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Emergent structures in faculty hiring networks, and the effects of mobility on academic performance

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Abstract
This paper is about the South African job market for Ph.Ds. Ph.D. to first job mobility involves the preferences of both the hiring institution and the candidate. Both want to make the best choice and here institutional prestige plays a crucial role. A university's prestige is an emergent property of hiring interactions, so we use a network perspective to measure it. Using this emergent ordering, we compare the subsequent scientific performance of scholars with different changes in the prestige hierarchy. We ask how movements between universities of different prestige from Ph.D. to first job correlates with academic performance. We use data of South African scholars from 1970 to 2012 and we find that those who make large movements in terms of prestige have lower research ratings than those who do not. Further, looking only those with large prestige movements, those with higher prestige Ph.Ds or first jobs have higher research ratings throughout their careers.

Keywords Academia · South Africa · Faculty hiring network · Institutional prestige · Institutional stratification · Scholars research performance · University system · Matched pair analysis

JEL Classification D7 · I2 · J15 · O3 · Z13

Introduction

Placement in an academic position directly after completing a Ph.D. is one of the most stressful events in an academic career. A good first job provides access to good colleagues, and a good affiliation from which to apply for funding. Anecdotes say that an academic's reputation is made in the first 6 years after the Ph.D., and these anecdotes are consistent

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with Robert Merton's Matthew Effect—early success provides the springboard for later success in academia (and many other venues). At the same time, from the side of the institution, a "good hire" constitutes an improvement to the quality of faculty, and future improvements in reputation. Many resources are spent on both sides of the Ph.D. job market, as recruiters and recruitees try to do as well as they possibly can.

But young faculty hiring is a classic problem of asymmetric information (Connelly et al. 2011). Ph.Ds usually have only a thin record of citations and publications, which it means that their intrinsic quality is largely unobservable by any hiring committee. In this type of situation, a committee will look for signals of quality, one of which is the status of the university granting the Ph.D. (Clauset et al. 2015). Moreover, since Ph.D. to first job mobility involves the preferences of both the hiring institution and the candidate (Barnard et al. 2016; Conti and Visentin 2015), and both want to make the "best choice", hiring decisions are pairwise assessments of quality between the two agents. The sorting of Ph.D. graduates through the first-job market can be seen to imply an emergent prestige ordering of universities, encoding the collective assessment of each others' quality (Clauset et al. 2015).

This paper is about the South African job market for Ph.Ds. In particular, we ask whether Ph.D.-to-first job mobility is correlated with future research performance. Our contribution looks at the South African Ph.D. job market as a system where universities' prestige plays a role not only in hiring but may also correlate with individuals' later academic performance. In particular we ask how movements between universities of different prestige from Ph.D. to first job correlates with future academic performance.

In our analysis we first develop a new measure of prestige of the South African universities, based on the idea that the Ph.D. job market contains information about how universities judge each other's graduates, and so, by implication, how they view each other's quality. There can be two reasons we might expect to observe a correlation between first job placement and future academic success: If recruiters are able to identify talent, even noisily, and academics want to work at "the best" institutions, then the quality of institutions at which graduates are hired correlates with their own intrinsic quality. In this way job placement is (perhaps just) a signal of quality, and so job placement should predict future success. On the other hand, even supposing that all graduates are of exactly equal quality, being affiliated with a top institution should give better access to resources and funds, and perhaps colleagues, which should provide a career advantage. Starting here we ask whether Ph.D. to first job movements are in fact correlated with future academic performance.

This analysis is aimed at increasing the understanding of our university system, looking at social inequalities, and career trajectories. These issues are of particular interest in the South African context. The country is still struggling to achieve social transformation post apartheid, especially within the university system (Barnard et al. 2016). A part of the difficulty of this transformation lies in bottlenecks in the general university hiring process. There is a large black population of students and faculty in the system as a whole, but the strongest universities, or those with the strongest research reputations, are the formerly white universities.[1] Here blacks are badly under-represented, both in the student population and especially in the faculty. The challenge of transforming the racial composition of the faculty of the those universities with the strongest reputations is to a great extent one of

[1] Language regarding racial or ethnic identity can be charged. As the empirical part of this paper is about South Africa, we follow the standard terminology accepted there.

hiring, and in particular of hiring recent Ph.D. graduates. Studying the processes by which people get into this profession is one of the first knowledge gaps to cover.

Our contribution reveals how the transition from Ph.D. to first job, operating within a hierarchical system made of interactions among the different institutions, has long-run effects also on scientific performance. We show that the 5 most prestigious South African universities produce more than 50% of Ph.Ds in the country and they tend to hire their own or each other's graduates. These findings are in line with previous US-based work which finds that faculty hiring obeys a hierarchical structure based on institutional prestige, which in turn produces or maintains social inequalities (Burris 2004; Clauset et al. 2015). A simple Kolmogorov–Smirnov (KS) test of the distributions of prestige rank-change indicates that under-represented groups (women and blacks) are more likely to move down in prestige than are white males, when moving from Ph.D. to first job, which can contribute to a different type of social inequality. Our main concern, though, is with the relationship between different prestige transitions from Ph.D. to first job, and academic performance. In this respect we find two results: a positive role of inertia, and a positive role of prestige. Our results on inertia show that scholars who make large movements in prestige tend to have lower performance than those who do not. The role of prestige is evident looking at scholars making large prestige movements: those with more prestigious Ph.Ds or first jobs have higher future career performance.

University prestige and young faculty hiring

To measure university prestige is not easy, in part due to the many definitions of prestige that are employed. Generally speaking prestige is associated with formal university rankings such as the Shanghai Jiao Tong Academic Ranking, or the Times Higher Education Ranking. But there are many other measures and methods that scholars have found to rank prestige of departments and universities: subjective survey based measures; output based measures; labour market based; or some combination of thereof all exist. During the 1970s and the 80s many works analysed the relationship between subjective reputational rankings based on surveys, and "objective" rankings based on research outputs and productivity (for example citations, citations per capita, number of paper published). Hagstrom (1971), for example, uses survey data of department prestige for hard sciences in the US, looking at the correlations between prestige and input/output variables of the universities. He finds that prestige correlates with size, research output, research facilities and opportunities, quality of faculty background, number of postdoctoral fellows, selectivity of the undergraduate program, and awards. Webster et al. (1991) present an extensive review of this debate looking at work published between 1965 and 1982. They collect 28 articles aimed at ranking Sociology departments in the US, and find both similarities and differences between reputational rankings and productivity rankings. In particular they underline the strong correlations between these two measures when the sample is restricted to the top departments. Additionally they highlight, as in the more recent contribution of Burris (2004), the persistence over time of department prestige, finding previous prestige to be the best predictor for current prestige no matter the level of previous productivity. Webster et al. (1991) conclude that future research on prestige rankings should incorporate the sociological stratification perspective in order to explain the link that university status has with job market placement and research performance. Some formal university rankings try to incorporate prestige using surveys. For example, QS world university ranking asks scholars, specialised in a specific field, to rank universities both in general and according to the discipline of the respondent.

Survey measures try to address the potential bias of productivity measures, as in fact the presence of few star scholars can boost research output of one department but not be representative of it as a whole (Barnett et al. 2010). But surveys suffer from a fundamental problem. It might be possible to have a reliable rank of the top universities (because everybody in the field knows more or less who they are and their relative stature) but moving down the ranking, at a certain point survey respondents are not able to perceive the differences between similar institutions. Part of the issue here has to do with localization: institutions (and the individuals in them) are much more cognizant regarding the institutions with whom they are competing (for students, faculty, resources), thus it is unlikely that faculty in top-ranked institutions will be able to differentiate between the 100th and 110th ranked institutions. But the latter two, competing with each other, are much more likely to have knowledge about each others' strengths and weaknesses. Thus knowledge about relative rankings of universities is likely to be quite localized within the ranking itself. For this intrinsic characteristic of how the university system operates, survey based measures are likely to be unreliable, particularly below the top (or perhaps second) tier institutions.[2] The algorithm we use below to create a university ranking is consistent with this localized knowledge, and in fact takes advantage of it.

In sociology, institutional stratification in higher education refers to a social process that causes a hierarchical differentiation among the universities, with elite and prestigious schools on one side and lower status ones on the other (Shavit 2007). University prestige enhances stratification, as Jung and Lee (2016) summarise, because it engages and attracts the talented experts and resources, often drawing them out of lower ranked universities. This causes structural inequalities within the higher education system. For example Mai et al. (2015) study the hiring network of Ph.Ds in the field of communication in the US. They find that the hiring patterns follow a strict hierarchy, in line with the stratification hypothesis. They also find that institutions' ability to place their Ph.D. graduates in other universities is particularly stratified. This supports the idea that the hiring network represents a bilateral assessment of quality among institutions because it signals an acknowledgement of the university that trained the Ph.D. More interestingly, it suggests that an examination of hiring patterns will reveal the consensus prestige ranking. Along the same lines Barnett et al. (2010) extract centrality measures of the faculty hiring network as a measure of the quality and prestige of doctoral education in the field of communication. Their logic is similar, driven by the idea that prestige rankings are emergent, and that Ph.D. placement is indicative of how universities or departments view each other.

Bair (2003) studies the link between university prestige of American finance Ph.D. programs and hiring. He finds that top ranked Ph.D. programs in finance preserve their reputations by hiring each other's graduates or directly their own graduates. His findings are also linked to previous work, where this pattern is evident in prestigious doctoral programs in other fields: law schools, mathematics, physical sciences, social sciences, chemical, engineering, psychology, and social work (Bair and Boor 1991; Bair and Bair 1998).

Bedeian and Feild (1980) study the stratification hypothesis using US data from 24 top graduate departments of management. They find that the academic placement in management departments is influenced by doctoral prestige (measured by a subjective survey-

[2] No doubt this explains why almost all rankings provide integer rankings only for a given number of top places, after which institutions are grouped into rather large groups (100–199; 200–299 and so on).

based measure); in particular they find a significant relationship between the prestige of scholars' Ph.Ds and the prestige of their current positions. The article ends with two possible, opposing, explanations: Either merit is irrelevant and hiring processes rely on prestige only; or the prestige of people's Ph.D. department is related to an unobserved variable indicating the scholar's intrinsic ability.

In the current paper we consider the prestige of a scholar's Ph.D. institution but look also at transitions in prestige from Ph.D. to first job, asking whether those transitions are correlated with future research performance. The implicit hypothesis here is that movements may indicate perceived quality of the individual that goes beyond using the Ph.D. institution as a signal of quality.

With respect to the relationship between university prestige and performance, results in the literature are mixed and available only for North America. The different results are mainly due to different models, measures of prestige and output, samples analysed, field considered, and to the time span of academic career included, since this effect is likely to affect academic output differently as time passes (Miller et al. 2005). Moreover, there is a clear circular causation: the prestige of a scholar's Ph.D. increases the likelihood of a prestigious job, and institutional affiliation may affect individual research output. Moreover it is well known that prestige of an institution is highly correlated with its research output. For this reason it is difficult to distinguish at the individual level whether those with prestigious affiliations are intrinsically more productive or if they gain cumulative advantages from their affiliation (Merton 1968).

Williamson and Cable (2003) study the predictors of research productivity of 152 young management faculty who find their first academic jobs after the Ph.D. in the period 1987–1995. Using a structural equation model, they find effects of supervisor's research productivity and department scholarly output (both for origin and placement departments) on early career performance. But they find no direct effect of the origin department's prestige. Prestige does appear to be important as a predictor of first job placement but there is no direct effect of Ph.D. institution prestige on individual performance.

The lack of a direct effect of prestige on performance could be related to the correlation between department prestige and scholarly output, both of which are present in their model. Alternatively, it could simply be attributed to the measure of prestige they used, the Gourman Report, which has never disclosed its criteria or its methods.

Miller et al. (2005) analyse the predictors of a prestigious job, looking in particular at prestige of the training institution and individual research output. They use a sample of 445 Business school graduates between 1977 and 1985, two measures of prestige (survey based and the Gourman Report measure), and as research output a composite index which considers the individual's journal publications and citations, discounted by contribution (i.e. single author, first author). Again using a structural equation model they find that the determinants of prestige of the employing institution are the prestige of the training department, which operates for many years of the career, and research output. In this line of research, the findings of Miller et al. (2005) are supported by results in other fields: Allison and Long (1987) (physics, chemistry, mathematics, and biology); Judge et al. (2004) (psychology); Baldi (1995) (sociology); Reskin (1977) (chemistry). On the other hand, though, Hurlbert and Rosenfeld (1992) looking at the field of psychology, find that prestige of later jobs is weakly affected by publications but not at all by the prestige of the Ph.D. institution; similarly Long (1978) find for biochemistry no effects at all of either of those two variables.

Interest in the relationship between the university prestige and career outcomes, including social inequalities and allocation of talent, extends beyond the university faculty job market. It is well known in non-academic job placement: Jung and Lee (2016) examine the relationship between university prestige and subsequent wages of workers in South Korea. They find that university prestige, measured using standard university rankings, matters for job market outcomes, particularly regarding salary. Araki et al. (2016) study employee promotion in Japanese manufacturing industries, finding again a crucial role for the prestige of the universities where workers got their degrees. To measure prestige they rely on standard university rankings and find that in the early stage of a worker's career university prestige is crucial because it corresponds to the employer's *a priori* ideas about the distribution of abilities among workers. So, among young employees the likelihood of being promoted is higher for those with prestigious degrees because the employer will decide who to promote according to his prior. These results in the non-academic markets underline how important are these studies that try to shed light on the mechanisms driving the academic job market. The academic job market has of course its specificities, but it shares common elements with other job markets (especially those for highly specialized occupations).

In this paper we explore the relationship between university prestige, young faculty hiring and individual research performance. Past research underlines how young faculty hiring follows a stratified hierarchy (Clauset et al. 2015; Burris 2004), and to connect to this literature we develop a network-based measure of the prestige of South African universities. In contrast to Clauset et al. (2015), who consider scholars' current affiliation, we build the faculty hiring network looking at the very first job right after the Ph.D. If the job market is being used to infer universities' views of each others' prestige, it is essential to apply that inference where prestige is most relevant. That is, when information about the candidates on the job market is least complete. Years after the Ph.D., presumably most academics have an established record, and good information about them is available. So it is the first job that contains the most accurate signal of how universities evaluate each others' quality. Moreover, Clauset et al. (2015) focused on 3 fields (computer science, business, and history) and they produced separated prestige rankings looking 60 top departments for each one. Their period of analysis is also limited to one year. Our goal is to investigate the entire university system of the country focusing at university level on a longer time scale. Again contrasting Clauset et al. (2015), we consider all universities together as an integrated system by defining broader fields, and we also take an historical perspective looking the first job market over more than 3 decades.

After computing our new measure of prestige, we compare the future research performance of scholars with different prestige movements in their Ph.D. to first job transition. In particular, in order to distinguish between individual performance and possible cumulative advantages gained from their affiliations, we match people with different movement in the prestige hierarchy but same gender, ethnic group, Ph.D. obtained year, and first job (or Ph.D.) institution. So we differentiate our work from past contributions giving a ranking of universities coherent with the mobility issue and predicting career success for different time spans looking not only at mobility but also the individual movements in the prestige hierarchies. As additional value added of the work, to measure individual career success we use a non-bibliometric measure based on the informed evaluation of international experts in the specific scientific field.

We find that inertia and university prestige are both positively related to a scholar's future performance. Related to inertia we find that the scholars who make large movements in prestige are considered to perform worse than those who do not. Related to prestige, instead, we find, looking those who experience large movements in prestige, that those with higher prestige Ph.D. or first job perform better. Our work addresses the knowledge gap regarding the relation between the role of university prestige in young faculty hiring and the subsequent individual performance of the scholars. This will increase awareness about the functioning of the higher education system in an emerging country such as South Africa and show whether it displays similarities with previous, mostly US based, work.

Data and variable construction

We use data from the South African National Research Foundation (NRF[3]) from 1970 to 2012 which contains detailed personal information of the scholars (i.e. gender, ethnic group, affiliation, career history, scientific field, and NRF rating). We restrict attention to academics who received their Ph.Ds from 1970 to 2004 (when the major reform of the university system took place). This also permits us to examine medium and long term effects on career. Our main variable is the NRF "rating" for years 1983–2012, which is a measure of individuals' academic performance. The process by which the NRF grades researchers is a very rigorous examination of a candidate's research output. The NRF solicits half a dozen international referees to evaluate the CV and published papers of the candidate for rating. This process ends with a rating: a scientific committee evaluates the content of the referee reports and assigns the rating: one of 13 ordered categories. Strong institutional incentives imply that almost all academics with a research-oriented career apply to be rated: NRF data cover the 30 percent of scholars in the country who produce about 90 percent of all South African peer-reviewed research outputs (Barnard et al. 2012; León et al. 2016).[4]

Our analysis focuses on scholars in the field of Science, Engineering and Technology (SET). In the field of Social Sciences and Humanities (SSH) language and schools of thought often put constraints on the Ph.D. to first job transition. These constraints are particularly relevant and in the past have represented a strong check on academic mobility in the South African context. In the main text that follows we present only the results for SET, as the results for SSH are less reliable. However, we include a parallel presentation of SSH in the "Appendix".

Separately for each field (SET and SSH) we construct the hiring network among the different South African institutions, based on scholars who found their first jobs in a South African university within 5 years of receiving the Ph.D. We then calculate our network-based measure of university prestige (*prestige ranking*) and for each individual his prestige rank-change from Ph.D. to first job (that is, the difference between the prestige ranking of the Ph.D. institution and that of the first job instituition). In the next sections we present the details of the faculty hiring network, prestige ranking, and prestige rank-change.

Faculty hiring network

The hiring network is a weighted and directed adjacency matrix M. It has 22 rows and columns that are the 22 South African universities,[5] where each entry m_{ij} represents the

[3] NRF (www.nrf.ac.za) is a state agency that has as its mission the promotion of research and the development of national research capacity.

[4] For more information on the rating system see http://www.nrf.ac.za/rating.

[5] In 2004 the university system was reformed: some universities were merged and changed names. The reform does not affect the big universities, excepting University of Johannesburg and KwaZuluNatal, but does have some effects on the lower ranked ones. We use the post-merger names because the data are more complete. We discuss this in "Appendix 1".

Table 1 Adjacency matrix of the hiring network for the years 1970–2004 in SET, rows are Ph.D. institutions and columns are first job institutions. Each entry represents the number for people with a Ph.D. in university *i* hired as first job in university *j*

First Job Institution

PhD Institution	CapeTown	NelsonMandelaMet.	Witwatersrand	Pretoria	Johannesburg	FreeState	SouthAfrica	Stellenbosch	KwaZuluNatal	NorthWest	Limpopo	Rhodes	WesternCape	FortHare	WalterSisulu	Venda	CentralUnivOfTech	TshwaneUnivOfTech	VaalUnivOfTech	MonashSA	DurbanInstituteOfTech	CapePeninsulaUnivOfTech
CapeTown	107	4	5	0	2	0	2	19	1	2	1	3	4	1	1	0	0	1	0	0	0	5
NelsonMandelaMet.	1	33	0	1	1	0	0	1	0	0	1	1	1	1	1	0	0	0	0	0	0	0
Witwatersrand	4	2	83	6	2	1	2	1	8	0	1	1	0	0	0	0	0	2	0	0	0	0
Pretoria	2	1	1	116	7	3	7	6	1	6	2	0	3	3	0	1	0	6	0	0	0	0
Johannesburg	0	2	2	5	30	4	7	1	0	4	4	0	1	0	0	0	0	0	1	0	0	0
FreeState	0	1	0	1	1	55	0	8	0	2	3	0	0	0	0	0	6	0	0	0	0	0
SouthAfrica	0	1	1	1	0	0	15	2	1	0	0	0	1	1	0	1	0	0	0	0	0	0
Stellenbosch	2	1	2	4	1	6	1	73	3	2	1	0	6	1	0	0	0	1	0	0	1	2
KwaZuluNatal	4	0	10	5	0	1	2	4	65	1	2	1	1	2	5	0	0	0	0	0	12	0
NorthWest	0	0	2	3	1	2	1	2	1	52	3	0	0	0	0	0	0	1	2	0	0	0
Limpopo	0	0	0	2	0	0	0	0	0	0	7	1	0	0	0	1	0	0	0	0	0	0
Rhodes	2	2	4	3	0	1	0	0	3	1	2	19	0	1	0	0	0	0	0	0	0	0
WesternCape	2	0	1	0	0	0	0	1	0	1	0	0	8	0	0	0	0	0	0	0	0	1
OfFortHare	0	0	0	0	0	0	1	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0
WalterSisulu	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0
Venda	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0
CentralUnivOfTech	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0
TshwaneUnivOfTech	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0
VaalUnivOfTech	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0
MonashSA	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
DurbanInstituteOfTech	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CapePeninsulaUnivOfTech	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1

number of scholars with a Ph.D. from university *i* and a subsequent first job in university *j*. To illustrate, the adjacency matrix for SET is shown in Table 1. Summary statistics are shown in Table 2, with populations subdivided by gender and race.[6]

In Table 2 we observe a common pattern for females and blacks: their networks are sparser than those of white males. That is, they have fewer edges and so lower density, but

[6] In South Africa there are formally four "racial" groups: black, white, Indian and coloured. The word "black" is sometimes used to refer to the aggregate of black, Indian and coloured, and this is the meaning we apply throughout this text.

Table 2 Summary statistics SET hiring network for the years 1970–2004. Network statistics are compute without considering self-loops

	All	Male	Female	White	Black
Number of nodes	22	22	22	22	22
Number of components	1	2	3	1	2
Number of isolated nodes	0	1	2	0	1
Statistics on the giant component					
Number of nodes	22	21	20	22	21
Number of edges	133	115	57	107	52
Edge density	0.288	0.274	0.15	0.232	0.124
Average path length	1.795	1.764	2.498	1.748	3.087
Diameter	9	6	12	9	15
Global clustering coefficient	0.648	0.588	0.511	0.578	0.41

also higher average path length, and a lower clustering coefficient. To a very great extent this is explained simply by the relative sizes of the three sub-populations.[7]

The geographic displays of the networks (Figs. 1 and 10) show common hiring corridors, where universities with high number of connections in hiring tend to send their graduates to a high number of different institutions (nodes with high/low in-degree tend to have high/low out-degree); indeed, the correlation (excluding self-hiring) between in-degree and out-degree is 0.72 for SET and 0.53 in SSH.[8] We observe that the universities with a high hiring and low placement connections are historically black universities, while those with an high placement and a low hiring connections are historical white universities, with the exception of KwaZulu-Natal.[9] This suggests that formerly black universities have been using hiring connections as a way to upgrade their faculty since the end of apartheid.

Prestige ranking

We consider university prestige as a social assessment, emerging from interactions among institutions. The well-known university rankings (THE, QS, Shanghai) can proxy prestige, but they remove interaction from the picture and so have questionable reliability, since prestige is not an individual attribute but it is part of a social process (Burris 2004; Clauset et al. 2015). Consequently, following Clauset et al. (2015), we develop a measure of prestige ranking where institutional status arises from the patterns observed in the faculty hiring network. We start from two hypotheses:

[7] The same patterns, and explanation, are present in SSH (Table 7).

[8] The exceptions to this strong correlation are for SET: Tshwane University of Technology, University of Fort Hare, and University of Limpopo that have a high connections in hiring (in-degree) and a low connections in placement (out-degree); while University of KwaZulu-Natal, and University of Cape Town instead show a high connections in placement (out-degree) and a low connections hiring (in-degree). See Table 5. For SSH we find the following exceptions: Walter-Sisulu University, Nelson Mandela Metropolitan University, and University of Limpopo with a high hiring connections (in-degree) and a low placement connections (out-degree); and University of Stellenbosch, and University of Cape Town with a high placement connections (out-degree) and a low hiring connections (in-degree).

[9] The University of KwaZulu-Natal was formed in 2004 by the merger of the University of Natal (white) and the University of Durban-Westville (Indian).

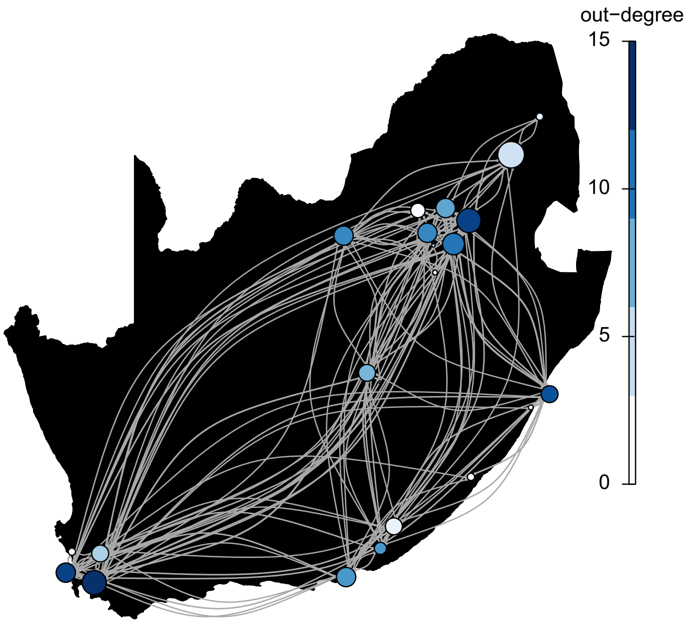


Fig. 1 Hiring networks 1970–2004 SET. The vertices are the South African Universities, plotted at their geographical coordinates (for the institutions located in the same area we separated manually). Vertex size represents in-degree, vertex colour out-degree

1. *Universities want to improve the quality of their research and teaching. A corollary is that they want to hire from universities that are "better" then themselves;*
2. *Scholars want to be hired by the best universities.*

Were the desires expressed in these two hypothesis to be perfectly satisfied, and if the Ph.D. institution is a reliable indicator of graduate "quality", it would be possible to order universities (the rows and column of the adjacency matrix M) so people only move down the ordering, implying that the adjacency matrix would have only zeros below the diagonal. Since actual hiring often departs from this "ideal" we search for an ordering that most closely approximates "zero weight below the diagonal". To do this we apply to the adjacency matrix M an algorithm inspired by Vries (1998) and Clauset et al. (2015). The algorithm starts with a random ordering of rows (columns always having the same ordering as rows) of the matrix o_0 and we compute the score s_o of this order, where:

Definition 1 An order o_k is an ordered n-tuple of universities names, and its score s_k is $\sum_i \sum_{j>i} m_{ij}$.

The algorithm tries to improve the score of the current order o_0 using local search. Each iteration swaps two randomly selected nodes (both row and column). If the swap does not decrease the score we keep the swap, otherwise we reject it. After 100 iterations we stop, and record the resulting order and its score.[10] We repeat this procedure 10,000 times to get a set O of 10,000 orders a the set S of 10,000 related scores.

[10] Checking manually, 100 iterations is almost always enough to find a local optimum.

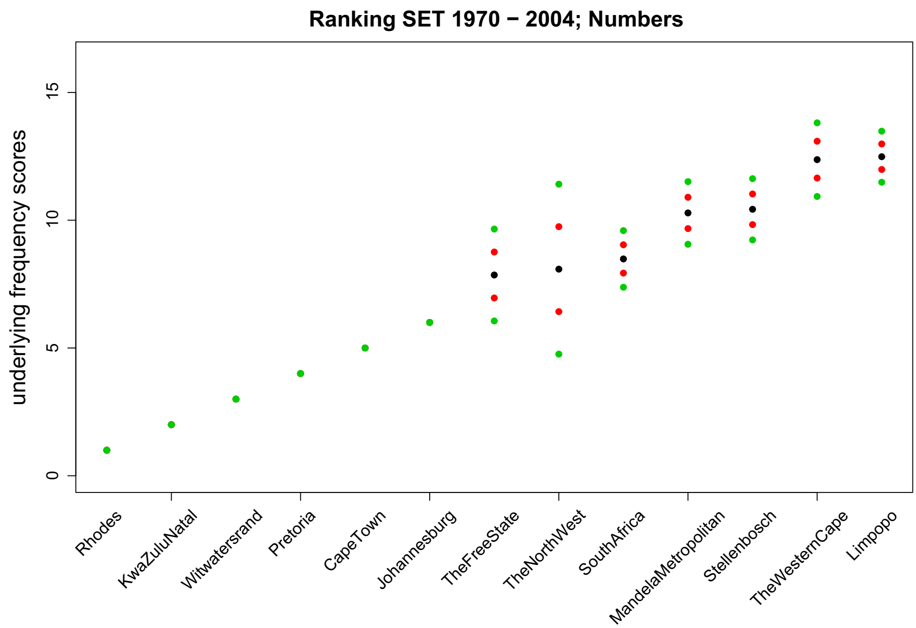


Fig. 2 Prestige ranking for SET 1970–2004. The frequency scores are in ascending order: the highest ranked university has the lowest score. The black dots are the mean of the orders with the maximum scores in set Q, red and green dots are one and two standard deviation from the average. Universities with fewer than 5 Ph.Ds are excluded. (Color figure online)

Definition 2 The set of orders O is $O = \{o_1, o_2, \ldots, o_{10000}\}$; The set of scores S is $S = \{s_1, s_2, \ldots, s_{10000}\}$.

Then we create the set Q of the orders $o \in O$ with the maximum scores:

Definition 3 Let Q be the set of orders with maximum scores $Q = \{o_k \in O | s_k = \max(s_k)\}$, where O is a set of orders and $k = 1, 2, \ldots, 10000$.

Then for each university we compute the mean of its ranks in the orderings in Q, to give the prestige scores, which provides a natural ordering or ranking of universities. Note that our prestige score is not a rank of natural numbers, it is an average value. This gives a better picture of university prestige where the distances in prestige among institutions are not of a fixed amount: pairs of universities adjacent in the ordering might have very different distances in terms of their scores.

We remove universities that graduated fewer than 5 Ph.Ds in the period. Figures 2 and 11 show the results of our prestige rankings for SET and SSH. The frequency scores are in ascending order from the highest prestige (which corresponds to a score of one) to the lowest.

Prestige ranking and other measures

We test whether the prestige hierarchy underlines by our measure is statistically different from a null model. We generate 5000 random matrices that preserve in- and out-degree,

Table 3 Ph.Ds hired from the top 5 prestigious universities in SET, according to our prestige ranking. The total of SET Ph.Ds Hired in the period is 1011

Rank	Ph.D. university	Placed in SA academia	Placed in top 5	Proportion placed in top 5
1	Rhodes	38	31	0.816
2	KwaZuluNatal	115	85	0.739
3	Witwatersrand	113	102	0.903
4	Pretoria	165	120	0.727
5	Cape Town	158	116	0.734
	Total of top 5	589	454	0.771
	Total Ph.D. hires	1011		0.583

and also preserve the diagonal. This holds constant the number of Ph.Ds each university graduates, the number each university hires, and the number of graduates who are hired by their Ph.D. institution. We apply our ranking algorithm to each of these 5000 matrices, and record the maximum score for each matrix. Taking these scores as the underlying distribution, we obtain a p value of 0.002. We conclude that our hiring matrix has more structure than an equivalent random matrix, and that the hierarchy present in the empirical matrix is statistically stronger than those present in a random graph with the same characteristics. As a further robustness check we examine the correlations between prestige and measures of research output. From Web Of Science (WOS) we download aggregated data of research output for each South African university.[11] In SET the correlation of our prestige score with total publications 1988–2004 is 0.6 (p value = 0.04); with average citations per paper 0.5 (p value = 0.06); with total number of citing articles 0.5 (p value = 0.08); citations per capita 0.7 (p value = 0.01); and papers per capita 0.8 (p value = 0).[12] In SSH we find statistically significant correlations of prestige scores with average citations per paper 0.7 (p value = 0.01); with total number of citing articles 0.6 (p value = 0.05); and with citations per capita 0.6 (p value = 0.05). Thus our measure of prestige correlates well with measures of research performance, but is not identical to it.[13] This is in line with past contributions (Burris 2004).

Institutional stratification

Tables 3 and 8 illustrate the institutional stratification hypothesis, for SET and SSH respectively. They show the number of Ph.Ds from the top 5 prestige universities hired within the other top 5 institutions, and those hired in other institutions. The results are striking. In SET the top 5 prestige universities produce 58 percent of all Ph.Ds within the country; among those, 77 percent find a first job within these 5 institutions.[14] This

[11] We select the university name in the address search, restricting to the period 1988–2004. For the universities that changed name we search pre and post merger names and we refine the WOS results looking at only journals publications. Last access February 2018.

[12] Per capita measures are obtained dividing total records by number of scholars in our database with a current affiliation in the particular university. This will over-estimate the per capita figures as there are (some, though few) South African authors in WOS who never apply for a rating. There is no reason to believe there is any bias in this over-estimate however.

[13] For SSH we find non statistically significant results for total number of publications and publications per capita. As discussed previously our methodology is less suited for SSH.

[14] These numbers are 48 and 74% respectively for SSH.

underlines the crucial role of prestige hierarchies in academia. Consistent with US-based work (Burris 2004; Clauset et al. 2015), we find deep inequalities among universities in terms of first job placement: South Africa shows a pattern of stratification similar to those found in more mature knowledge systems. Moreover, the lower percentage of the first job placement of the top universities in SSH with respect to SET highlights the diverse hiring processes of the two fields. SSH are often governed by schools of thought and in South Africa language and culture also play important roles. This makes hiring processes more complex, more constrained, and less predictable.

Effects of rank change on future career

Changing university when taking up a first job after the Ph.D. means moving within the prestige hierarchy. In particular, scholars move *Up* (*Down*) the hierarchy when hired by an institution with a higher (lower) prestige ranking than the one from which they received the Ph.D. And they *Stay* in the hierarchy when hired by a university of the same prestige of the Ph.D., which is in practice means being hired by their own Ph.D. institution.

Given the structural hierarchies in faculty hiring, people moving up the hierarchy are relatively rare, though it does happen. An obvious question to ask is whether this constitutes a signal regarding future career prospects. If the job market is able to identify promising (or weak) young scholars, a movement up (or down) would be predict a stronger (or weaker) future academic career. Further, it could also be that those who move up, relative to those who move down, on average work at higher prestige places, which could imply stronger colleagues and collaborators, and better resources. So there are *a priori* reasons to believe that movements in prestige between Ph.D. and first job could be correlated with future research performance. But there lurks the issue of whether any link between prestige movements and performance is driven by individual quality or by the resources available at the receiving institution.

Matched pairs

To address this issue we do a matched pair analysis. We compare scholars' NRF ratings at different points in time (5, 10, 15 and 20 years after they were granted their Ph.D.), asking whether people with different prestige transitions (Up, Down, or Stay) but having the same individual characteristics differ in rating. For each time span, we do a matched pair analysis comparing the transitions: Up vs. Stay, Down vs. Stay, and Up vs. Down. We match on gender, ethnic group, year of Ph.D., and either receiving or sending university. So, for each of the three comparisons we look at pairs of scholars from the same receiving or sending institution. When we match people with the same receiving university we compare people with same characteristics hired into the same institution, but having different Ph.D. institutions. The match using the same sending institution, instead, compares individuals with a Ph.D. granted by the same university, but who are hired in different places. To differentiate between sending and receiving institutions is important also because it is a control for possible Matthew effects on performance driven by university prestige. That is, the more prestigious a university is, the greater its ability to attract resources and this can result in higher productivity of the scholars and therefore higher NRF ratings. We solve this possible source of endogeneity by matching people with same receiving institution. Matching on the same sending institution controls for the fact that there is more scope for upward (downward) movement for those whose Ph.Ds come from

Fig. 3 Up versus stay comparison. The black curves are cumulative distribution functions of the proportion of observations in which $R_{up} > R_{stay}$ was the case for $p\%$ of the matched pairs. Grey curves are the CDFs for the $R_{stay} > R_{up}$ proportions. From top to bottom 5,10,15, and 20 years after Ph.D. Pairs matched using gender, race, Ph.D. obtained years and first job university (left column) or Ph.D. institution (right column). **a** First job, 5 years after Ph.D. **b** Ph.D., 5 years after Ph.D. **c** First job, 10 years after Ph.D. **d** Ph.D., 10 years after Ph.D. **e** First job, 15 years after Ph.D. **f** Ph.D., 15 years after Ph.D. **g** First job, 20 years after Ph.D. **h** Ph.D., 20 years after Ph.D.

the bottom (top) of the prestige ordering. It also controls for training effects incurred during the Ph.D. The matching technique also controls for the other confounding factors on which we match: gender, race and year of degree.

We use a re-sampling technique as follows. To do the Up vs. Stay comparison, we start with the set U of size N_u of people who move Up, and a set S of people who Stay. Then we sample with replacement, N_u people from the set U getting U'. For each member in U' we find the matches in S, and select one at random if there is more than one match. In this way we create matched pairs Up-Stay. Then we calculate and store the proportion of those pairs in which the Up person had a higher NRF rating (R) than the Stay person: $R_{up} > R_{stay}$, and vice versa: $R_{stay} > R_{up}$. We repeat this procedure 10000 times, obtaining distributions of those proportions, $F(p|R_{up} > R_{stay})$ and $F(p|R_{stay} > R_{up})$.

Results

The major concern of this paper is whether prestige movements from Ph.D. to first job correlate with the future research performance of the scholars. We compare, for different points in time, the NRF rating of individuals with the same characteristics but different prestige rank-change movements: Up vs. Stay, Down vs. Stay, and Up vs. Down. Since prestige could influence individual careers differently as time passes; we look at people's ratings 5, 10, 15 and 20 years after their Ph.D. For each comparison we study separately people hired by the same (receiving) university and those with a Ph.D. granted by the same (sending) institutions. Moreover, our matching technique accounts also for additional confounding factors: gender, ethnic group, and Ph.D. obtained year. As we are interested in the effects of rank change, our null hypothesis, **H0**, is that prestige movements are unrelated to research performance:

$$\mathbf{H0}: F(p|R_{up(or\ down)} > R_{stay}) = F(p|R_{stay} > R_{up(or\ down)}). \tag{1}$$

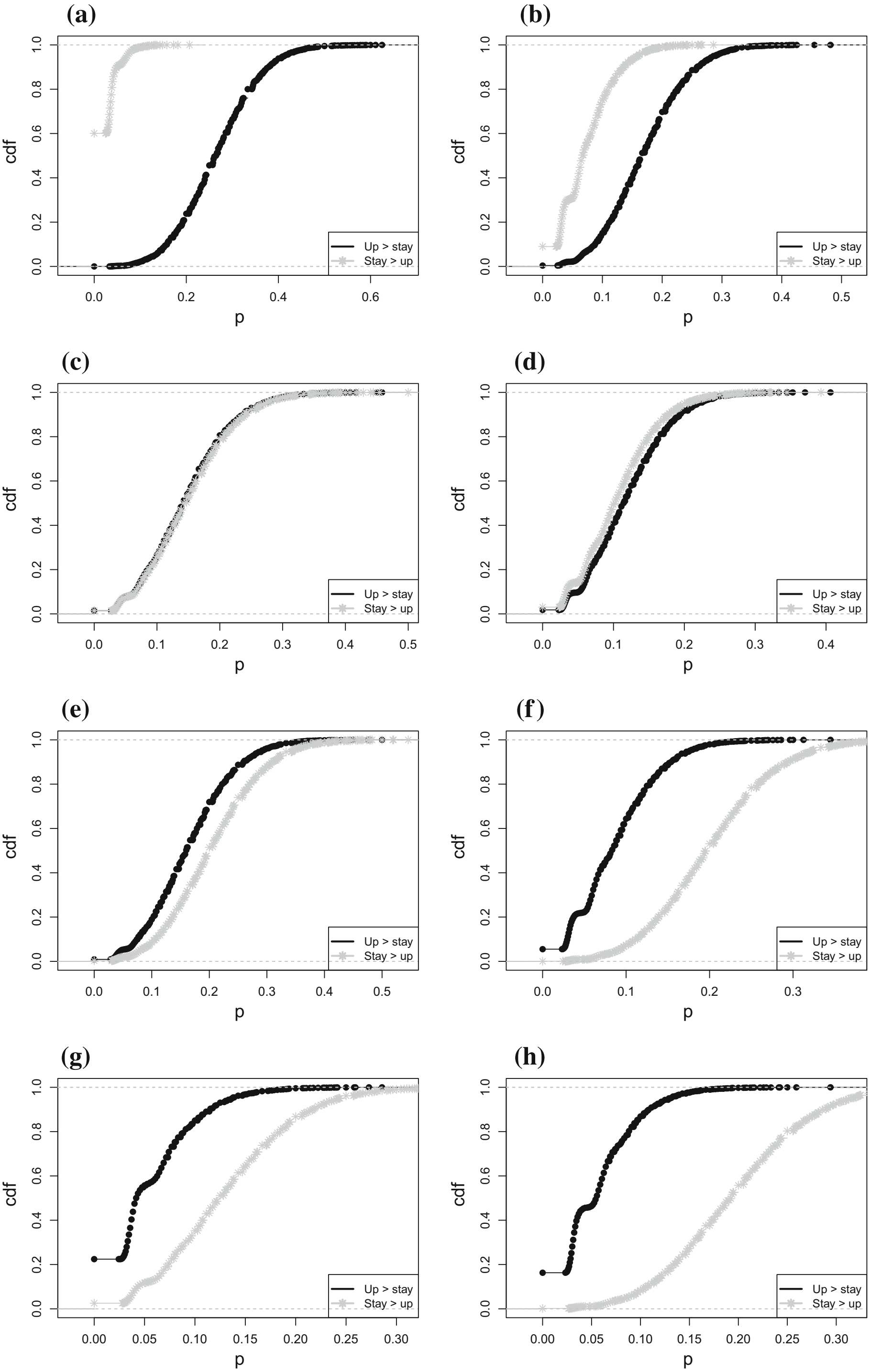
Performing two-sided KS tests, we find that this is not the case; in each comparison the distributions are different. Given that the distributions are different from each other, we can ask whether one stochastically dominates the other (less and greater one-sided KS tests). The results for the tests are in "Table 9".[15]

The definition of first order stochastic dominance is typically given as

Definition 4 A CDF $F(x)$ First-Order Stochastic Dominates $G(x)$ *iff* $F(x) \leq G(x)$ for all x (Mas-Colell et al. 1995).

Figure 3 shows the results of Up vs. Stay. Looking at people hired by the same institutions but different Ph.Ds (left column), and at those with the same Ph.D. institution but different first jobs (right column), we find consistent results. After 5 years $F(p|R_{up} > R_{stay})$ (black

[15] Additionally we perform a robustness check following a bootstrap technique in "Appendix 7"



(a)
(b)
(c)
(d)
(e)
(f)
(g)
(h)
cdf
p
Up > stay
Stay > up

Fig. 4 Down versus stay comparison. The black curves are cumulative distribution functions of the proportion of observations in which $R_{\text{down}} > R_{\text{stay}}$ was the case for $p\%$ of the matched pairs. Grey curves are the CDFs for the $R_{\text{stay}} > R_{\text{down}}$ proportions. From top to bottom 5, 10, 15, and 20 years after Ph.D. Pairs matched using gender, race, Ph.D. obtained years and first job university (left column) or Ph.D. institution (right column). **a** First job, 5 years after Ph.D. **b** Ph.D., 5 years after Ph.D. **c** First job, 10 years after Ph.D. **d** Ph.D., 10 years after Ph.D. **e** First job, 15 years after Ph.D. **f** Ph.D., 15 years after Ph.D. **g** First job, 20 years after Ph.D. **h** Ph.D., 20 years after Ph.D.

curve) stochastically dominates the other $F(p|R_{\text{stay}} > R_{\text{up}})$ (grey curve); while 15 and 20 years later we have the reverse: $F(p|R_{\text{stay}} > R_{\text{up}})$ dominates $F(p|R_{\text{up}} > R_{\text{stay}})$. This tells us a consistent story. In the short term, those who are promoted, moving up in prestige, have higher ratings than do those who stay; but in the long term the opposite is true: those who do not move (stay) have higher ratings. So in the long term, looking at people with the same first job, we find that those with "better" Ph.Ds (stay) do better; while looking at people with same Ph.D. institution, those with "worse" jobs (stay) perform better. Intuitively, the former seems reasonable, the latter odd. We return to this below.

Figure 4 shows the results for the Down vs. Stay comparison. With two exceptions (first job match 20 years, and Ph.D. match 5 years) we find that $F(p|R_{\text{stay}} > R_{\text{down}})$ stochastically dominates $F(p|R_{\text{down}} > R_{\text{stay}})$. That is: those who stay have higher ratings than those who move down in prestige. In particular looking at those with the same first job (left column) we have that those with "worse" Ph.Ds (stay) do better; while when we look at people with same Ph.Ds institution (right column), those with "better" jobs (stay) perform better. Again we find that in general those who do not move after their Ph.D. have higher ratings.

In the case of Down versus Stay, matched on Ph.D., the value of staying seems reasonable: of two people with equivalent Ph.Ds , the one who stays will have the higher prestige job and a higher rating. Similarly in the case of Up versus Stay matched on first job: of two people with the same job, the one with the more prestigious Ph.D. (the one who stays) will have a higher rating. However, Down-Stay matched on job, and Up-Stay matched on Ph.D. seem somewhat paradoxical, as in the first case the less prestigious Ph.D. (with the same job) does better, and in the second the less prestigious job (with the same Ph.D.) does better. We discuss this apparent paradox below.

Figure 5 shows the Up versus Down comparison. We should note that because in both groups the sample is relatively small, this comparison is less reliable, and needs cautious interpretation. To have a reasonable number of matches we relax the matching of Ph.D. obtained year, here considering an interval of six years. That is, two agents match on Ph.D. year if they are within ± 3 years of each other. Figure 5 shows, looking at researchers hired by the same institution (left column), that $F(p|R_{\text{down}} > R_{\text{up}})$ dominates $F(p|R_{\text{up}} > R_{\text{down}})$. Those moving down to a job from a higher prestige Ph.D. institution do better than those moving up to the same job from a lower prestige institution, and the gap increases over time (the distance between the two cumulative distributions increases). This seems reasonable: all else equal, a higher prestige Ph.D. is good. Matching people with the same Ph.D. institution (right column) we find that $F(p|R_{\text{up}} > R_{\text{down}})$ dominates $F(p|R_{\text{down}} > R_{\text{up}})$. That is, those who move up in prestige (hired by a more prestigious institution) perform better in ratings than those hired by less prestigious universities. This also seems reasonable: all else equal, a higher prestige job is good. So comparing people who experience mobility in the transition from Ph.D. to first job we have that, holding job constant, coming from "better" Ph.D. (down) is good; while holding Ph.D. constant, going to "better" job (up) is good.

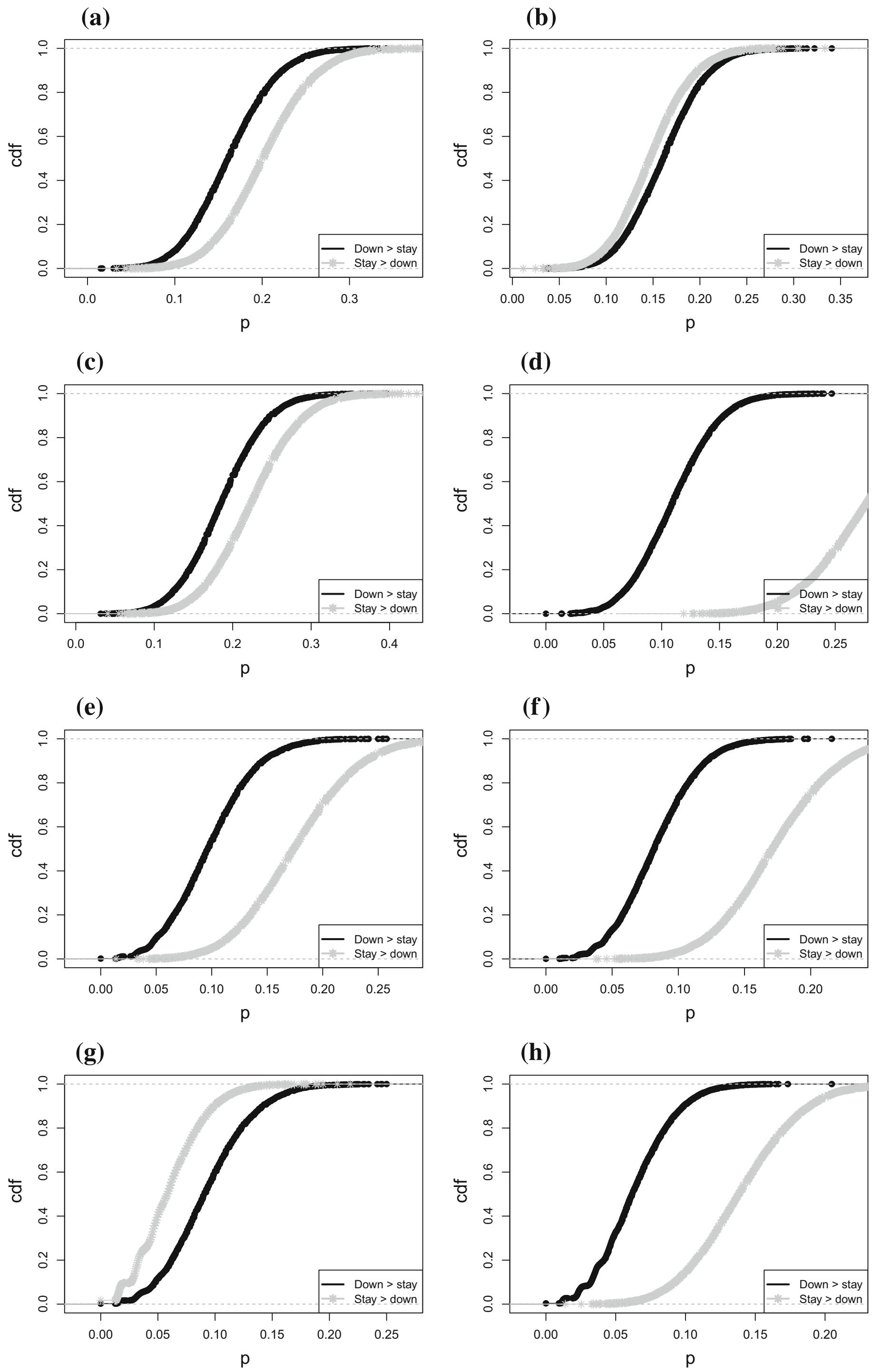

(a)
(b)
(c)
(d)
(e)
(f)
(g)
(h)
cdf
p
Down > stay
Stay > down

Fig. 5 Up versus down comparison. The black curves are cumulative distribution functions of the proportion of observations in which $R_{up} > R_{down}$ was the case for $p\%$ of the matched pairs. Grey curves are the CDFs for the $R_{down} > R_{up}$ proportions. From top to bottom 5, 10, 15, and 20 years after Ph.D. Pairs matched using gender, race, Ph.D. obtained years and first job university (left column) or Ph.D. institution (right column). **a** First job, 5 years after Ph.D. **b** Ph.D., 5 years after Ph.D. **c** First job, 10 years after Ph.D. **d** Ph.D., 10 years after Ph.D. **e** First job, 15 years after Ph.D. **f** Ph.D., 15 years after Ph.D. **g** First job, 20 years after Ph.D. **h** Ph.D., 20 years after Ph.D.

We can then summarise the results in a more intuitive way. When we compare people who experience transitions from the Ph.D. to first job with those who do not (that stay) we find a beneficial inertia effect. Generally speaking, those who stay in the same university after the Ph.D. have higher rating. This positive effect of inertia might be due to various factors. In some instances training effects from the Ph.D. work to support the result: those trained at a particular institution will have skills and expertise which fit well into the research taking place there, and perhaps complement that of the institution very well. This argument may be particularly pertinent in a small country like South Africa, where not all universities are expert in all fields. There is considerable specialization and "division of labour" among the universities regarding research fields, implying that in many disciplines there are only few institutions with strong research presence. This would also explain the heavy diagonal in our hiring matrix.

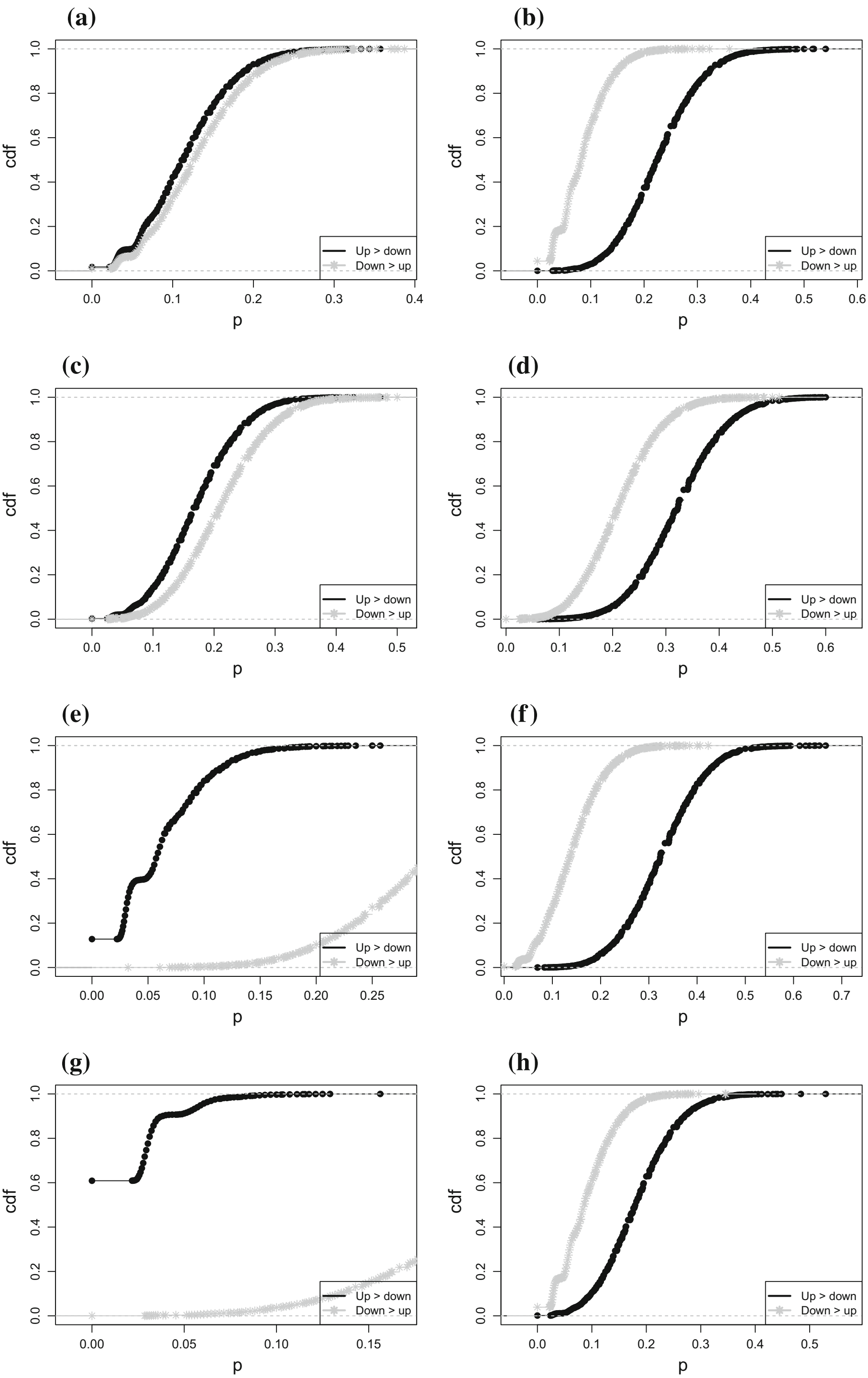
However, the value of institutional inertia may also simply relate to the way the Ph.D. job market works. A university has better information about its own graduates, and so it can make better judgements with respect to their intrinsic quality. Moreover, any research-focussed university will have strong incentives to keep its best graduates so as to enhance its own reputation rather than that of its rivals. The comparison of Up vs. Down instead tells us the role of university prestige; when people experience Ph.D. to first job mobility their movements in prestige are crucial: holding Ph.D. constant, moving to a more prestigious first job is better; and holding first job constant, having a more prestigious Ph.D. is better. It appears that training and resources (broadly defined) both contribute.

Possible cohort effects

We observed that there are some differences in the effects of prestige movements depending whether we observe the scientist 5, 10, 15 or 20 years after Ph.D. One possible explanation is cohort effects. These could drive this observation because the cohort composition is different in each time sample. Specifically, since our rating data run only from 1983 to 2012, observations on the '5-year' ratings include Ph.Ds from 1970 to 2004; whereas 20-year ratings include only Ph.Ds from 1970 to 1992. To test for this cohort effect we repeat the analysis restricting the sample to only older scholars, with a Ph.D. granted before 1992. Figures 7, 8, and 9 in "Appendix 4" show the results for the restricted sample. These results are consistent with the ones discuss above, so we can exclude this hypothesis: our results are not driven by changes in the cohort composition.

Size effects

Ph.D. production and graduate hiring are very skewed, and some universities are bigger then others. Our prestige ranking looks not only at faculty production but it considers in particular the quality of placement. So a small institution could achieve high prestige by


(a)
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(g)
(h)
cdf
p
Up > down
Down > up

placing a small number of graduates at high prestige universities. In order to exclude the possibility that size effects drive our measure we re-run our algorithm using the logs of the entries in our matrix. This is a monotonic transformation of university sizes but makes the differences between them much smaller, so results are less likely to be driven by size alone. The prestige ranking results are almost identical. Further, the correlation of out and in-strength of the adjacency matrix, is not statistically distinguishable from zero (cor $= 0.3$; p value $= 0.3$).[16] This implies that amounts of hiring and placement are unrelated, so universities with high production of Ph.Ds are not the ones that hire more. One other suggestion that the results are not driven by size comes from the fact that Rhodes University, consistently ranked first in prestige, is much smaller than the other "top 6".

Discussion and conclusion

The paper reveals important aspects of how the Ph.D. job market works in South Africa and our results tend to be in line with previous work. As is often observed in other settings, we find that institutional stratification in higher education holds in the South African context. The 5 most prestigious universities produce between 48 and 58% of all Ph.D. graduates (who enter academia) in the country and they tend to hire graduates from this elite group. Occupational segregation is also present in South Africa as elsewhere: under-represented groups are less likely to get jobs in higher prestige universities than are white males.

Looking at the relation between prestige transitions from Ph.D. to first job and individual research performance we find two main results. On the one hand, comparing people who experience a prestige transition with those who do not, we find a positive inertia effect. Those who stay in the same institution after the Ph.D. have higher performance than those who move. At first glance, what appears to matter is not moving up or down the prestige hierarchy, but rather resting in an established environment. However, when we compare explicitly those who make upward and downward transitions, we find that university prestige is deeply related with academic performance, consistent with previous literature (Burris 2004; Clauset et al. 2015). Holding Ph.D. prestige constant, those with a more prestigious first job have better long run performance then those with a less prestigious first job. But similarly, holding first job constant, those having a Ph.D. from a more prestigious institution have better long run performance than those with a less prestigious Ph.D. This suggests that prestige is at the very least a signal of quality, but possibly also has causal effects. More prestigious Ph.D. programmes may attract better students and or give better training. More prestigious universities may attract better junior faculty and or may provide better resources. Extracting these causal relationships is certainly worth doing, though beyond the scope of this work.

Our results underline the big role played by inertia in the South African Ph.D. job market. In our data, of the rated researchers in South Africa, historically roughly two thirds of those going into the professoriate do not change institutions at the completion of the Ph.D.[17] This is maybe related to culture, institutional organisation, and history. But it seems likely that it will disappear over time. In many locations it has been common in the

[16] This is done removing the diagonal of the matrix.

[17] In spite of the 2004 reforms, this feature remains part of the SA academic world: in the period 2004 to 2012 it still the case that about two thirds of graduate receive their first appointment at their Ph.D. institution. The fraction is slightly higher in SET, slightly lower in SSH.

past, but today in North America (or the anglo-saxon world more generally) it is rare that a department will hire its own graduates, and while still more common in Europe, it appears to be disappearing, even in countries like France and Italy.

We observe that those who do not change institutions after the Ph.D. tend to have higher NRF ratings later in their career. To return to the discussion in the introduction, this suggests that imperfect information is fairly severe in Ph.D. hiring: universities have good information about their own graduates, and can successfully "pick the winners". Of their own students, they have better information on candidates' intrinsic qualities than do other institutions, and so can make better judgements. Further, they have strong incentives to encourage their best students to stay, rather than to let them drift away to strengthen competing institutions. This is consistent Robert Merton's observation that *"leading universities manage to identify early, and to retain to their faculties, those scientists of exceptional talent: they keep 70 percent of future [Nobel] laureates, in comparison with 28 percent of other Ph.D.'s they have trained."* (Merton 1968 p. 7).

To understand why those internally selected perform better over a long period of time our research suggests to look further at the deep causes of the positive role played by inertia. The role of inertia might be related not only to the general dynamics of the university system and the Ph.D. job market, but might also be linked to the behaviour of the scholars in terms of co-authorship and specialization. In particular, young researchers who do not experience mobility may have different collaboration patterns than do their counterparts. They can have more stable co-authorship linkages able to sustain their careers, especially in the early stages. Coupled with the Matthew effect this would create both short and longer term positive effects of inertia. Furthermore, the research orientations of those who stay and those who move may be different in terms of specialization. Those internally selected could be more specialized in a particular area of research that is more germane to the home department, and this specialization could drive their long-run performance. This would be true in any small country whose institutions have specialized in particular areas. This type of further research at micro level could shed new light on the university system not only of South Africa but also of other countries with low first job mobility.

It is important to realize that this is an historical analysis. The most recent Ph.D. in our data is from 2004, and the most recent ranking from 2012. Nonetheless, university reputations change slowly (Burris 2004), so even given the major re-organizations of 2004, we expect that the patterns of prestige ranking will not have had significant changes in the past decade. That said, we should observe that particularly among the formerly black universities there have been several notable changes in research output (University of Fort Hare or the University of the Western Cape for example), suggesting that some of these universities may be entering a different era and playing a different role in the system. However, there is little reason to believe that information asymmetries surrounding Ph.D. hiring will disappear any time soon, in South Africa or elsewhere, so the results regarding effects of mobility on career success are likely to be robust.

Because in principle universities have as their raison d'être the creation and diffusion of knowledge, and because by its nature knowledge changes relatively slowly (that is to say, what is true does not change quickly) universities tend to evolve relatively slowly, and so do their standings relative to each other.[18] Seen from this perspective, stratification, and to

[18] For a discussion of this see for example Cowan et al. (2010) pp. 278–299.

a lesser extent inertia, in hiring is a natural outcome. These two forces are a source of the Matthew effect at the university level, and tend to create stasis, or possibly even reinforce the gaps in university hierarchies. Whether or not in general a hierarchical or even two-tier university system is good or bad, in the South African context where the current hierarchy is born of the apartheid period, one can argue that the existing hierarchy is not ideal. The top universities in the current structure tend to be the historically white universities, and there, even 20 years after apartheid ended, the professoriate remains predominantly white, and for structural reasons is likely to remain so for many years (Barnard et al 2017). Here the hierarchy of the universities is socially problematic. In this respect a policy devoted to increasing the in-house capabilities of the latter and the exchange of expertise between universities could help to reverse this trend, and to create a more equal and productive system.

Acknowledgements Financial support was provided through the Institut Universitaire de France. Much of this work was done when Rossello and Cowan were visiting scholars at the Centre for Research on Evaluation, Science and Technology (CREST) at Stellenbosch University, South Africa. We gratefully acknowledge the comments and suggestions of participants of the seminar at CREST, as well as those of Prof. Pierre Mohnen, Dr. Moritz Müller, and Prof. Giorgio Fagiolo. We would like also to thank an anonymous referee for the helpful comments.

Appendix 1: University reform in 2004

The South African university system saw a major reform in 2004. The reform merged and split university departments in the spirit of a geographical rationalization and racial integration. In our analysis we use post-merger names mostly because the data are more complete. More precisely, it is possible to make an accurate translation from pre- to post-merger names, but not from post- to pre-merger names, so by using pre-merger names we would lose a significant number of observations. Moreover, the use of post-merger names represents a value added of the work. It is a way to produce the prestige ranking of the South African universities that can be compared to the actual system. From the point of view of the analysis we note the following. The University of Johannesburg came into existence as the result of a merger between Rand Afrikaans University, Technikon Witwatersrand, and Vista University, where the latter two have almost no Ph.Ds (3 in total) in the period. So using University of Johannesburg instead of its disaggregation pre-merger would not make much difference. Similarly, Nelson Mandela Metropolitan University was created by the merger of Port Elizabeth Technikon, University of Port Elizabeth, and Vista University where the sample is dominated by Ph.Ds from Port Elizabeth. NorthWest University is a merger of University of the North West and Potchefstroom University, and the latter dominates Ph.D. production, particularly if we restrict attention to SET where 32 Ph.Ds are from Potchefstroom versus 6 from the University of the North West. The only possible problem could arise for the case of University of KwaZulu Natal which is the merger of University of Durban West Ville and University of Natal. Though, restricting to SET, Natal dominates with 32 Ph.Ds versus 6 in Durban West Ville.

Table 4 Prestige ranking for SET 1970–2004 using pre-merger names. The prestige ranking is in ascending order from the highest prestige which correspond to one. The number is the average of the orders with the maximum scores of the 10,000 repetitions. The algorithm is run on the adjacency matrix of pre-merger university names of the hiring network. Universities with fewer than 5 Ph.Ds are excluded

University	Prestige ranking	Language
NorthWestUniversity	1.873418	Afr
RhodesUniversity	2.721519	Eng
UniversityOfWitwatersrand	4.417722	Eng
UniversityOfCapeTown	4.506329	Eng
UniversityOfTheOrangeFreeState	4.658228	Afr
UniversityOfNatal	5.78481	Eng
UniversityOfPretoria	7.088608	Afr
PotchefstroomUniversity	7.721519	Afr
UniversityOfDurbanWestVille	8.35443	Eng
RandAfrikaansUniversity	10.658228	Afr
UniversityOfTheFreeState	11.139241	Afr
UniversityOfStellenbosch	12.101266	Afr
UniversityOfSouthAfrica	12.367089	Afr/Eng
MedicalUniversityOfSouthAfrica	13.139241	Afr/Eng
UniversityOfPortElizabeth	14.683544	Afr/Eng
UniversityOfTheWesternCape	14.78481	Eng

As a robustness check we redo the prestige ranking in SET with those observations for which we have full data using pre-merger names. Table 4 shows the results which are quite consistent to those of the full sample. We must also be cognizant of the fact that in the period there was to some extent a language divide which appears mitigated using post-merger names. Indeed, looking separately at English and Afrikaans language universities in Table 4 we can observe a more informative pattern. English universities have the same rankings here as in the main analysis. The exception being KZN: University of Natal is ranked 4th in the analysis using old names whereas KZN was ranked second among english universities in the main analysis. Afrikaans universities have almost the same ranking here as they do in the main analysis; and if UNW (NWO and Potchefstroom) are excluded.

We have also repeated the matched pairs analysis with pre-merger names, and notwithstanding the reduced sample size, results are in line with our main findings.

Appendix 2: Faculty hiring network

See Table 5.

Table 5 Indegree and outdegree SET hiring network for the years 1970–2004. Network statistics are compute without considering self-loops

	SET		SSH	
	Indegree	Outdegree	Indegree	Outdegree
UniversityOfCapeTown	8	14	4	11
NelsonMandelaMetropolitanUniversity	8	9	6	2
UniversityOfWitwatersrand	9	11	4	6
UniversityOfPretoria	10	14	5	8
UniversityOfJohannesburg	8	10	5	4
UniversityOfTheFreeState	7	7	3	2
UniversityOfSouthAfrica	8	8	8	9
UniversityOfStellenbosch	10	15	5	14
UniversityOfKwaZuluNatal	7	13	8	8
UniversityOfTheNorthWest	8	10	4	6
UniversityOfLimpopo	11	3	7	0
RhodesUniversity	5	9	5	5
UniversityOfTheWesternCape	7	5	2	5
UniversityOfFortHare	7	1	2	0
WalterSisuluUniversity	3	0	5	1
UniversityOfVenda	3	1	2	0
CentralUniversityOfTechnology	1	1	1	1
TshwaneUniversityOfTechnology	6	0	4	1
VaalUniversityOfTechnology	2	1	2	0
MonashSAUniversity	0	1	0	0
DurbanInstituteOfTechnology	2	0	1	0
CapePeninsulaUniversityOfTechnology	3	0	0	0

Appendix 3: Prestige ranking aggregating SET and SSH

See Fig. 6.

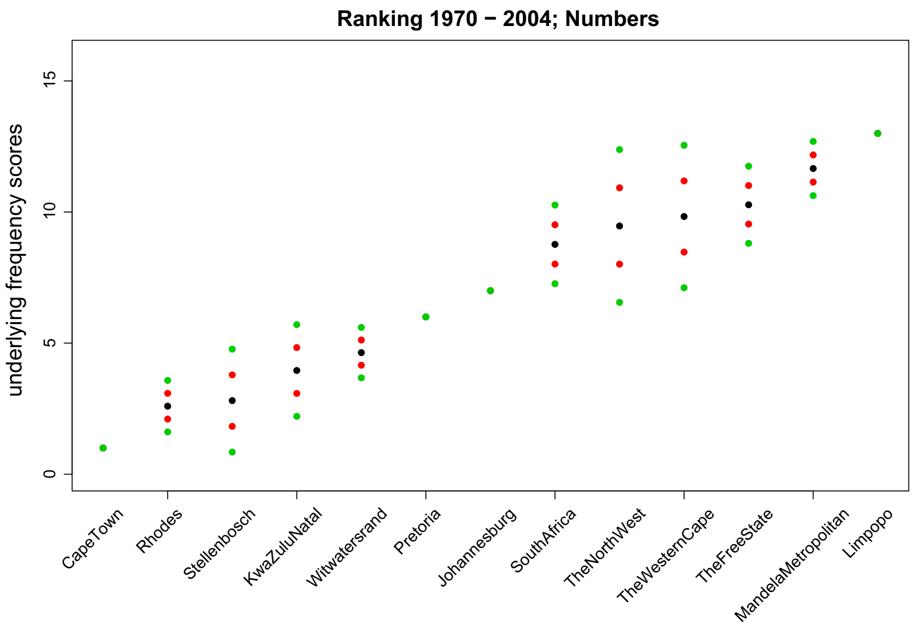

Fig. 6 Prestige Ranking 1970–2004 without distinction of fields. The frequency scores are in ordered left to right from the highest prestige which corresponds to one. The Black dots represent the average placement of each university in the maintained orderings, red dots and green dots are respectively one and two standard deviation from the average. Our algorithm runs on the adjacency matrix of the hiring network. Universities with fewer than 5 Ph.Ds are excluded. (Color figure online)

Appendix 4: Cohort effects

See Figs. 7, 8 and 9.

In this "Appendix" we present the results of the matched pair analysis but restrict the sample to those who received a Ph.D. prior to 1992. This way we reduce significantly any possible cohort effects.

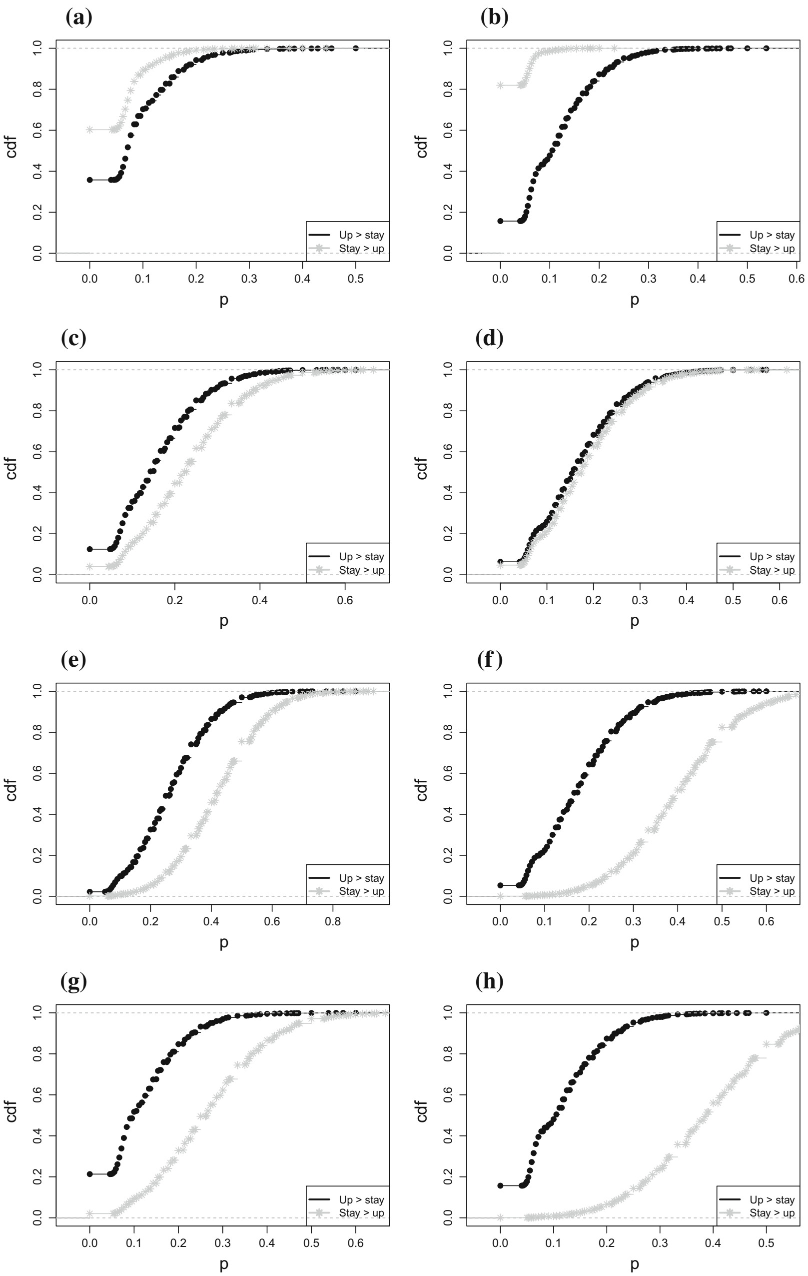

Fig. 7 Up versus stay comparison, with the sample restricted to those who received their Ph.D. degrees prior to 1992. The black curves are cumulative distribution functions of the proportion of observations in which $R_{\mathrm{up}} > R_{\mathrm{stay}}$ was the case for $p\%$ of the matched pairs. Grey curves are the CDFs for the $R_{\mathrm{stay}} > R_{\mathrm{up}}$ proportions. From top to bottom 5, 10, 15, and 20 years after Ph.D. Pairs matched using gender, race, Ph.D. obtained years and first job university (left column) or Ph.D. institution (right column). **a** First job, 5 years after Ph.D. **b** Ph.D., 5 years after Ph.D. **c** First job, 10 years after Ph.D. **d** Ph.D., 10 years after Ph.D. **e** First job, 15 years after Ph.D. **f** Ph.D., 15 years after Ph.D. **g** First job, 20 years after Ph.D. **h** Ph.D., 20 years after Ph.D.

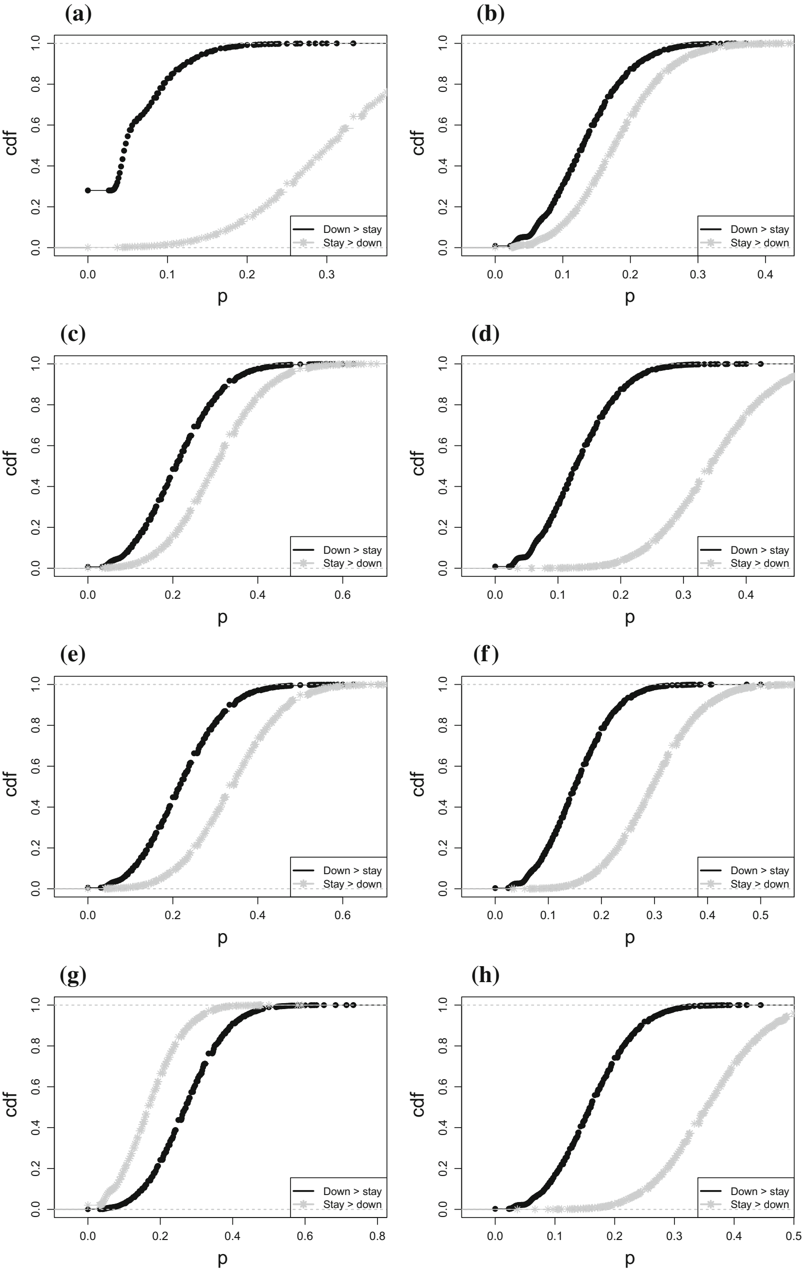

Fig. 8 Down versus stay comparison, with the sample restricted to those who received their Ph.D. degrees prior to 1992. The black curves are cumulative distribution functions of the proportion of observations in which $R_{\text{down}} > R_{\text{stay}}$ was the case for $p\%$ of the matched pairs. Grey curves are the CDFs for the $R_{\text{stay}} > R_{\text{down}}$ proportions. From top to bottom 5, 10, 15, and 20 years after Ph.D. Pairs matched using gender, race, Ph.D. obtained years and first job university (left column) or Ph.D. institution (right column). **a** First job, 5 years after Ph.D. **b** Ph.D., 5 years after Ph.D. **c** First Job, 10 years after Ph.D. **d** Ph.D., 10 years after Ph.D. **e** First Job, 15 years after Ph.D. **f** Ph.D., 15 years after Ph.D. **g** First Job, 20 years after Ph.D. **h** Ph.D., 20 years after Ph.D.

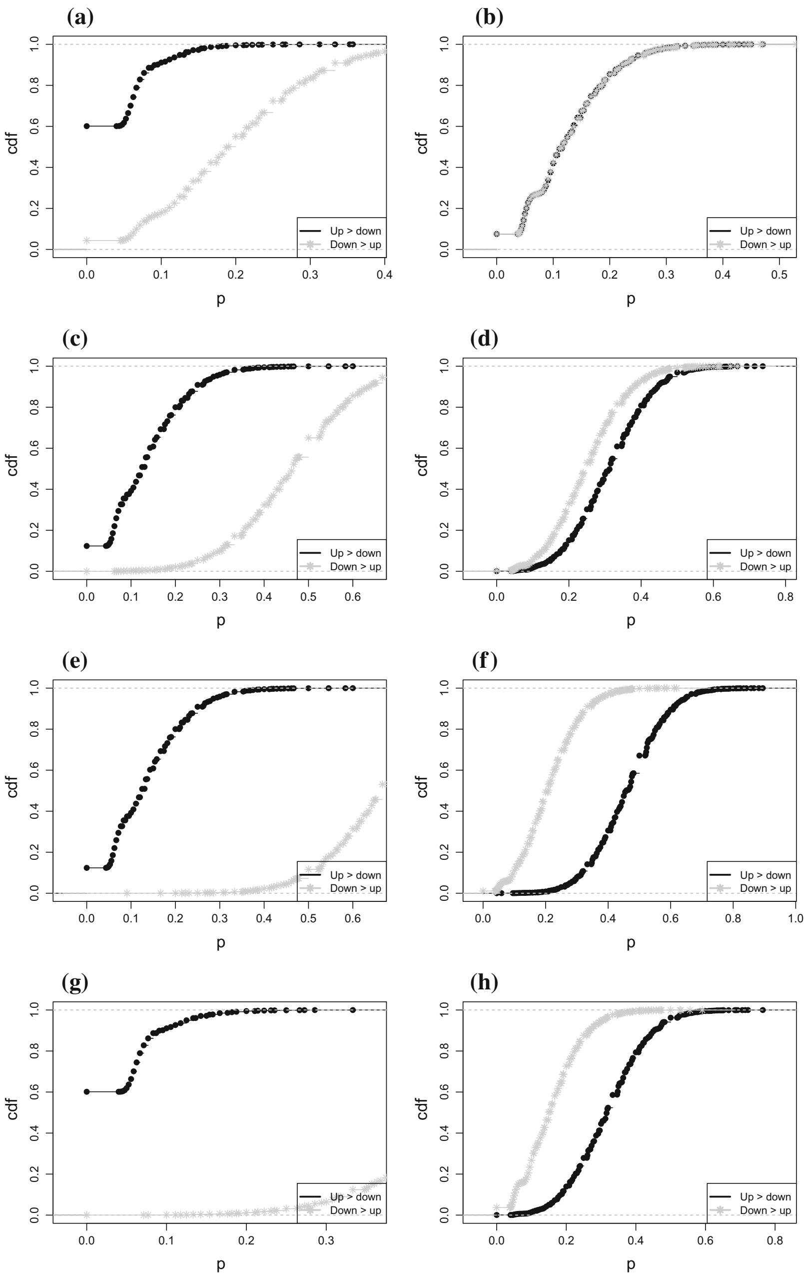

Fig. 9 Up versus down comparison, with the sample restricted to those who received their Ph.D. degrees prior to 1992. The black curves are cumulative distribution functions of the proportion of observations in which $R_{\rm up} > R_{\rm down}$ was the case for $p\%$ of the matched pairs. Grey curves are the CDFs for the $R_{\rm down} > R_{\rm up}$ proportions. From top to bottom 5, 10, 15, and 20 years after Ph.D. Pairs matched using gender, race, Ph.D. obtained years and first job university (left column) or Ph.D. institution (right column). **a** First job, 5 years after Ph.D. **b** Ph.D., 5 years after Ph.D. **c** First job, 10 years after Ph.D. **d** Ph.D., 10 years after Ph.D. **e** First job, 15 years after Ph.D. **f** Ph.D., 15 years after Ph.D. **g** First job, 20 years after Ph.D. **h** Ph.D., 20 years after Ph.D.

Appendix 5: SSH results

Table 6 gives the adjacency matrix of Ph.D. to first job transition in SSH.

See Figs. 10 and 11.

Table 7 contains summary statistics of the SSH hiring network.

See Tables 7 and 8.

Table 6 Adjacency matrix of the hiring network for the years 1970–2004 in SSH, rows are Ph.D. institutions and columns are first job institutions. Each entry represents the number for people with a Ph.D. in university i hired as first job in university j

PhD Institution \ First Job Institution	CapeTown	NelsonMandelaMetropolitan	Witwatersrand	Pretoria	Johannesburg	TheFreeState	SouthAfrica	Stellenbosch	KwaZuluNatal	TheNorthWest	Limpopo	Rhodes	TheWesternCape	FortHare	WalterSisulu	Venda	CentralUnivOfTechnology	TshwaneUnivOfTechnology	VaalUnivOfTechnology	MonashSA	DurbanInstituteOfTechnology	CapePeninsulaUnivOfTechnology
CapeTown	30	0	1	0	0	0	3	1	5	1	1	3	4	1	1	1	0	0	0	0	0	0
NelsonMandelaMetropolitan	0	11	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0
Witwatersrand	3	0	27	3	0	0	2	0	2	0	0	1	0	0	1	0	0	0	0	0	0	0
Pretoria	0	1	3	48	5	1	10	0	0	4	4	0	0	0	0	0	0	3	0	0	0	0
Johannesburg	0	0	0	1	16	0	4	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0
TheFreeState	0	0	0	0	0	24	0	0	1	0	0	0	0	0	0	0	2	0	0	0	0	0
SouthAfrica	1	4	0	11	1	2	69	0	3	5	3	0	0	0	0	0	0	1	0	0	0	0
Stellenbosch	4	2	1	3	1	4	2	42	1	0	1	1	5	1	1	1	0	0	0	0	0	0
KwaZuluNatal	1	2	1	0	0	0	1	1	36	0	0	1	0	0	2	0	0	0	0	0	2	0
TheNorthWest	0	0	0	0	3	0	5	1	0	36	1	0	0	0	0	0	0	2	2	0	0	0
Limpopo	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
Rhodes	0	1	0	0	1	0	3	0	2	0	0	7	0	0	1	0	0	0	0	0	0	0
TheWesternCape	0	1	0	0	0	0	0	2	0	0	1	1	14	0	0	0	0	1	0	0	0	0
FortHare	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
WalterSisulu	0	0	0	0	0	0	0	0	1	0	0	0	0	0	2	0	0	0	0	0	0	0
Venda	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CentralUnivOfTechnology	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
TshwaneUnivOfTechnology	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
VaalUnivOfTechnology	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MonashSA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
DurbanInstituteOfTechnology	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CapePeninsulaUnivOfTechnology	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

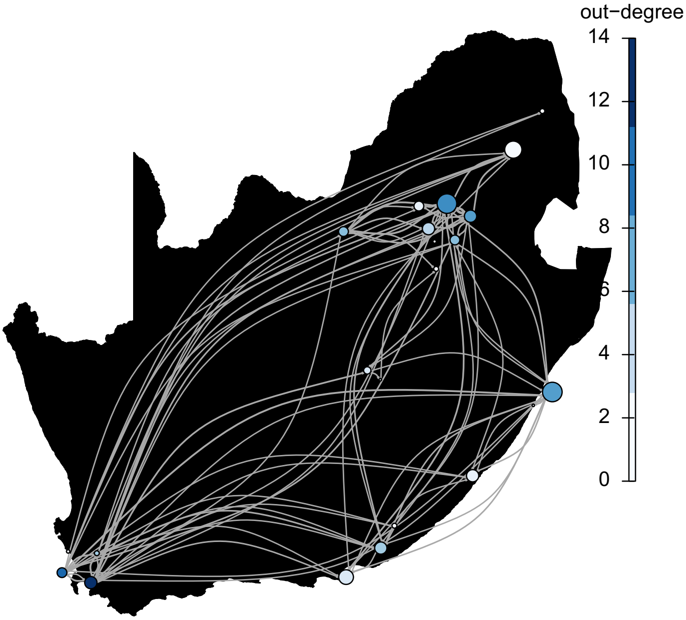

Fig. 10 Hiring network 1970–2004 SSH. The vertex are the South African Universities, plotted according to their geographical coordinates (for the institutions located in the same area we separated manually). Vertex size in-degree, vertex colour out-degree. Where the correlation between in-degree and out-degree 0.53

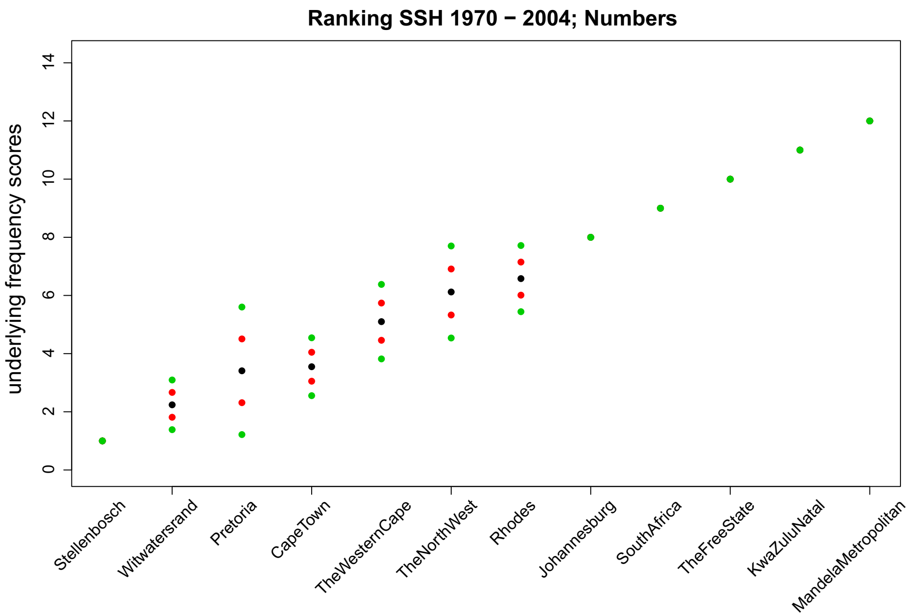

Fig. 11 Prestige Ranking for SSH 1970–2004. The frequency scores are in ascending order from the highest prestige which correspond to one. The black dots is the average of the orders with the maximum scores under 10,000 repetition, red dots and green dots are respectively one and two standard deviation from the average. Our algorithm runs on the adjacency matrix of the hiring network. Universities with fewer than 5 Ph.Ds are excluded. (Color figure online)

Table 7 Summary statistics SSH hiring network for the years 1970–2004. Network statistics are compute without considering self-loops

	All	Male	Female	White	Black
Number of nodes	22	22	22	22	22
Number of components	3	3	5	3	7
Number of isolated nodes	2	2	4	2	6
Statistics on the giant component					
Number of nodes	20	20	18	20	16
Number of edges	83	63	43	74	26
Edge density	0.218	0.166	0.141	0.195	0.108
Average path length	1.959	1.976	2.386	2.02	2.037
Diameter	8	11	7	9	5
Global clustering coefficient	0.525	0.429	0.35	0.51	0.308

Table 8 Ph.Ds hired from the top 5 prestigious universities in SSH, according to our prestige ranking. The total of SSH Ph.Ds Hired in the period is 542

Rank	Ph.D. university	Placed in SA academia	Hired by top 5	Proportion placed in top 5
1	Stellenbosch	70	55	0.786
2	Witwatersrand	39	33	0.846
3	Cape Town	52	36	0.692
4	Pretoria	79	51	0.646
5	WesternCape	20	16	0.8
	All in top 5	260	191	0.735
	Total Ph.D. hires	542		0.480

Appendix 6: KS test matched pairs

See Tables 9 and 10.

Table 9 Results of KS test relative to Fig. 3, 4, and 5. For two tailed test the null hypothesis is that cdf are different, for the less/greater test the first cdf lies below/above the other

	Up-stay		Down-stay		Up–down	
	First job	Ph.D.	First job	Ph.D.	First job	Ph.D.
5 years after Ph.D.						
Two tailed	$D = 0.97$; p value $< 2.2 \times 10^{-16}$	$D = 0.61$; p value $< 2.2 \times 10^{-16}$	$D = 0.32$; p value $< 2.2 \times 10^{-16}$	$D = 0.15$; p value $< 2.2 \times 10^{-16}$	$D = 0.10$; p value $< 2.2 \times 10^{-16}$	$D = 0.77$; p value $< 2.2 \times 10^{-16}$
Less	$D = 0.97$; p value $< 2.2 \times 10^{-16}$	$D = 0.61$; p value $< 2.2 \times 10^{-16}$	$D = 0$; p value $= 1$	$D = 0.15$; p value $< 2.2 \times 10^{-16}$	$D = 0$; p value $= 1$	$D = 0.77$; p value $< 2.2 \times 10^{-16}$
Greater	$D = 0$; p value $= 1$	$D = 0$; p value $= 1$	$D = 0.32$; p value $< 2.2 \times 10^{-16}$	$D = 0$; p value $= 1$	$D = 0.10$; p value $< 2.2 \times 10^{-16}$	$D = 0$; p value $= 1$
10 years after Ph.D.						
Two tailed	$D = 0.02$; p value $= 0.013$	$D = 0.09$; p value $< 2.2 \times 10^{-16}$	$D = 0.30$; p value $< 2.2 \times 10^{-16}$	$D = 0.96$; p value $< 2.2 \times 10^{-16}$	$D = 0.23$; p value $< 2.2 \times 10^{-16}$	$D = 0.54$; p value $< 2.2 \times 10^{-16}$
Less	$D = 7 \times 10^{-4}$; p value $= 0.995$	$D = 0.09$; p value $< 2.2 \times 10^{-16}$	$D = 0$; p value $= 1$	$D = 0$; p value $= 1$	$D = 0$; p value $= 1$	$D = 0.54$; p value $< 2.2 \times 10^{-16}$
Greater	$D = 0.02$; p value $= 0.007$	$D = 0$; p value $= 1$	$D = 0.30$; p value $< 2.2 \times 10^{-16}$	$D = 0.96$; p value $< 2.2 \times 10^{-16}$	$D = 0.23$; p value $< 2.2 \times 10^{-16}$	$D = 0$; p value $= 1$
15 years after Ph.D.						
Two tailed	$D = 0.21$; p value $< 2.2 \times 10^{-16}$	$D = 0.65$; p value $< 2.2 \times 10^{-16}$	$D = 0.64$; p value $< 2.2 \times 10^{-16}$	$D = 0.80$; p value $< 2.2 \times 10^{-16}$	$D = 0.95$; p value $< 2.2 \times 10^{-16}$	$D = 0.81$; p value $< 2.2 \times 10^{-16}$
Less	$D = 0$; p value $= 1$	$D = 0$; p value $= 1$	$D = 0$; p value $= 1$	$D = 0$; p value $= 1$	$D = 0$; p value $= 1$	$D = 0.81$; p value $< 2.2 \times 10^{-16}$
Greater	$D = 0.21$; p value $< 2.2 \times 10^{-16}$	$D = 0.65$; p value $< 2.2 \times 10^{-16}$	$D = 0.64$; p value $< 2.2 \times 10^{-16}$	$D = 0.80$; p value $< 2.2 \times 10^{-16}$	$D = 0.95$; p value $< 2.2 \times 10^{-16}$	$D = 0$; p value $= 1$
20 years after Ph.D.						
Two tailed	$D = 0.51$; p value $< 2.2 \times 10^{-16}$	$D = 0.79$; p value $< 2.2 \times 10^{-16}$	$D = 0.39$; p value $< 2.2 \times 10^{-16}$	$D = 0.76$; p value $< 2.2 \times 10^{-16}$	$D = 0.97$; p value $< 2.2 \times 10^{-16}$	$D = 0.58$; p value $< 2.2 \times 10^{-16}$
Less	$D = 0$; p value $= 1$	$D = 0$; p value $= 1$	$D = 0.39$; p value $< 2.2 \times 10^{-16}$	$D = 0$; p value $= 1$	$D = 0$; p value $= 1$	$D = 0.58$; p value $< 2.2 \times 10^{-16}$
Greater	$D = 0.51$; p value $< 2.2 \times 10^{-16}$	$D = 0.79$; p value $< 2.2 \times 10^{-16}$	$D = 0$; p value $= 1$	$D = 0.76$; p value $< 2.2 \times 10^{-16}$	$D = 0.97$; p value $< 2.2 \times 10^{-16}$	$D = 0$; p value $= 1$

Table 10 Results of KS test relative to Figs. 7, 8, and 9. Sample restricted to those who received their Ph.D. degrees prior to 1992. For two tailed test the null hypothesis is that cdf are different, for the less/greater test the first cdf lies below/above the other

	Up-stay		Down-stay		Up–down	
	First job	Ph.D.	First job	Ph.D.	First job	Ph.D.
5 years after Ph.D.						
Two tailed	$D = 0.25$; p value $< 2.2 \times 10^{-16}$	$D = 0.66$; p value $< 2.2 \times 10^{-16}$	$D = 0.90$; p value $< 2.2 \times 10^{-16}$	$D = 0.30$; p value $< 2.2 \times 10^{-16}$	$D = 0.73$; p value $< 2.2 \times 10^{-16}$	$D = 0.007$; p value $= 0.97$
Less	$D = 0.25$; p value $< 2.2 \times 10^{-16}$	$D = 0.66$; p value $< 2.2 \times 10^{-16}$	$D = 0$; p value $= 1$	$D = 0$; p value $= 1$	$D = 0$; p value $= 1$	$D = 0.007$; p value $= 0.64$
Greater	$D = 0$; p value $= 1$	$D = 0$; p value $= 1$	D = 0.90; p value $< 2.2 \times 10^{-16}$	$D = 0.30$; p value $< 2.2 \times 10^{-16}$	$D = 0.73$; p value $< 2.2 \times 10^{-16}$	$D = 0.007$; p value $= 0.62$
10 years after Ph.D.						
Two tailed	$D = 0.27$; p value $< 2.2 \times 10^{-16}$	$D = 0.06$; p value $< 2.2 \times 10^{-16}$	$D = 0.37$; p value $< 2.2 \times 10^{-16}$	$D = 0.86$; p value $< 2.2 \times 10^{-16}$	$D = 0.86$; p value $< 2.2 \times 10^{-16}$	$D = 0.24$; p value $< 2.2 \times 10^{-16}$
Less	$D = 0$; p value $= 1$	$D = 0$; p value $= 1$	$D = 0$; p value $= 1$	$D = 0$; p value $= 1$	$D = 0$; p value $= 1$	$D = 0.24$; p value $< 2.2 \times 10^{-16}$
Greater	$D = 0.27$; p value $< 2.2 \times 10^{-16}$	$D = 0.06$; p value $< 2.2 \times 10^{-16}$	$D = 0.37$; p value $< 2.2 \times 10^{-16}$	$D = 0.86$; p value $< 2.2 \times 10^{-16}$	$D = 0.86$; p value $< 2.2 \times 10^{-16}$	$D = 0$; p value $= 1$
15 years after Ph.D.						
Two tailed	$D = 0.45$; p value $< 2.2 \times 10^{-16}$	$D = 0.69$; p value $< 2.2 \times 10^{-16}$	$D = 0.47$; p value $< 2.2 \times 10^{-16}$	$D = 0.69$; p value $< 2.2 \times 10^{-16}$	$D = 0.98$; p value $< 2.2 \times 10^{-16}$	$D = 0.77$; p value $< 2.2 \times 10^{-16}$
Less	$D = 0$; p value $= 1$	$D = 0$; p value $= 1$	$D = 0$; p value $= 1$	$D = 0$; p value $= 1$	$D = 0$; p value $= 1$	$D = 0.77$; p value $< 2.2 \times 10^{-16}$
Greater	$D = 0.45$; p value $< 2.2 \times 10^{-16}$	$D = 0.69$; p value $< 2.2 \times 10^{-16}$	$D = 0.47$; p value $< 2.2 \times 10^{-16}$	$D = 0.69$; p value $< 2.2 \times 10^{-16}$	$D = 0.98$; p value $< 2.2 \times 10^{-16}$	$D = 0$; p value $= 1$
20 years after Ph.D.						
Two tailed	$D = 0.53$; p value $< 2.2 \times 10^{-16}$	$D = 0.82$; p value $< 2.2 \times 10^{-16}$	$D = 0.43$; p value $< 2.2 \times 10^{-16}$	$D = 0.82$; p value $< 2.2 \times 10^{-16}$	$D = 0.98$; p value $< 2.2 \times 10^{-16}$	$D = 0.61$; p value $< 2.2 \times 10^{-16}$
Less	$D = 0$; p value $= 1$	$D = 0$; p value $= 1$	$D = 0.43$; p value $< 2.2 \times 10^{-16}$	$D = 0$; p value $= 1$	$D = 0$; p value $= 1$	$D = 0.61$; p value $< 2.2 \times 10^{-16}$
Greater	$D = 0.53$; p value $< 2.2 \times 10^{-16}$	$D = 0.82$; p value $< 2.2 \times 10^{-16}$	$D = 0$; p value $= 1$	$D = 0.82$; p value $< 2.2 \times 10^{-16}$	$D = 0.98$; p value $< 2.2 \times 10^{-16}$	$D = 0$; p value $= 1$

Appendix 7: Robustness check of KS test

See Tables 11 and 12.

Table 11 Proportion of p values lower than 0.05 of Bootstrap KS test repeated 100 times on repeated re-samples of size = 100 for $p\%$

	Up-stay		Down-stay		Up–down	
	First job	Ph.D.	First job	Ph.D.	First job	Ph.D.
5 years after Ph.D.						
Two tailed	1	1	1	0.54	0.28	1
Less	1	1	0	0.65	0	1
Greater	0	0	1	0	0.42	0
10 years after Ph.D.						
Two tailed	0.03	0.26	0.99	1	0.94	1
Less	0	0.38	0	0	0	1
Greater	0.06	0	0.99	1	0.96	0
15 years after Ph.D.						
Two tailed	0.89	1	1	1	1	1
Less	0	0	0	0	0	1
Greater	0.94	1	1	1	1	0
20 years after Ph.D.						
Two tailed	1	1	1	1	1	1
Less	0	0	1	0	0	1
Greater	1	1	0	1	1	0

Table 12 Proportion of p values lower than 0.05 of Bootstrap KS test repeated 100 times on repeated re-samples of size = 100 for p%. Sample restricted to those who received their Ph.D. degrees prior than 1992

	Up-stay		Down-stay		Up–down	
	First job	Ph.D.	First job	Ph.D.	First job	Ph.D.
5 years after Ph.D.						
Two tailed	0.94	1	1	0.99	1	0.05
Less	0.96	1	0	0	0	0.03
Greater	0	0	1	0.99	1	0.07
10 years after Ph.D.						
Two tailed	0.96	0.14	1	1	1	0.98
Less	0	0	0	0	0	0.98
Greater	0.99	0.21	1	1	1	0
15 years after Ph.D.						
Two tailed	1	1	1	1	1	1
Less	0	0	0	0	0	1
Greater	1	1	1	1	1	0
20 years after Ph.D.						
Two tailed	1	1	1	1	1	1
Less	0	0	1	0	0	1
Greater	1	1	0	1	1	0

To address the well known problem of excess of sensitivity of KS test with large samples, we perform a robustness check, following a bootstrap technique. For each comparison of the distributions of proportions obtained with our matched pairs technique, we sample with replacement 100 samples of size 100 and each time we compute the KS test,[19] then we store the obtained p values and we count how many times the p values are lower than 0.05. Under the null hypothesis, p values are distributed as a uniform, so if the fraction of p values under 0.05 is larger that 0.05, then we can conclude in a more consistent way that the two distributions are different. Table 11 shows the results of this procedure for Figs. 3, 4, and 5. Observing the table the results of KS tests are confirmed.

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[19] According to Sekhon (2011) to account for possible presence of ties we use the ks.boot command under the R library Matching.

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