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In search of future excellence: the information value of bibliometric indicators in predicting doctoral students' future research performance

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Introduction

In recent decades, there has been a clear shift in Swedish research policy with an increasing emphasis on targeted initiatives to support excellent researchers and strategic research areas (Hallonsten & Sillander 2012). This development is not unique for Sweden but is part of an international trend towards a more active research policy motivated by an awareness of the strategic importance of scientific knowledge production as a means to solve social problems, and provide a competitive advantage in a globalized economy (Hallonsten & Sillander 2012; Whitley 2006). The changing political climate, marked by a move towards more active research policies, with targeted support for strong researchers and strong research environments, has also coincided with an extensive institutional reform in which Swedish university leaders have been given increased autonomy and ability to formulate their own strategic initiatives.

An active and excellence-oriented research policy increases the need for non-experts to evaluate and compare the outcome of research in various specialized research areas. Indicators are needed so as to evaluate the outcome of strategic initiatives, and to identify strong researchers and strong research environments that can be said to be excellent (Danell 2011). However, using bibliometric indicators to inform employment decisions and allocate research funding or time for research to specific individuals is only reasonable if the indicators are informative for future research performance.

The predictive power of bibliometric indicators has been tested in previous research (e.g. Danell, 2011; Penner et al., 2013; Havemann & Larsen, 2015; Lindahl & Danell, 2016). However, previous studies are based on an analysis of performance within specific research fields, and the variation among those contributing to research in the field is large. Since prediction of research performance relies on sufficient variation in the group whose performance is to be predicted, it is motivated to test the validity of previous findings in a local organizational context.

The purpose of this study is to investigate the predictive value of using bibliometric indicators for the post-PhD research performance of Swedish doctoral students employed at a single Swedish university. Predicting the performance of doctoral students is especially interesting

and challenging since they are not expected to exhibit great internal variation according to research performance.

Previous studies

In this study, we expect that doctoral students who publish more in scientific journals and also publish excellent work when preparing their PhD will have a higher probability of doing excellent research in the future. Long et al. (1993) showed that publication volume is the best predictor of career advancement in academia. In a recent review, publication volume during doctoral studies was identified as an important factor in the formation of active early career researchers (Sinclair, Barnacle, & Cuthbert, 2014). Previous studies have shown that citation-based indicators are better predictors of future excellence than publication-based indicators (see e.g. Danell, 2011; Havemann & Larsen, 2014). Lindahl (2017) examined researchers in an early career setting and found that having many publications in top journals and many highly cited publications, which implicitly requires a high publication volume, were two important factors in attaining future excellence.

We expect that doctoral students who are closely integrated into their research environment will have a higher probability for future excellence. Especially within the natural and life sciences, with a more collective model for researcher education, the doctoral thesis work is an important contribution to the supervisor's project and the doctoral student is an integral part of a larger research group, which also influences the form and content of the doctoral student's education (Austin 2009; Bech and Trowler 2001; Delamont, Atkinson, & Parry 2000; Golde 2005; Knorr Cetina 1999; Pyhältö, Stubb, and Lonka 2009). Doctoral students within large research teams are usually more productive during and after graduate education (Platow 2012), as the actual tutoring of doctoral students is distributed among more individuals, which is important for the students' socialization and intellectual development (Austin 2002; Fenge 2012; Lee & Boud 2009).

We expect to observe gender bias in career development. There is a considerable number of empirical studies that has identified gender differences in working conditions and career development for male and female researchers, observed in various national contexts. In summary, three statements clearly support the literature: women's scientific efforts are valued lower (Wennerås & Wold 1996; Bornmann et al 2007); female researchers still have a poorer career development than their male colleagues (Xie & Shauman 2003; Ginther & Kahn 2006; Kumar 2012; Danell & Hjerm 2013), female researchers tend to publish less than their male colleagues (Cole and Zuckerman 1984; Long 1992; Xie & Shauman 1998; Prpic 2002; Fox 2005).

We also expect age to be a significant predictor. Completing doctoral studies at a young age is a sign of talent, and such individuals should have a higher probability of future excellence. Finishing doctoral studies at a more advanced age, on the other hand, presumably has a negative influence on the probability for future excellence, because such an individual's entry into the scientific community implies a marked deviation from the general life cycle of age-related research productivity pattern and age-creativity patterns that are visible in many research fields (Jones & Weinberg, 2011; Rørstad & Aksnes, 2015).

Materials and method

Data

The data consists of 479 doctoral students who completed their studies at a Swedish university between 2003 and 2009 at the faculties of natural sciences and medicine. We performed the analyses on 304 of these authors who were employed or associated with the university at least five years after the year of completing their thesis. Publication data were collected from DiVA, a Swedish repository for research publications, and the citation indices accessible through Web of Science. Everyone employed at or associated with the Swedish university has a personal identification code, which was used to match doctoral students with their publications. We also utilized the salary system of the Swedish university we studied to acquire information about employment, gender, and age.

Variables

The dependent variable indicates whether an author had attained relative excellence in the second to fifth year after the year of completing their thesis. In order to operationalize the indicator for relative excellence, we identified documents that were among the top 10 % cited documents in their field (subject category), taking into account document type and year. Since a document can belong to more than one subject category, it may be equal to or above the 90th percentile in one category and not in others. We therefore calculated in what fraction of categories the document was equal to or above the 90th percentile.

For each author, we summed the top 10 % fractions for all documents that belonged to that author. An author that was equal to or above the 90th percentile in the distribution of summed top 10 % fractions was defined as being an excellent author. Excellent authors had produced a sum of top 10 % fractions of at least two and constituted 12 % of the sample.

We constructed five predictors for the analyses:

(1) Publication volume during doctoral studies is operationalized as the number of publications indexed in the Web of Science (Coding: #Publications during doctoral studies).

(2) Relative excellence during doctoral studies was operationalized in the same way as the relative excellence after completion of the thesis. (Coding: Top 10 % articles).

(3) Collaboration and the degree of integration into the research community was operationalized with the collaborative coefficient (Ajiferuke, Burell, & Tague, 1988). The collaborative coefficient is a weighted mean that incorporates the average number of authors per paper and the proportion of multi-authored papers in a single measure that can be defined as:

$$\text{Collaborative coefficient} = 1 - \frac{f_1 + (1/2)f_2 + \dots + (1/k)f_k}{N} = 1 - \frac{\sum_{j=1}^k (1/j)f_j}{N}$$

where f_j denotes the number of j -authored papers, N denotes the total number of publications, and k is the greatest number of co-authors per paper of an author (Coding: Degree of collaboration).

(4) Age was operationalized as the age of the doctorate at the year of the defence of the thesis (Coding: Age at completion of doctoral studies).

(5) The effect of gender bias was examined with a binary predictor where the value 1 represent males and 0 represent females (Coding: Male doctoral student).

Model

We used a probit model to model the probability for future excellence in research. A probit model uses the standard normal cumulative distribution function (CDF) in order to find the probability for an event.

$$\Pr(y = 1|\mathbf{x}\boldsymbol{\beta}) = \Phi(\mathbf{x}\boldsymbol{\beta}) \equiv \int_{-\infty}^{\mathbf{x}\boldsymbol{\beta}} \phi(v)dv,$$

where

$$\phi(v) = \frac{1}{\sqrt{2\pi}} e^{-\frac{v^2}{2}},$$

is the standard normal density. This means that the interpretation of value of $\mathbf{x}\boldsymbol{\beta}$ for each observation is as a standard deviation for the standard normal CDF. It also means that the partial effects of changes in the predictors are not constants, since changes in probabilities are largest when $\mathbf{x}\boldsymbol{\beta} = 0$.

A potential problem with the data set concerns the independence of the observation.¹ It is possible that the performance of an observed doctoral student is not statistically independent from the performance of other doctoral students in the same department, since they could be part of the same research group. Moreover, some departments for various reasons have a higher probability of producing excellent research. This problem affects inference, since correlated errors can lead to underestimated standard errors. We have, therefore, estimated robust clustered standard errors which allow for intragroup correlation, relaxing the requirement that the observations must be independent, i.e. the observations are independent across groups, but not necessarily within groups. When we calculated the robust clustered standard errors, the observations were grouped into research areas in accordance with the classification scheme *Standard for Swedish classification of research areas 2011* (HSV, 2011). The dissertations are classified with the second level in this scheme, where level 1 and level 2 correspond in essence to the OECD classification scheme *Field of Research and Development*.

Results*Predicting future excellence among doctoral students*

Table 1 displays the robust clustered standard errors, p-values, and 95 % confidence intervals for the estimated coefficients in the probit regression model. We found that the doctoral students' research performance during their education, i.e. number of publications and attaining relative excellence during doctoral studies coded as top 10% articles, are complicated by a significant ($p < 0.05$) interaction effect. The interpretation of the coefficients for these variables must, therefore, be made with the effect of the interaction taken into account. Degree of collaboration and age at completing doctoral studies are significant predictors for future research excellence. However, the coefficient for the male doctoral student variable was not significant, even though the coefficient indicates that male doctoral

¹ Another potential problem with the data set was that the doctoral students who stayed at the university after thesis completion may have been selected on the variables used in our model in such a way that the estimates may be biased. To test for selection bias, we estimated a Heckman selection model (Greene, 2012) which indicated that there was no selection bias in our model. The Heckman procedure was left out of the manuscript due to space limitations.

students will, independent of their performances as doctoral students, have a higher probability of future excellence.

Table 1. Probit regression estimating probability for future excellence

Predictors	Coef.	Robust Std. Err.	z	P>z	95% Conf. Interval	
#Publications during doctoral studies	0.047	0.014	3.46	0.001	0.020	0.073
Top 10% articles	-0.885	0.481	-1.84	0.066	-1.828	0.058
Degree of collaboration	0.034	0.016	2.09	0.036	0.002	0.065
Male doctoral student	0.340	0.223	1.52	0.128	-0.098	0.777
Age at completing doctoral studies	-0.031	0.011	-2.90	0.004	-0.053	-0.010
Top 10% articles * #Publications during doctoral studies	0.261	0.085	3.06	0.002	0.094	0.428
Constant	-3.127	1.455	-2.15	0,032	-5.979	-0.275

Note. Std. Err. adjusted for 10 clusters. Number of obs. = 304. Wald chi2(6) = 1194.57. Prob > chi2 = 0.0000. Log pseudolikelihood = -82.58488. Pseudo R-square = 0.2532.

In order to interpret the coefficients, we calculated the predictive margins displayed in Figure 1. Plotting the predictive margins for the number of publications during doctoral studies and distinguishing between doctoral students who had attained relative excellence (i.e. the sum of at least two 10 % publications coded as Top 10 % articles) and those without, it is apparent that the information value of publication volume differs quite considerably between the groups. For the doctoral students in the sample who have not attained relative excellence during their education, publication volume is a weak predictor of future excellence in research. For the doctoral students who have attained relative excellence during their education, the probability of future excellence in research increases quite rapidly for each additional publication when the total number of publications is larger than five. It should be noted that five publications is the upper quartile, so the group of doctoral students with a high probability of future relative excellence in research is rather extreme considering both their productivity and their citedness.

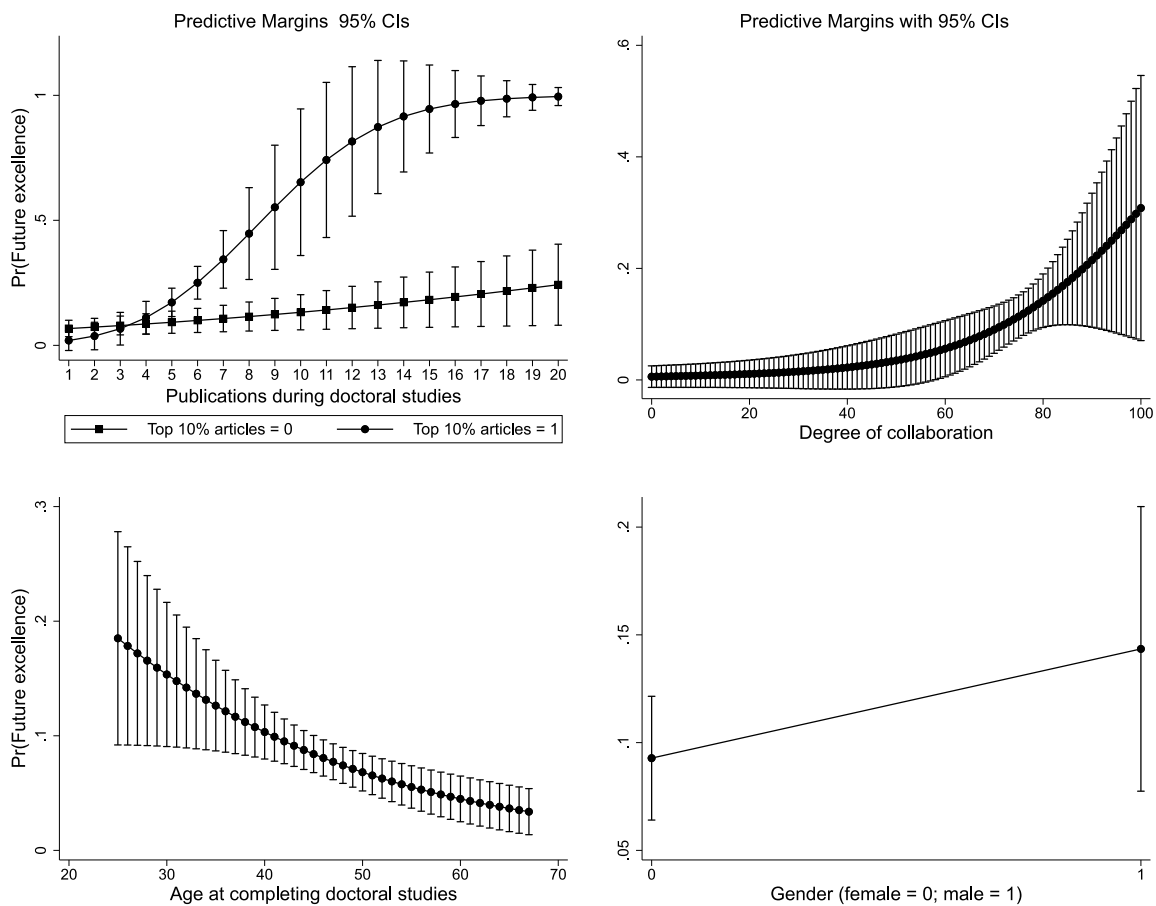
The predictive margins for degree of collaboration is flat until a value of about 50 and increases quite rapidly thereafter. It should be noted that the tenth percentile is a collaboration degree of 53.6, and the average collaboration degree is 71.5. The fact that the degree of collaboration is a positive predictor can be due to the importance of social integration of doctoral students, even though it is hard to specify exactly why this integration is of importance for a doctoral student's future research performance. It could be a combination of different factors that are embedded in this predictor, such as learning tacit knowledge, future integration into a research project or increased awareness of future research of potential interest.

The age of the doctoral student when completing their education is a significant predictor of future research excellence. This relationship is negative. However, the uncertainty is much greater among younger doctoral students than among older students, indicating that we can be more confident about the negative effect of age on future excellence among older doctoral students (i.e., students with an age above 39) than among younger students. The average age

of the doctoral students when completing their studies is 38.5 years and the median is 35. It should be noted that there is an age difference between the faculties. The average age in the faculty of natural science and technology is 32.4 years, while the average age in the faculty of medicine is 41.

The coefficient for the gender variable indicates that male researchers will perform better in the future. However, the coefficient is not significant. This variable was included to adjust for an expected gender bias. However, since a change in alpha level would make this predictor significant, it would be erroneous to conclude that there is no gender bias. Both genders are fairly equally represented in the sample. Male doctoral students represent 46.4% and female doctoral students 53.6%. Viewing the confidence interval for the predicted margins, it is apparent that the size of the interval is much bigger for male doctoral students, indicating greater variability in that group.

Figure 1. Predicted margins for predictors included in the probit regression model.

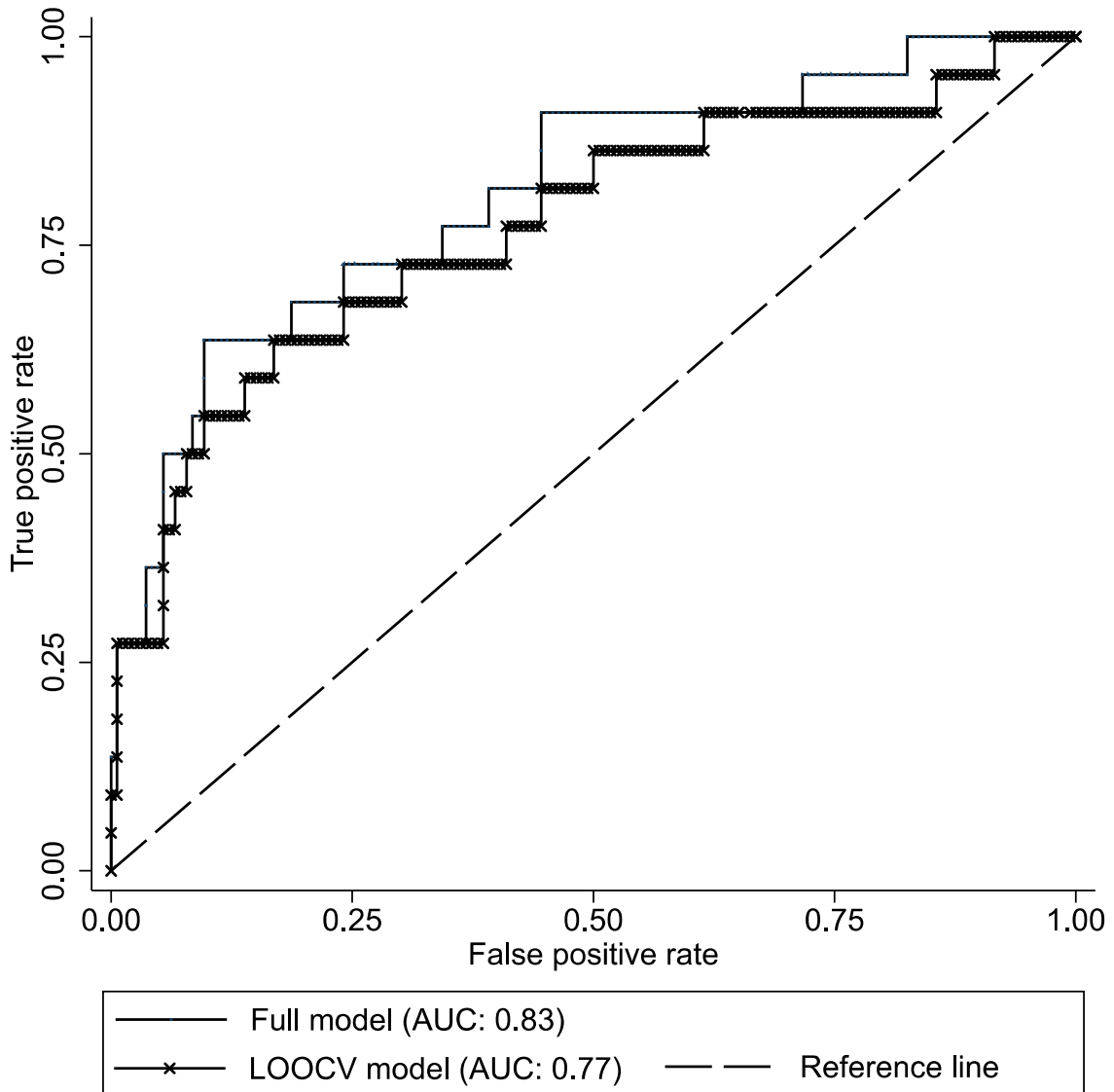


Predictive value of the model

To estimate the information value of the probit model (Table 1) in terms of predicting future excellence, we generated a ROC curve by plotting the true positive rate (i.e. the fraction of doctoral students attaining future excellence that was correctly predicted to do so) against the false positive rate (i.e. the fraction of doctoral students that did not attain future excellence but was predicted to attain future excellence) for each value of $x\beta$ (Fawcett, 2006). In Figure 2, the y-axis denotes the true positive rate (TPR) and the x-axis denotes the false positive rate

(FPR). If the ROC curve is above the diagonal line, our model performs better than expected according to a random model. If the ROC curve is below the diagonal line, our model would perform worse than a random model. If the ROC curve passes through the point (0, 1), it is a perfect classifier (Fawcett, 2006). As a summary measurement of the predictive value of the model the Area Under the Curve (AUC) was calculated. The AUC is 1 when the curve passes through the (0, 1) point. If the ROC curve coincides with the diagonal line the AUC is 0.5.

Figure 2. ROC analysis of the model’s ability to classify doctoral students according to their future performance (Leave one out cross validation).



In Figure 2, two ROC curves are displayed with associated ROC areas. One ROC curve for the full model, i.e. the model accounted for in Table 1, and a second ROC curve for the leave-one-out cross validation of the full model (i.e., the LOOCV model in Figure 2). In this leave-one-out cross-validation, 304 probit models have been calculated. For each calculated model, one observation has been left out and a probit model is estimated for all remaining observations. The estimated model was then used to estimate a predicted value for the excluded observation, and this procedure was repeated for all 304 observations. We can then

estimate the accuracy of our model by its ability in predicting the outcome for the excluded observation, and, as can be seen in Figure 1, the predictive ability of the model is quite good.

Model diagnostics

We have conducted tests for model mis-specification and test for choice of functional form on the estimated probit model presented in Table 2. In testing for mis-specification of the arguments of the estimated function, we have followed Ruud (1984). We used the estimated $\mathbf{x}\hat{\boldsymbol{\beta}}$, i.e.

$$\mathbf{x}\hat{\boldsymbol{\beta}}^{MLE} = \hat{\beta}_1 + \hat{\beta}_2 x_2 + \dots + \hat{\beta}_k x_k.$$

In order to test for mis-specification the following procedure is suggested by Ruud (1984). First, we estimate

$$P(y = 1 | \mathbf{x}) = \Phi(\mathbf{x}\hat{\boldsymbol{\beta}} + \gamma_1(\mathbf{x}\hat{\boldsymbol{\beta}})^2 + \gamma_2(\mathbf{x}\hat{\boldsymbol{\beta}})^3).$$

With the coefficient on $\mathbf{x}\hat{\boldsymbol{\beta}}$ is set equal to one and under the null hypothesis that our model is correctly specified, we have $\gamma_1 = \gamma_2 = 0$.

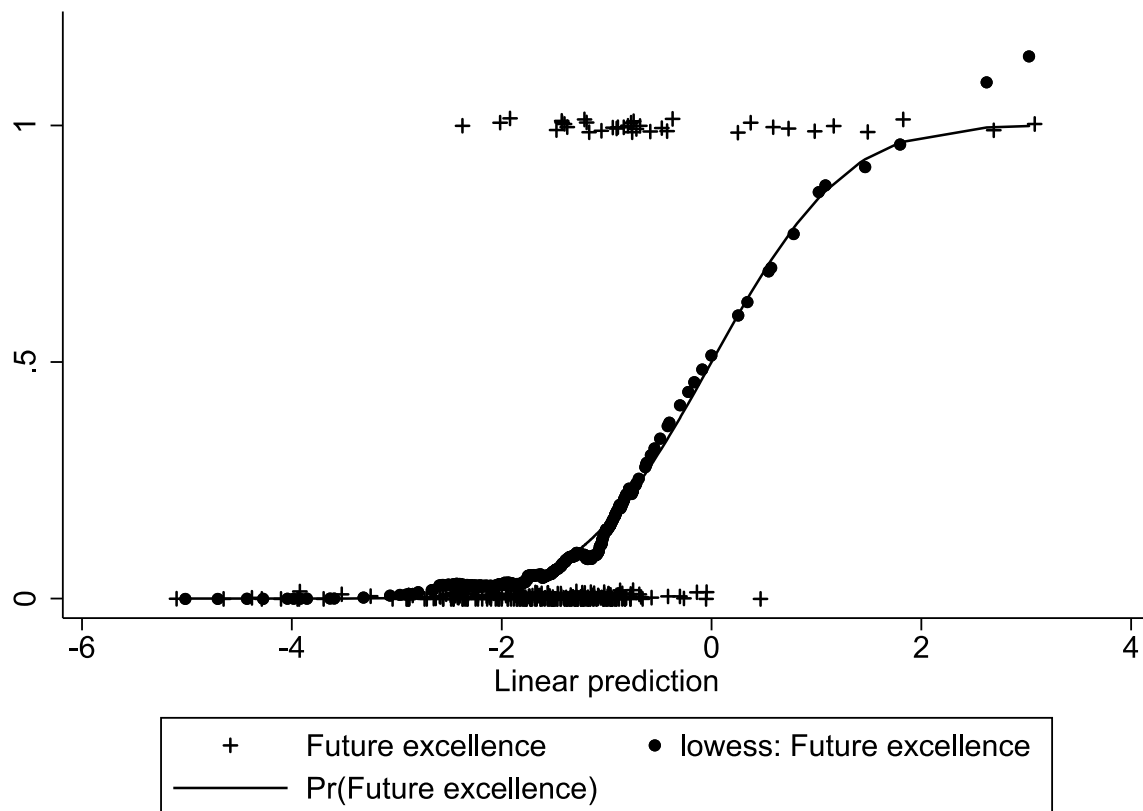
Table 2. Test for mis-specification of arguments

	Coef.	Std. Err.	z	P>z	95% Conf. Interval	
$\mathbf{x}\hat{\boldsymbol{\beta}}^2$	-0.029	0.103	-0.28	0.776	-0.231	0.172
$\mathbf{x}\hat{\boldsymbol{\beta}}^3$	-0.019	0.049	-0.38	0.700	-0.115	0.078
$\mathbf{x}\hat{\boldsymbol{\beta}}$	1	(offset)				

Test $\gamma_1 = \gamma_2 = 0$. Chi2(2) = 0.16. Prob. > chi2 = 0.9234

The result of this test is found in Table 2 and indicates that there are no mis-specifications of the argument in our probit model.

Figure 3. Comparison of estimated probabilities from probit regression with Lowess estimates (bandwidth for Lowess estimates = 0.4).



The chosen functional form, that is the standard normal CDF, was tested by comparing the estimated probabilities assuming a standard normal CDF with estimated probabilities without specifying any particular form for the CDF, given the value of $\mathbf{x}\beta$. In order to estimate the probabilities allowing for a flexible functional form, we used the semi parametric Lowess smoothing method. Figure 3 displays the results, and we conclude that there is a reasonable correspondence between the estimated probabilities.

Conclusion

The purpose of this study is to investigate the predictive value of using bibliometric indicators for post-PhD research performance by Swedish doctoral students in a local organizational context. We conclude that bibliometric indicators have some predictive validity for the post-PhD performance of the doctoral students. It is notable that a combination of quantity and quality in doctoral students' performance is indicative of post-PhD research performance. We can also conclude that the degree of collaboration and age are significant predictors of post-PhD research performance. We included a gender variable in our model in order to adjust for a potential gender bias. The results indicated that male doctoral students have a higher probability of attaining future excellence. However, the effect was not significant. We conclude that examining the potential gender bias in a larger sample may generate more conclusive results.

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