- ence	16453	0.01	0.12	10218	0.01	0.12	6573	0.00	0.00
Architecture, interior design	16453	0.03	0.17	10218	0.03	0.18	6573	0.05	0.22
Spatial planning	16453	0.00	0.06	10218	0.00	0.05	6573	0.00	0.00
Civil engineering	16453	0.03	0.17	10218	0.03	0.17	6573	0.05	0.21
Surveying	16453	0.01	0.11	10218	0.01	0.11	6573	0.00	0.00
Art, aesthetics, generally	16453	0.00	0.06	10218	0.00	0.06	6573	0.00	0.00
Fine art	16453	0.00	0.03	10218	0.00	0.03	6573	0.00	0.00
Design	16453	0.01	0.11	10218	0.01	0.11	6573	0.00	0.00
Performing art, film and televi- sion	16453	0.00	0.04	10218	0.00	0.03	6573	0.00	0.00
Music	16453	0.00	0.07	10218	0.00	0.07	6573	0.00	0.00

States

Schleswig-Holstein	16252	0.03	0.17	10218	0.03	0.17	6573	0.03	0.17
Hamburg	16252	0.02	0.14	10218	0.02	0.14	6573	0.02	0.14
Niedersachsen	16252	0.10	0.30	10218	0.10	0.31	6573	0.10	0.31
Bremen	16252	0.01	0.08	10218	0.01	0.08	6573	0.01	0.09
Nordrhein-Westfalen	16252	0.16	0.37	10218	0.17	0.38	6573	0.16	0.37
Hessen	16252	0.06	0.24	10218	0.06	0.24	6573	0.06	0.24
Rheinland-Pfalz	16252	0.04	0.20	10218	0.04	0.19	6573	0.04	0.20
Baden-Württemberg	16252	0.15	0.36	10218	0.14	0.35	6573	0.14	0.35
Bayern	16252	0.15	0.36	10218	0.13	0.33	6573	0.14	0.35
Saarland	16252	0.01	0.08	10218	0.01	0.08	6573	0.01	0.07
Berlin	16252	0.03	0.17	10218	0.04	0.18	6573	0.04	0.19
Brandenburg	16252	0.04	0.18	10218	0.04	0.19	6573	0.04	0.19
Mecklenburg-Vorpommern	16252	0.02	0.15	10218	0.02	0.15	6573	0.02	0.15
Sachsen	16252	0.09	0.29	10218	0.10	0.30	6573	0.09	0.29
Sachsen-Anhalt	16252	0.04	0.19	10218	0.04	0.19	6573	0.04	0.19

Educational Background

High School GPA	16261	2.27	0.61	10218	2.27	0.61	6573	2.25	0.62
-----------------	-------	------	------	-------	------	------	------	------	------

Year of HEEQ	16346	1999.80	3.08	10218	1999.64	3.06	6573	1999.55	3.00
Field-specific HEEQ	16363	0.02	0.16	10218	0.02	0.14	6573	0.02	0.14
HEEQ from vocational school	16363	0.13	0.33	10218	0.13	0.33	6573	0.14	0.34
Foreign HEEQ	16363	0.01	0.09	10218	0.00	0.02	6573	0.00	0.02
High School at vocational school	16390	0.06	0.23	10218	0.05	0.22	6573	0.06	0.23
<i>University</i>									
Grade of University degree	15441	1.87	0.54	10218	1.86	0.54	6573	1.88	0.55
Type of degree: Magister	16453	0.05	0.22	10218	0.06	0.23	6573	0.04	0.20
Type of degree: Bachelor	16453	0.12	0.32	10218	0.10	0.30	6573	0.10	0.30
Type of degree: State Examination	16453	0.11	0.31	10218	0.08	0.27	6573	0.09	0.28
Type of degree: Teaching degree	16453	0.12	0.32	10218	0.11	0.31	6573	0.08	0.27
Type of degree: Other	16453	0.00	0.05	10218	0.00	0.05	6573	0.00	0.01
General University	16453	0.63	0.48	10218	0.62	0.48	6573	0.64	0.48
<i>Experience before graduation</i>									
Vocational training before university	16408	0.28	0.45	10218	0.29	0.45	6573	0.31	0.46
Employment before university	16391	0.31	0.46	10218	0.32	0.47	6573	0.32	0.47
Voluntary internship	16232	0.38	0.48	10218	0.39	0.49	6573	0.38	0.48
Mandatory internship	16420	0.55	0.50	10218	0.53	0.50	6573	0.51	0.50
Student assistant	16404	0.33	0.47	10218	0.34	0.47	6573	0.36	0.48
Working student	16404	0.34	0.47	10218	0.35	0.48	6573	0.37	0.48
<i>Family Information</i>									
Married	16328	0.21	0.41	10218	0.20	0.40	6573	0.20	0.40
Married and female	16326	0.11	0.31	10218	0.10	0.30	6573	0.09	0.29
Child-dummy	16315	0.15	0.35	10218	0.14	0.35	6573	0.14	0.35
Children and female	16313	0.07	0.25	10218	0.06	0.24	6573	0.06	0.23
<i>State variables</i>									
GDP per capita	15246	31.64	7.51	10218	31.37	7.54	6573	31.65	7.54
Imports per capita	15246	9.02	6.04	10218	8.89	6.09	6573	8.99	6.11
Exports per capita	15246	9.09	4.05	10218	8.87	4.02	6573	8.96	4.04
Research and development expenses from businesses per capita	15246	0.59	0.36	10218	0.57	0.35	6573	0.58	0.35
Research and development expenses from the states per capita	15246	0.13	0.07	10218	0.13	0.07	6573	0.13	0.07
Patents per capita	15246	0.63	0.42	10218	0.60	0.41	6573	0.61	0.41
Producing sector in percent	15246	0.07	0.01	10218	0.07	0.02	6573	0.07	0.02
Manufacturing sector in percent	15246	0.18	0.05	10218	0.18	0.05	6573	0.18	0.05
Density of universities	15246	2.26	0.57	10218	2.29	0.57	6573	2.30	0.57
<i>NUTS-2 Variables</i>									
Unemployment rate	12420	7.18	3.16	10218	7.18	3.17	6573	7.09	3.10
Income	12420	187.47	21.65	10218	187.67	21.65	6573	188.50	21.64

Notes: The table shows summary statistics for all covariates used in the empirical analysis, pooled over both survey waves. The first column of observations only excludes individuals without a full-time job. The second column of observations contains only individuals for which all information in the RPA regression are available. The third further drops individuals with areas not ranked by the QS. Source: DZHW Graduate Panel 2005 and 2009, own calculations.

Table 3: Main OLS & IV regression results - QS ranking

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS				IV			
QS ranking	-0.0000 (0.0002)				0.0010* (0.0004)			
Indikator if ranked by QS		-0.0053 (0.0126)				0.0822* (0.0322)		
Top quartile of QS ranking			0.0186 (0.0119)				0.1036*** (0.0308)	
Top decile of QS ranking				0.0234 (0.0143)				0.1337*** (0.0338)
Basic individual information	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wave and cohort	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Area of study	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Educational Background	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
University variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Work experiment before grad.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Marriage and children	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.526	0.526	0.526	0.526	0.522	0.522	0.522	0.521
Observations	6573	6573	6573	6573	6573	6573	6573	6573
F-Statistics 1. Stage					560	623	774	677

Notes: Individual cluster and heteroskedastic robust standard errors in parentheses. $^+ p < 0.10$, $^* p < 0.05$, $^{**} p < 0.01$, $^{***} p < 0.001$

Table 4: Main OLS and IV regression results - RPA ranking

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS				IV			
Mean HS GPA	-0.0384* (0.0164)				-0.1135* (0.0559)			
RPA ranking		0.0003* (0.0001)				0.0010* (0.0005)		
Top quartile of RPA ranking			0.0132 (0.0090)				0.0485* (0.0239)	
Top decile of RPA ranking				0.0307** (0.0114)				0.0825*** (0.0248)
Basic individual information	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wave and cohort	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Area of study	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Educational Background	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
University variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Work experiment before grad.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Marriage and children	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.556	0.556	0.556	0.556	0.555	0.555	0.555	0.555
F-Statistics 1. Stage					728	858	1400	1600
N	10218	10218	10218	10218	10218	10218	10218	10218

Notes: Individual cluster and heteroskedastic robust standard errors in parentheses. $^+ p < 0.10$, $^* p < 0.05$, $^{**} p < 0.01$, $^{***} p < 0.001$

Table 5: Wave specific IV regression results - QS ranking

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	First wave				Second wave			
QS ranking	0.0012*				0.0007			
	(0.0005)				(0.0005)			
Indikator if ranked by QS		0.0975*				0.0619		
		(0.0384)				(0.0457)		
Top quartile of QS ranking			0.1446***				0.0424	
			(0.0371)				(0.0425)	
Top decile of QS ranking				0.1670***				0.0518
				(0.0418)				(0.0471)
Full set of control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
adj. R^2	0.488	0.488	0.486	0.485	0.298	0.297	0.300	0.301
First state F-Statistics	466	514	680	610	320	362	412	360
N	4112	4112	4112	4112	2461	2461	2461	2461

Notes: Individual cluster and heteroskedastic robust standard errors in parentheses. ⁺ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Wave specific IV regression results - RPA ranking

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	First wave				Second wave			
Mean HS GPA	-0.0593				-0.1537*			
	(0.0722)				(0.0756)			
RPA ranking		0.0005				0.0014*		
		(0.0006)				(0.0007)		
Top quartile of RPA ranking			0.0251				0.0663*	
			(0.0305)				(0.0327)	
Top decile of RPA ranking				0.0833*				0.0893**
				(0.0327)				(0.0338)
Full set of control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
adj. R^2	0.537	0.537	0.537	0.537	0.349	0.347	0.346	0.347
First state F-Statistics	418	494	795	901	296	343	580	649
N	6408	6408	6408	6408	3810	3810	3810	3810

Notes: Individual cluster and heteroskedastic robust standard errors in parentheses. ⁺ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Gender specific IV regression results - QS ranking

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Man				Women			
QS ranking	0.0003 (0.0005)				0.0015** (0.0006)			
Indikator if ranked by QS		0.0284 (0.0445)				0.1242** (0.0475)		
Top quartile of QS ranking			0.0281 (0.0418)				0.1715*** (0.0470)	
Top decile of QS ranking				0.0417 (0.0442)				0.2273*** (0.0545)
Full set of control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
adj. R^2	0.471	0.471	0.471	0.471	0.510	0.510	0.509	0.505
First state F-Statistics	318	337	445	392	255	293	318	286
N	3372	3372	3372	3372	3201	3201	3201	3201

Notes: Individual cluster and heteroskedastic robust standard errors in parentheses. ⁺ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: Gender specific IV regression results - RPA ranking

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Men				Women			
Mean HS GPA	-0.0713 (0.0882)				-0.1139 (0.0789)			
RPA ranking		0.0007 (0.0008)				0.0010 (0.0007)		
Top quartile of RPA ranking			0.0314 (0.0388)				0.0480 (0.0331)	
Top decile of RPA ranking				0.0545 (0.0410)				0.0920** (0.0356)
Full set of control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
adj. R^2	0.499	0.498	0.498	0.498	0.537	0.537	0.538	0.537
First state F-Statistics	189	204	387	410	304	387	525	584
N	4706	4706	4706	4706	5512	5512	5512	5512

Notes: Individual cluster and heteroskedastic robust standard errors in parentheses. ⁺ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: Excluding small areas of study - QS ranking

	Areas > 30	Areas > 40	Areas > 50	Areas > 60	Areas > 70	Areas > 80	Areas > 90
Top decile of QS ranking	0.1387*** (0.0402)	0.1437*** (0.0410)	0.1383** (0.0436)	0.1788*** (0.0493)	0.1847*** (0.0495)	0.1959*** (0.0512)	0.1187 (0.0770)
Full set of control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
adj. R^2	0.543	0.536	0.491	0.473	0.470	0.408	0.382
First state F-Statistics	483	474	430	354	351	334	178
N	5501	5317	4723	4019	3948	3683	2537

Notes: Individual cluster and heteroskedastic robust standard errors in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Excluding small areas of study - RPA ranking

	Areas > 30	Areas > 40	Areas > 50	Areas > 60	Areas > 70	Areas > 80	Areas > 90
Top decile of RPA ranking	0.1223*** (0.0315)	0.1259*** (0.0315)	0.1323*** (0.0325)	0.1462*** (0.0356)	0.1556*** (0.0422)	0.1044+ (0.0588)	-0.0181 (0.1039)
adj. R^2	0.598	0.596	0.585	0.589	0.542	0.425	0.391
First state F-Statistics	615.250	608.245	578.360	500.205	376.432	214.766	81.053
N	6956	6772	6178	5474	4585	3683	2537

Notes: Individual cluster and heteroskedastic robust standard errors in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11: Excluding small universities - QS ranking

	Unis > 300	Unis > 400	Unis > 500	Unis > 600	Unis > 700	Unis > 800	Unis > 900
Top decile of QS ranking	0.1545*** (0.0332)	0.1610*** (0.0330)	0.1593*** (0.0330)	0.1644*** (0.0328)	0.1662*** (0.0328)	0.1656*** (0.0331)	0.1577*** (0.0322)
adj. R^2	0.512	0.514	0.515	0.517	0.516	0.516	0.518
First state F-Statistics	699.562	705.943	706.090	717.024	716.056	710.388	739.464
N	6323	6185	6026	5828	5719	5630	5507

Notes: Individual cluster and heteroskedastic robust standard errors in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12: Excluding small universities - RPA ranking

	Unis > 300	Unis > 400	Unis > 500	Unis > 600	Unis > 700	Unis > 800	Unis > 900
Top decile of RPA ranking	0.0828** (0.0264)	0.0832** (0.0268)	0.0796** (0.0263)	0.0842** (0.0273)	0.0868** (0.0276)	0.0812** (0.0280)	0.0848** (0.0284)
adj. R^2	0.551	0.550	0.550	0.552	0.554	0.553	0.555
First state F-Statistics	1032.832	998.348	1100.420	1046.354	1027.601	1001.681	980.610
N	9840	9602	9323	9033	8846	8694	8470

Notes: Individual cluster and heteroskedastic robust standard errors in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$