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Abstract

We study the pay of UK universities chief executives ('vice-chancellors') over a ten year period. Although there is a correlation between pay and performance, with better performing institutions paying higher salaries, we find limited evidence that this relationship is causal; that is, we find no statistically significant link that a change in pay leads to a change in performance, or vice-versa. Instead, we find strong support for an asymmetric benchmarking behaviour, where those institutions with below average pay increase their vice-chancellor's salaries quicker than those with above average pay. We simulate a model whereby different institutions target different places of the distribution of salaries and demonstrate that inflation of pay can be explained by this behaviour.

Keywords: Executive Compensation, Performance Pay, Efficiency Wages, Benchmark.

JEL classification: G3, J33, Z13

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Non-Technical Summary

The pay of university vice-chancellors (VC) in the UK has caused a strong debate in the press recently leading to some VCs having to resign.

Academics protest that at a difficult time for UK academia caused by the insecurity faced in the outset of Brexit, the gap between VC and staff pay is increasing. Students claim that at a time when tuition fees are increasing and they are accumulating high levels of debt the increase in VC's pay is unacceptable. Remuneration committees of universities however, argue that the increase is justified giving the VCs outstanding performance, especially during these turbulent times.

The present study analyses the relationship between performance and pay using established econometric models and ample empirical evidence from UK academia. It uses a dataset consisting of 154 universities in the UK over a period of ten years and a comprehensive set of key performance indicators related to both student numbers and student evaluations of the university (league tables) as well as its research and funding performance.

The key result of the study is that even though there is a correlation between pay and performance it is not causal and therefore, a better performance of the VCs is not what causes a higher pay. It is much rather a benchmarking behaviour where those universities with below average pay increase their VC pay quicker than those with above average pay.

'Keeping up with VC Jones' is what seems to explain the recent inflation of VC pay, rather than their good performance.

1 Introduction

The salaries of university directors in the UK (called vice chancellors, henceforth 'VC') have been under severe scrutiny recently. The VCs of two Universities (the University of Bath and Bath Spa University) have resigned in 2017 after receiving criticism for excessive pay. Attention is now subsequently focused on the pay of other VCs in the UK. Academics protest that at a time when student numbers are decreasing in the outset of Brexit, and academic jobs are reduced, the ratio between VC and staff pay is increasing, with VCs at some institutions earning 12 times more than academic staff and 35 times more than the average workers in the local area (Bennett 2017). Students and their representatives complain that this is unacceptable at a time with accumulation of high debts due to increased tuition fees.[1] As a consequence, the payment agreements of VCs have been called under investigation by the university regulator, the Office for Students, and the universities minister has called on universities to restrain pay for senior management.

Remuneration committees of the University of Bath and Bath Spa University argue, however, that the performance of their VCs was outstanding during a turbulent time for UK higher education and that the institutions have been flourishing during their tenure; therefore, their salaries reflected 'value for money'. Other parties highlight that it is problematic to compare average academic pay with that of VCs as the latter are recruited in 'a distinctive labour market' which 'doesn't operate under the same rules as those that apply to other - even senior academics'. It is further argued that if a VC is tackling 'much more important' issues such as the pay and conditions of early career academics, or those on teaching-only, research-only or other part-time and fixed-term contracts, then they 'deserve to be well remunerated'.[2] This suggestes that if pay is tied to performance of the VCs, their high salaries are justified.

The present study analyses the relationship between university performance and VC pay in the UK higher education sector. It does this by using a comprehensive dataset including 154 universities in the UK over ten years (between 2007 and 2016) and a comprehensive set of key performance indicators. Although several articles have extensively discussed the VC-pay situation in the UK and presented comprehensive statistics related to it, to our knowledge, no other study has analysed the pay-performance relationship as comprehensively, attempting to determine the direction of causation (Baker 2017, Bennett 2017, Langdon & Leino 2017). Moreover, the present study complements the existing 'classical models' in labour economics explaining the relationship between pay and performance with a salary 'benchmarking model' (DiPrete et. al, 2010; Faulkender & Yang, 2010).

Our results provide more support for benchmarking behaviour leading to increased VC pay than performance based explanations; in this respect, our findings are in line with Faulkender & Yang (2010). Although we find evidence of a correlation between pay and performance, there is no statistically significant link between a change in pay being associated with a change in performance. That is, high performing institutions pay higher salaries to their chief executive, but changes in either pay or performance is not associated with changes in the other. We provide evidence of an asymmetric benchmarking behaviour whereby those institutions paying their VC below the average of their peers, increase pay relative to this average faster than those universities paying above the average. This is in line with literature which suggests that remuneration committees setting salaries benchmark against higher paying institutions Nagel (2007), Faulkender & Yang (2010), Bizjak et al. (2011). Our results suggest that 64% of the variance explaining pay changes is explained

[1] BBC News 7 December 2017 available at: http://www.bbc.co.uk/news/uk-england-bristol-42260090

[2] William Locke, director of the Centre for Higher Education Studies at UCL Institute of Education.

by this benchmarking-to-average behaviour, but that this figure is 71% for those paying below the average, and only 25% above the average. We build a theoretical models to reconcile these empirical results and past literature and demonstrate that this asymmetric benchmarking behaviour can explain inflation in chief executive salaries in UK universities well.

The rest of the paper is organised as the following. Section 2 outlines the pay and performance as well as the salary benchmarking literature. Section 3 presents descriptive statistics on our underlying dataset of 154 UK institutions over the past ten years. Section 4 presents empirical results whilst testing the relationship between pay and performance, and Section 5 presents both empirical evidence and theoretical simulations for benchmarking behaviour. Section 6 concludes.

2 Theoretical background and related literature

The literature on the pay-performance relationship distinguishes between the influence of performance on pay and the influence of pay on performance (see Devers et al. 2007, for a comprehensive review). The distinction is important in order to determine if a better performance leads to a better pay or if rather a better pay motivates individuals into a better performance. This is further important for formulation of the main hypotheses to be tested in our study:

2.1 H_1: *A high pay is the result of a good performance*

Studies analyzing the pay-performance relationship usually come from finance and researchers examining the influence of performance on executive pay by depicting compensation as a reward for prior performance (Fama 1980).[3] Often this concept is related to the notions of 'Principal-Agent' of 'Agency Theory'. The general idea being that the stockholders (the 'Principals') hire one or more executive officers (the 'Agents') to maximise their wealth (shares value). The 'Principals' try to incentivise their 'Agents' by tying their pay to (stock) performance in various ways (bonuses or other forms of compensation). Researchers refer to the effect that performance has on pay as the sensitivity of pay to performance and maybe the most famous study in this area is by Jensen & Murphy (1990). The authors show that an increase of \$1,000 in shareholder wealth (as a measure for CEO performance) translates into a compensation of 'just' \$3.25 (pay) maybe suggesting that the interests of the 'Principals' and the 'Agents' are not well aligned or may even conflict. The benchmark specification used in Jensen & Murphy (1990) is the following:

$$\Delta X_{i,t} = \alpha + \beta \Delta \ln (Y_{i,t}) + \varepsilon_{i,t} \tag{1}$$

where $Y_{i,t}$ is the measure for performance (shareholder wealth), $X_{i,t}$ is the measure for pay (CEO salary plus bonus) and Δ stands for change (Jensen & Murphy 1990, p.228). Therefore, VC's change in compensation is explained by a change in the performance of the University. In an attempt to gauge causation a lagged performance term is additionally introduced in equation (1) above (Jensen & Murphy 1990, p.230).

[3]Note that the pay of VCs is often compared to the ones of chief executives of private companies. Turnover in some high profile universties is £600 million or more Fearn (2009).

$$\Delta X_{i,t} = \alpha + \beta_1 \Delta \ln (Y_{i,t}) + \beta_2 \Delta \ln (Y_{i,t-1}) + \varepsilon_{i,t} \tag{2}$$

Various controls and measures are added to (1) and (2) and other measures for pay and performance are tested. The benchmark result is that the pay-performance sensitivity is small and decreasing over time. Performance does not seem to have a strong impact on pay in the top management of a large sample of financial companies in the US spanning five decades and, even though bonuses represent 50 percent of CEO salary, they seem to be awarded in ways that are not highly sensitive to performance. Moreover, the variability of CEO compensations form year to year is very low. The authors conclude that political forces operating both in the public sector and inside organizations limit large payoffs for exceptional performance and that the abscence of management incentives in public corporations is a puzzle. In this seminal study the 'pay-for-performance' hypothesis seems to find little empirical support.

2.2 H_2: *A good performance is the result of high pay*

The idea that pay influences performance is closely related to the 'efficiency wages hypothesis'. This hypothesis argues that if agents/employees are paid more than the market-clearing wage their efficiency will be increased and this efficiency will lead to higher productivity which will pay for the higher wages. At the same time, because agents will want to keep their high wages, costs associated with turnover will be reduced and this will also pay for the higher wages. The idea being that that higher wages may increase the efficiency of the agents/employees by various channels making it worthwhile for the principals/employers to offer wages that exceed a market-clearing level. This hypothesis goes back at least to Marshall (1890) and found initially empirical support in the car industry. Raff & Summers (1987) showed that the introduction of a generous pay scheme (the 'five dollar a day') in 1914 has lead to substantial productivity benefits and profits for Ford. Hanlon et al. (2003) using a large sample of 1,069 firms show that a higher pay offered to top executive in form of option grant value, lead to higher operating income. Specifically, they found that \$1.00 of option grant value was associated with approximately \$3.71 of future undiscounted operating income growth over the 5 years following the grants. The empirical specification used in this study is basically the following:

$$Y_{i,t} = \alpha + \beta_1 \sum_{k=0}^{5} X_{i,t-k} + \beta_2 \sum_{k=0}^{5} (x_{i,t-k})^2 + Z_{i,t} + \varepsilon_{i,t} \tag{3}$$

where $Y_{i,t}$ stands for operating income as a measure of performance, $X_{i,t-k}$ stands for the grants received by executives in the previous 5 years as a measure for increased pay and $Z_{i,t}$ is a set of controls. The term $X_{i,t-k}$ is introduced also at the power of two in order to allow for non-linearities. To give another example, Kato et al. (2005) examined the adoption of stock-option compensation by Japanese firms following a regulatory change in 1997 that permitted their use. They found abnormal returns of 2% around announcement dates and increased operating performance post-adoption. Banker et al. (1996) argued that increased performance resulting from the adoption of incentive pay plans derives from self-selection and effort. Results showed that capable employees seek out jobs where superior skills are rewarded; thus, they are drawn to jobs with greater levels of incentive pay. The empirical specification used is:

$$Y_{i,t} = \alpha + \beta_p \sum_{p=1}^{k} X_{i,t,p} + \beta_s \sum_{s=1}^{n} D_{i,s} + \varepsilon_{i,t} \tag{4}$$

where $Y_{i,t}$ are the sales of employee i at time t as a measure for performance, $X_{i,t,p}$ are the various incentive plans to which the employee is subjected to and $D_{i,s}$ summarizes a set of dummies which represent store, merchandise group, if the employer is temporary employed or not etc. The basic idea being that pay influences performance.[4]

In an effort to accommodate both directions of causation (performance → pay and pay → performance), MacLeod & Malcomson (1998) develop a theoretical model that explains the relationship between pay and performance depending on market conditions. Provided there is sufficient rent from employment, firms may use either efficiency wages (high wages combined with the threat of dismissal) or performance pay (workers paid an end-of-period bonus if their subjectively assessed performance is satisfactory) to motivate employees. If the number of jobs (J) in an industry is larger than the number of workers in that industry (L) then bonuses have to be paid for good performance, or else workers would easily move to another job with a higher pay. Since workers can always get another job, they will shirk unless there is a bonus to compensate them for the disutility of work. This leads to a 'pay for performance' equilibrium (hypothesis H_1), called 'performance pay equilibria' in their study. Efficiency wages would not work in this case as the workers would shirk and change jobs. If on the contrary, the number of jobs is less than the number of workers ($J < L$) and the cost of creating a job is sufficiently high, then in order to keep high quality workers, employers will have to pay wages above the average market rate, and an 'efficiency wages equilibria' (hypothesis H_2) is more efficient. MacLeod & Malcomson (1998) apply their model to a two sector economy where one sector is 'capital intensive' and the other is 'labour intensive'. The authors claim that the essential characteristics of capital-intensive jobs is that they have higher productivity and that there is a sunk cost to creating vacancies that cannot be recouped if the vacancy is not filled. They argue that this description fits with the Ford's \$5-day example in Raff & Summers (1987) and with the 'efficiency wages hypothesis'. It is precisely the cost of not having each position filled at all times that makes it efficient in the model for the market to allocate a higher wage. This 'efficiency wage' will then ensure that the post does not remain unfilled for a long period of time. One result from the analysis is that while efficiency wage equilibria have unemployment, performance pay equilibria do not. Therefore, if the unemployment rate for an occupation is low ($J > L$), then the use of bonuses or other forms of compensations for performance should be observed, while in a high unemployment environment where $J < L$, efficiency wages should be observed. Arguably, the number of vice chancellor jobs in the UK is scarce and $J < L$; therefore, according to the MacLeod & Malcomson (1998) model we should rather find empirical evidence for the 'efficiency wage hypothesis' where a better performance is the result of higher pay (hypothesis H_2) than vice-versa (hypothesis H_1).

[4]There are serveral reasons why paying above the market salary might not be an inefficient outcome such as: monitoring, turnover, motivation, and many other. This may be the reason why evidence from other sectors than finance tests some of the suggested outcomes/implications/hypotheses of efficiency wages, rather than the whole model itself.

2.3 Benchmarking

We complement the two models described above with a consideration of pay 'benchmarking' (whereby the pay of an individual is set in the context of those deemed to be the individual's peers), which has received recent attention in the literature. DiPrete et al. (2010) construct a hypothesis that benchmarking behaviours of CEO pay lead to a ratcheting (a significant increase beyond that which would be expected) of pay since the 1990s. They propose that through selective sampling of a benchmark group, a powerful rent seeking executive can consistently get pay rises to push remuneration into the upper tail of the distribution. This power of certain CEOs has an externality effect as it pushes up average remuneration, which can be used by those CEOs with less power; the impact of those with the ability to leapfrog has an inflationary effect for everyone else in the market. In many ways, these leapfroggers provide an asymmetric benchmarking behaviour, certain members of the distribution are using different distributions from which to benchmark. Indeed, Schmidt & Dworschak (2006) use the prevalence of benchmarking in pay negotiations in the UK to explain why wage inflation has been higher than that of Germany, despite higher German trade union power.

Faulkender & Yang (2010) present results to suggest that the median salary of benchmarked companies explains more of the variation in CEO pay than all other attributes, including performance and the size of the firm; that is, the salaries of those in the group against which CEO pay is benchmarked is the most important element determining executive pay. Further, Faulkender & Yang (2010) find that after controlling for other characteristics (such as industry and size) a CEO with a higher salary is more likely to be selected for a benchmarking group by the remuneration committee of particular organisation; that is, committees are more inclined to have higher paid CEOs in their group with which to compare their own executives. Bizjak et al. (2011) too find that the selection of CEOs for comparison by a remuneration committee is biased in such a way to ensure that higher pay raises can be justified. Faulkender & Yang (2012) find that this benchmark group manipulation - whereby remuneration committees deliberately target firms with high executive pay in order to justify paying likewise - increased since 2006, when the US legislated that firms pre-announce the companies against they will benchmark pay. Laschever (2013) use data from S&P900 firms in 2007 and 2008 to demonstrate that, controlling for other characteristics, remunerations committees are more likely to chose higher CEO-compensating firms for benchmarking purposes; moreover, remuneration committees are more likely to chose larger firms for benchmarks, holding all else constant. Further Laschever (2013) apply an instrumental variable strategy to estimate an elasticity of CEO compensation with respect to the benchmark group average pay of 0.5.

Nagel (2007) finds evidence that those firms who underpay their CEO relative to the market increase their pay in order to reduce this inequality; as such, the growth rate of the median CEO salary has increased above inflation due to transparency of pay. Although Nagel (2007) does not specifically address asymmetries in the benchmarking process, it is found that whereas the number of underpaid CEOs has decreased since the 1970s, those CEOs who are overpaid have not; the interpretation given is that whereas frugal executive boards correct underpayment but do not overcorrect, those paying high salaries do not regress downwards.

When asked about pay benchmarking for CEOs, remuneration committees and boards provide arithmetically challenging results. For example, 35% of the firms surveyed in Crystal (1992) stated that they aimed to be at the 75^{th} percentile, and 65% at the 50^{th} percentile. Bizjak et al. (2008) used proxy statements to identify that 73% of sampled S&P 500 firms target the mean or median of CEO pay distribution; in the appendix of Faulkender & Yang (2010), it is illustrated that 98% of boards target a minimum of the prior year CEO peers' median pay. Bizjak et al. (2008) find that CEO turnover is less in companies which pay more than the median salary, whereas Nagel (2007) find that those companies who pay below the average executive salary perform worse. The literature suggests that there is a push for an arithmetically impossible number of CEOs to be paid above average.

Bizjak et al. (2008) document that a majority of companies whose CEOs receive below average pay receive increases, and this proportion increases with the performance of the company; that is, if a CEO has below average pay, they are more likely to receive a large pay increase, and this is more likely when the performance of the firm is strong. Bizjak et al. (2008) find that approximately a third of all CEOs with below average pay receive increases which take them above average each year.

Moreover, Garvey & Milbourn (2006) find an asymmetry in the pay of executive pay with respect to luck; that is, CEOs will be rewarded for good luck, but will not be punished for bad luck. Having consider the theoretical and empirical literature on executive pay, we now turn to testing these results on date from UK university VCs.

3 Descriptive statistics

3.1 Measures of pay

Since the academic year 2006/07 *Times Higher Education* have compiled data on the pay of vice-chancellors of UK institutions. This data has included details on salary, pensions and benefits, and has further included data on academic staff pay (separated by professor and non-professor and by gender). Table 1 highlights descriptive statistics on pay, where total remuneration (including salary, pension and other benefits) is included as our benchmark measure.[5] We adjust for inflation using a GDP deflator for the UK and all values are in 2017 prices. To give a perspective on the size of the student market during this period, total first year first degree acceptances are also provided in the second column.

Table 1: Descriptive statistics on pay and 'performance'

Year end	Students acceptances	VC pay	Academic pay
2007	413,400	235,311	47,829
2008	456,640	256,912	48,287
2009	481,850	277,915	51,430
2010	487,310	275,196	51,462
2011	492,010	267,702	50,526
2012	464,770	265,267	49,553
2013	495,540	266,778	49,083
2014	512,340	271,357	48,866
2015	532,225	283,888	49,496

Descriptive statistics illustrating: the cycle year end in the first column; the number of students accepted, the mean average vice-chancellor pay; and the mean average academic pay. Wages are reported at December 2017 prices.

[5] Approximately 12% of total pay is received by vice-chancellors in pensions, and this fraction is stable throughout the sample period.

During the sample period, student numbers increased by 29% whereas the real pay of vice-chancellors increases by 41% compared to 3% real pay increases in academic staff (and 3.4% specifically for professors). It is also possible to discern that there are falls in real pay of both vice-chancellor and academics after the financial crash, but whereas academic pay was at its peak in 2009/2010, the pay of vice-chancellors has seen an upward trend since 2013, and remuneration is at its highest in the most recent figures. Moreover, staff pay fell four consecutive years after the crisis (2011, 2012, 2013, 2014), while VC pay fell only in 2011 and 2012 after which it started to increase again.

Given that the regulation of the higher education sector is different for different countries of the UK, the distribution of pay across these geographical lines may differ. From Table 2 one can see that the vice-chancellors and academics of Wales have had the best outcomes with respect to growth in pay but the worst outcomes with respect to growth in student acceptances. These pay changes bring Welsh averages up to the average for the UK; in 2007, Welsh VCs and academics received 80.0% and 93.0% of the UK average, respectively, whereas in 2015 these fractions were 103.5% and 95.8%.

Table 2: Descriptive statistics on pay and 'performance' by country

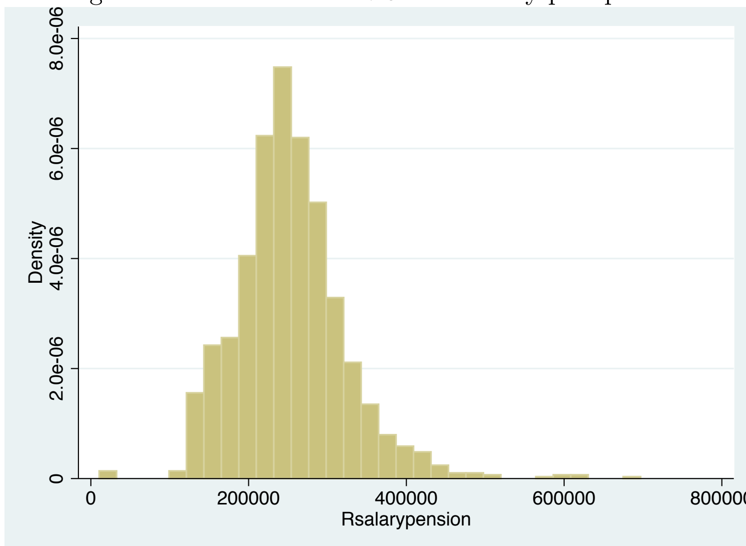
	Student acceptances	VC pay	Academic pay
UK	29.45%	20.87%	3.49%
England	28.19%	21.09%	3.59%
Northern Ireland	11.31%	7.73%	4.26%
Scotland	32.51%	17.79%	2.16%
Wales	6.46%	56.27%	6.63%

Descriptive statistics illustrating: the specific country of the UK in the first column; the number of student acceptances, the percentage increase in the mean average vice-chancellor pay; and the percentage increase in the mean average academic pay. Wages reported at December 2016 prices.

Figure 1 presents the distribution of real total salary and pension pay for vice chancellors: the minimum value (£11k) is for Heythorp College (University of London) in 2011 and the maximum (£669k) for the University of Southampton in 2016. In the case of the former, there is no discussion in the original source as to why this is so low, and the observation is dropped from future analysis. In the case of the latter, there was a change in the VC during the year and £253,000 of the total represents compensation for loss of office. A dummy variable for if there was a change in vice-chancellor during the year will be included in the regression analysis; on average we observe a 13% rate for annual change in vice-chancellor in our sample. Further, to ensure that pay outliers do not have overdue weight in the regression analysis, the variable will be transformed using a natural logarithm. Beyond these two outliers, there is a slight positive skew in the data, and it is possible to observe that there is a large degree of variability in pay. The positive skew suggests that the data has rather a lower bound than an upper bound.

Of the remaining variables related specifically to the vice-chancellor, we report that on average vice-chancellors have spent 5.92 years in their current position; this result reconciles with those from the Hillman (2016) which suggest that current tenure of UK VCs is between five and seven years. Finally, we report that only 17% of observations have a female vice-chancellor. This number has increased with time, with the figure being 13% in 2007 and 21% in 2016. If one compares salary by gender throughout the sample, females receive lower salaries by £12k (4.7% of total salaries, with a p-value of 0.010 on a bivariate t-test of statistical significance assuming unequal variances) and have been in post for half a year less than their

Figure 1: Distribution of VCs real salary plus pension



Histogram presenting results for the distribution of real salaries and pensions of vice-chancellors.

male counter-parts (with associated p-value of 0.075).

3.2 Measures of performance

For our benchmark results, we use six measures of university performance, encompassing different elements of the business. These performance measures come in the form of: student numbers and competition for places; league table performance; and research.

3.2.1 Student numbers and competition for places

Students represent a substantial revenue flow for universities. Thus one of our measures of performance is the number of students accepted to study at an institution in a given year. In additional to this, we also look at the number of applications to study a university has received from potential candidates. Until 2015 student numbers for each course were capped by the UK government for UK and EU applicants. Measuring the number of applications allows for a measure of performance which considers the popularity to study at an institution beyond these student caps. Finally, as historically larger institutions are likely to have more applications and acceptances, we derive a measure of performance of applications-per-place which represents relative demand for an institution. This measure considers how sought after a specific institution. Data on applications and acceptances is available from the Universities and Colleges Admissions Service (UCAS) for students applying to their first undergraduate degree. This is the system through which all UK and EU students apply for their degree and each student has the ability to apply for five courses on an application.

3.2.2 League tables

The second set of measures of performance come from university league tables produced annually within the UK. These take into consideration different attributes with respect to teaching and research at an institution and provide an overall score and ranking for each university. Although there are many university league tables in the UK, we focus on those which have been published over our sample period and which are freely available; this leaves those published by the Guardian Newspaper and the Complete University Guide (CUG). For each league table, we obtain data on all individual attributes which make up the final overall score; however, as a benchmark level of performance we focus on the overall score achieved in the assessment which subsequently leads to league table ranking.[6]

3.2.3 Research

The most popular metric with which to measure the research performance of UK institutions through scores received from nationally conducted 'research excellent reviews'.[7] Not only is this the measure of research to which the most time, effort and finances are allocated, it is also one which is associated with substantial funding through (indirectly) the UK government. Over our sample we have three periods of research excellence scores: pre-December 2008, between 2009 and 2014, and post-2014 (there were research excellence assessments in 2001, 2008 and 2014). As this measure is not updated annually, when comparing research excellence scores across institutions we split out sample into three time periods: before 2008; 2008 - 2014; and after 2014. In each period, the research score is that provided by the assessments, and for all over variables we take the within period average of the annual data we have obtained.

3.2.4 Descriptive statistics

Table 3 presents correlation coefficients across our six benchmark measures of performance as well as (in the final column) a measure of correlation between a variable and the lag of itself (to show the relative persistence of these performance measures). In general there are high degrees of correlation between our performance measures (note that larger scores in each of our performance measures suggest better outcomes for an institution), with only the correlation coefficient between first year acceptances and the score in the Guardian league table having a p-value > 0.05. In general, universities with high league table rankings have also higher research quality assessment scores (with correlation coefficients of 0.790 and 0.690 depending on which league table is applied); they also have more demand per place (correlation coefficients of 0.510 and 0.479) and more applications.

Maybe not surprisingly, there is also a high degree of persistence in a specific performance measure, with large correlation coefficients between a variable and its lag; this is measured in the final column of Table 3. For all measures, there is a strong correlation from one period to the next suggesting relatively consistent

[6]Although the methodology of the league tables change, as of 2017 both tables in our dataset use qualifications on entry, student feedback (administered centrally in the UK, known as the 'National Student Survey' or the 'NSS'), employability, student spend and staff-to-student ratios in their aggregate measure. In addition to this, the Complete University Guide use measures of research excellence and intensity, completion rates, and graduation grades. The Guardian league table, on the other hand, use a measure of 'value added' above those listed above, which evaluates the grades achieved of graduates against the qualifications with which those students entered the institution.

[7]Before 2014, these reviews were known as 'Research Excellence Assessment', or REA, and since 2014 these have been performed under the 'Research Excellence Framework', or 'REF'.

Table 3: Correlation between performance measures

	Applications	Acceptances	AccAppRatio	CUG	Guardian	REF	Lagged
Applications	1						0.994
							(0.000)
Acceptances	0.952	1					0.99
	(0.000)						(0.000)
AccAppRatio	0.222	0.135	1				0.741
	(0.000)	(0.000)					(0.000)
CUG	0.324	0.089	0.523	1			0.977
	(0.000)	(0.003)	(0.000)				(0.000)
Guardian	0.265	0.062	0.493	0.916	1		0.950
	(0.000)	(0.062)	(0.000)	(0.000)			(0.000)
REF	0.408	0.239	0.486	0.808	0.689	1	0.772
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)

Correlation coefficients between performance measures. The final column represents the correlation between a performance variable and its lagged value which gives the persistence of a variable. P-values in parentheses.

levels of performance from institutions. One can observe, for example, that there is an extremely high persistence in league table scores, with correlation coefficients of 0.980 and 0.950 depending on the table.

We perform both Harris-Tzavalis and Levin-Lin-Chu tests for unit roots in both performance and pay variables.[8] With the exception of applications the null hypothesis of a unit root is strongly rejected. In the analysis below, we apply empirical specifications including both the level and change in variables to account for any unit root issues. Further descriptive statistics are presented in the Appendix in Tables A1 - A9.

4 Association between pay and performance

4.1 Empirical specifications

Hypothesis 1 above states that pay is a result of performance. To test for this relationship, we estimate the following specification:

$$\ln(X_{1,i,t}) = \alpha + \beta_1 \ln(Y_{i,t}) + \beta_2 \ln(Y_{i,t-1}) + \gamma VC_{i,t} + \delta Z_{i,t} + \varepsilon_{i,t} \tag{5}$$

where $X_{1,i,t}$ is the pay of the VC of university i at time t, $VC_{i,t}$ is a set of variables related to the vice-chancellor of university i in period t including both their gender, their year in service, and whether the VC was new in the year of question; and $Z_{i,t}$ are a set of other control variables including the geographical location of the university (separated between England, Northern Ireland, Scotland and Wales), time period dummy variables, and the group of universities the institution belongs (for example, the Russel Group).[9] The variable $Y_{i,t}$ represents performance of institution i at time t, which given the levels of collinearity (see Table 3), we enter into estimations of 5 one at a time; as discussed above, we use the number of student applications, the number of student acceptances, the ratio between the two, the two university league tables (the Complete University Guide and Guardian League Table), and the research performance as assessed

[8] Note that both the Harris-Tzavalis and Levin-Lin-Chu tests account for the panel nature of the time series.

[9] An association of UK universities regarded as having the highest academic standards.

by the Research Excellence Framework (REF). For our benchmark results, we only include one lag of the performance variables in our specifications; sensitivity of the results to this assumption is performed in Section 4.5. The inclusion of lags is meant to try to detect Granger type causation. If past university performance should impact significantly on today's VC pay then a potential causation from performance to pay can be assumed.[10]

In order to further investigate the potential causal relationship between VC pay and performance, the following additional difference in differnce specification will be estimated:

$$\Delta\left[\ln\left(X_{1,i,t}\right)\right] = \alpha + \beta\Delta\left[\ln\left(Y_{i,t}\right)\right] + \gamma VC_{i,t} + \delta Z_{i,t} + \varepsilon_{i,t} \tag{6}$$

where $\Delta\left[\ln\left(X_{1,i,t}\right)\right]$ is the change in VC pay from previous year, and $\Delta\left[\ln\left(Y_{i,t}\right)\right]$ the change in performance from the previous year (and all the other variables are as above). As illustrated in Table 3 there is a high degree in persistence of the performance of a university; that is, a good university one year is very likely to maintain this level of performance. Through estimating specification (6) we are assessing whether changes in performance are associated with changes in pay. This can provide more conclusive evidence of causality compared to the specification in the levels of pay and performance (5).

To assess hypothesis 2 (that performance is a result of high pay) we estimate the following two specifications:

$$Y_{i,t} = \alpha + \beta_1 \ln\left(X_{1,i,t}\right) + \beta_2 \ln\left(X_{1,i,t-1}\right) + \lambda \ln\left(X_{2,i,t}\right) + \gamma VC_{i,t} + \delta Z_{i,t} + \varepsilon_{i,t} \tag{7}$$

$$\begin{aligned}\Delta \ln\left(Y_{1,i,t}\right) = {} & \alpha + \beta_1\Delta\left[\ln\left(X_{1,i,t}\right)\right] + \beta_2\Delta\left[\ln\left(X_{1,i,t-1}\right)\right] + \lambda_1\Delta\left[\ln\left(X_{2,i,t}\right)\right] \\ & + \lambda_2\Delta\left[\ln\left(X_{2,i,t-1}\right)\right] + \gamma VC_{i,t} + \delta Z_{i,t} + \varepsilon_{i,t}\end{aligned} \tag{8}$$

where $X_{2,i,t}$ represents academic staff pay.

4.2 Empirical Results

Tables 4 and 5 present the main results for the empirical specifications outlined above. Full regression results including all controls can be found in Tables A10 and A11 in the Appendix. Table 4 presents the results for hypothesis H_1 which stipulates that performance influences pay. The dependent variable is VCs pay and the performance measures are as described above.

Focusing on the results from specification (5) from Table 4, there is a statistically significant association between contemporaneous higher performance and higher pay for applications, acceptances, and scores in the REF; higher performance is associated with higher pay in the same period. For league table scores, statistically significance is associated with lagged performance, that is, better performance in the previous period leads to higher pay this period. This result could come from directional causality (pay decisions *respond* to better previous performance) or due to the nature of league tables, being composite measures of prior performance. It is also possible to conclude that the estimates suggest that improvements in the research scores of an institution having higher impact on VC pay than other performance indicators. It is estimated that a 10% improve in REF leads to a 4.8% increase in pay, compared with similar improves

[10]Even though Granger causality is not a guarantee for true causality.

Table 4: The impact of performance on pay

	Specification (5): Dependent variable $\ln(X_{1,i,t})$					
	App	Acc	AppAccR	CUG	Guardian	REF
$\ln(Y_{i,t})$	0.528***	0.193***	0.025	0.093	0.046	0.488***
	(0.000)	(0.000)	(0.668)	(0.346)	(0.613)	(0.000)
$\ln(Y_{i,t-1})$	-0.391***	-0.052	0.000	0.205**	0.187**	0.008
	(0.000)	(0.328)	(0.996)	(0.034)	(0.041)	(0.883)
n	1,219	1,218	1,218	925	717	213
R^2	0.469	0.464	0.323	0.357	0.391	0.439
	Specification (6): Dependent variable $\Delta[\ln(X_{1,i,t})]$					
	App	Acc	AppAccR	CUG	Guardian	REF
$\Delta[\ln(Y_{i,t})]$	-0.039	-0.033	0.010	-0.104	0.001	-0.192
	(0.331)	(0.372)	(0.766)	(0.273)	(0.986)	(0.338)
$\Delta[\ln(Y_{i,t-1})]$	0.065	0.016	0.018	0.081	0.076	-0.066
	(0.150)	(0.662)	(0.601)	(0.322)	(0.301)	(0.426)
n	1064	1063	1063	792	591	97
R^2	0.079	0.077	0.077	0.07	0.064	0.194

Regressions from specifications (5) and (6) for the six different measures of performance (as labelled in the first heading row). For each result, the coefficient on the performance variable is reported with the p-value associated with this coefficient reported in parentheses underneath. *, **, *** represent significance at 10%, 5% and 1% respectively. Results for all coefficients can be found in Table A10.

in other performance variables leading to approximately a 2% increase in pay (with the exception of the application to acceptances ratio which is not estimated to be important for determining pay).

The results from specification (6) in Table 4 are never statistically significant which suggests that improvements in performance do not lead to a higher pay and that the relationship between performance and pay is not causal. That is, there is a correlation between performance and pay (as illustrated by the results from specification (5)) but that changes in performance are not correlated to change in pay (as illustrated by the results from specification (6)). These results imply that higher performing institutions pay their VC a higher salary, but that were performance to improve (reduce), higher (lower) pay does not follow.

Table 5 presents the results for testing the second hypothesis (H_2) suggesting that pay may impact on performance, presenting results both for VC pay (X_1) and for staff pay (X_2). The results are similar to those from Table 4. Focusing on specification (7), there is a statistically significant association between contemporaneous VC pay and performance in applications, student acceptances and REF scores. Interestingly, there is now more of an association between lagged pay and performance, with larger coefficients and statistically significant results for all performance variables with the exception of the applications-per-place ratio. These results suggest that higher VC pay in previous periods lead to higher student applications, acceptances, league table and REF results today; this result (and its consistency across different performance measures) suggesting some evidence for the 'efficiency wages' hypothesis. A 10% increase in pay is estimated to increase applications and acceptances by over 15.4%, improve league table scores by 12% and research quality by 2.9%.

Although there appears to be strong evidence for correlation there limited evidence that a change in pay leads to a change in performance. Focusing on results from specification (8) in Table 4, there is estimated to be a limited link between a change in pay and change in performance; indeed, the two places where

Table 5: The impact of pay on performance

	Specification (7): Dependent variable $\ln(Y_{i,t})$					
	App	Acc	AppAccR	CUG	Guardian	REF
$\ln(X_{1,i,t})$	0.680***	0.676***	0.024	0.051	0.044	0.159***
	(0.001)	(0.001)	(0.784)	(0.187)	(0.331)	(0.009)
$\ln(X_{1,i,t-1})$	0.894***	0.964***	-0.048	0.122***	0.120**	0.132**
	(0.000)	(0.000)	(0.596)	(0.003)	(0.012)	(0.045)
$\ln(X_{2,i,t})$	-1.089	-2.513***	1.416***	-0.193	-0.302	-0.073
	(0.285)	(0.008)	(0.001)	(0.325)	(0.299)	(0.770)
$\ln(X_{2,i,t-1})$	1.142	1.709*	-0.544	0.043	-0.246	0.539**
	(0.253)	(0.066)	(0.191)	(0.821)	(0.408)	(0.037)
n	783	782	782	686	585	224
R^2	0.494	0.467	0.279	0.765	0.643	0.716
	Specification (8): Dependent variable $\Delta[\ln(Y_{i,t})]$					
	App	Acc	AppAccR	CUG	Guardian	REF
$\Delta[\ln(X_{1,i,t})]$	-0.024	-0.046	0.015	-0.036*	-0.002	-0.053
	(0.582)	(0.291)	(0.738)	(0.094)	(0.963)	(0.419)
$\Delta[\ln(X_{1,i,t-1})]$	-0.022	0.046	-0.072*	0.011	0.021	-0.026
	(0.591)	(0.258)	(0.097)	(0.580)	(0.462)	(0.757)
$\Delta[\ln(X_{2,i,t})]$	0.321	0.257	0.109	0.003	0.019	-0.196
	(0.154)	(0.241)	(0.642)	(0.977)	(0.924)	(0.573)
$\Delta[\ln(X_{2,i,t-1})]$	-0.176	0.017	-0.075	-0.201**	-0.152	-0.529
	(0.322)	(0.920)	(0.687)	(0.027)	(0.392)	(0.094)
n	577	576	576	506	405	104
R^2	0.191	0.075	0.193	0.164	0.181	0.26

Regressions from specifications (7) and (8) for the six different measures of performance (as labelled in the first heading row). For each result, the coefficient on the pay variable is reported with the p-value associated with this coefficient reported in parentheses underneath. Results for all coefficients can be found in Table A11.

there is a statistically significant result in changes in VC pay impacting changes in performance (albeit significant only at 10%), the estimated coefficient is with the unexpected sign with higher pay leading to lower performance. Results from both specifications (5) and (8) suggest that there is no statistically significant consistent relationship between academic pay and performance (in levels or changes).

4.3 What explains pay?

Table A10 in the appendix presents full regression results with VC pay as the dependent variable. If there has been a change in VC, overall remuneration is higher reflecting the fact that there may be an overlap between two VCs (therefore increasing the cost to the institution - note the variable for VC pay is to total cost to the institution which may include pay for more than one individual in the year) and any additional pay which may come at the termination/ending of a contract. Moreover, the longer a VC has been in post, the more pay they receive, all other things being equal. Although each specification predicts that being female means that a VC is paid less, this is only once statistically significant at the 10% level. Holding all else constant, there is evidence to suggest that VCs of Scottish institutions get paid more and those in Northern Irish institutions less (compared to the benchmark of England).[11] Further, an institution's affiliation to a specific university-group can effect salaries with the highest paying institutions are in the Russell Group, holding all

[11] This might seem surprizing as Scottish Universities do not charge fees to Scottish students.

else constant. In each case, these correlations are present when looking at the levels of pay (specification (5)) but are not present when looking at changes in pay (specification (6)) suggesting a lack of causation.

4.4 What explains performance?

Similarly, Table A11 in the appendix presents full regression results with performance as the dependent variable. A VC being in post for longer is correlated with better performance, although this is only statistically significant for applications, and the applications-per-place ratio; a change in VC is not correlated with either better or worse performance. Institutions with a female VC are statistically significantly associated with lower applications and acceptances of students, but are strongly statistically significantly associated with better league table performance. Note again that these results are only present when looking at the levels of performance (specification (7)) and not changes (specification (8)); therefore, we interpret this to be a signal that female VCs are employed by institutions with lower student numbers, holding all else constant.

4.5 Sensitivity

We have subjected the above results to a number of different sensitivity checks, the results for which are presented in Tables A12 to A19. Including more lags of either performance (Table A12) or pay (Table A13) provides similar results to those presented above. As there is a high degree of correlation in both pay and performance (see Table 3), including more lags of these variables increases multicollinearity and therefore weakens statistical significance of the impact of performance on pay and vice-versa, but the key intuition from the benchmark specifications are maintained. When we test for the optimal number of lags in specifications (looking at the adjusted-R^2 coefficient) we find that the one lag (as presented above) consistently outperforms alternatives. However, looking at higher lags is important as decision making in universtieies is very long term and changes might happen slowely.

When estimating the above specifications using a fixed effect panel (Tables A14 and A15) similar results as from specifications (6) and (8) are produced. A fixed effects panel is in effect looking at the impact at an institutional level, looking at what would happen to pay if performance changed, and vice-versa. In this respect these fixed effects results resemble those from specifications (6) and (8). When applying random effects panel regressions (Tables A16 and A17) results are in line with the benchmark from Tables 4 and 5. This process is using variation across institutions and is therefore akin to the estimations when pooling together the data.

We also consider looking over longer time horizons than the one year analysis performed in the benchmark. For this, we take average values over the independent and dependent variables for two, three and four years and run the same regressions as those performed in the benchmark; results for three year time horizons are presented in Tables A18 and A19. Again, results are similar to those presented above, with many correlations between the levels of pay and performance, but limited associations between changes in one leading to changes in another. Similar to Table 5, this process also finds that lagged VC pay can have a positive impact on present performance.[12]

[12]We have also considered estimations of specifications (7) and (8) now including all annual performance measures simultaneously; note that this excludes REF scores (which are not annual) and applications be per place, which when logged would be perfectly collinear with the log of applications and places. In levels, first year student acceptances are more associated with higher pay than applications, and the CUG league table more than the Guardian league table. Similar to the benchmark

Overall, the results seem to support rather a relationship going from pay to performance than the other way round, as more coefficients are significant in the frist part of Table 5 than in the first part of Table 4. Therefore, results seem to support for the 'efficiency wages hypothesis' - as the model by MacLeod & Malcomson (1998) would suggest in the case of a market where the number of jobs is lower than the number of applicants ($J < L$). Howerer, the evidence does not seem to be compelling as almost no coefficient is significant in the second part of these tables.[13] Therefore, we will turn our attention to the results for the benchmarking model.

5 Benchmarking

Although there is a correlation between performance and pay in the results above, with higher performing institutions on average paying their VCs more, there is limited evidence of causality between these two variables. We therefore look to other explanations to consider how pay for VCs is determined, and why the rate of inflation in VC pay outstrips that of academic pay (Table 1).

When the data on VC and academic pay is published by the THE a corresponding article discussing the results is also published. In these articles, university spokes-people are cited discussing and accounting for the change in vice-chancellor pay. Reviewing these comments by universities, and codifying these by themes: 27% of the responses discuss the pay of VCs in light of the performance of the institution; 20% justify high wages through retention concerns; and 29% discuss complications of leaving VCs and having overlapping contracts of incoming and outgoing chief executives. The most common explanation, although not a majority, are the 36% of responses from university spokespeople citing benchmarking issues when setting vice-chancellor pay.[14] We therefore consider the role of benchmarking in the setting of vice-chancellor pay.

5.1 Asymmetric benchmarking

From the literature discussed in Section 2.3, it can be hypothesised that benchmarking is more of a concern for those institutions who are currently below their target chief executive pay than above. For example, 35% of the firms surveyed in Crystal (1992) stated that they aimed to be at the 75^{th} percentile, and 65% at the 50^{th} percentile, with similar results from Bizjak et al. (2008) and Faulkender & Yang (2010). Given these proportions, it would be logical for those firms already at or above their target position in the distribution of executive pay to feel less pressure to implement large pay rises. Further, the literature does not explicitly discuss any firm which deliberately targets lower than average pay.

Therefore, one can hypothesise that benchmarking is an important factor in the setting VC pay, and that benchmarking would be more of an issue for those in the bottom of the pay distribution (those with below average VC pay) than those above. We consider this hypothesis, by estimating regressions of the following form:

$$\Delta\left[\ln\left(X_{1,t}\right)\right] = \alpha + \phi\left[\ln\left(X_{1,t-1}\right) - \ln\left(\bar{X}_{1,t-1}\right)\right] + \gamma Z_t' + \varepsilon_t \quad (9)$$

results, there are no statistically significant changes in performance that are associated with changes in pay.

[13]And if they are significant, then with the wrong sing.

[14]Note that any given response from university spokespeople may reference more than one reason for changes and levels of VC pay, and thus the total of all individual explanations adds to over 100%.

which compares changes in current pay ($\Delta X_{1,t}$) against the difference between lagged pay and the mean from the industry ($X_{1,t-1} - \bar{X}_{1,t-1}$); where Z_t are a set of control variables as in specifications from Section 4.1, with the inclusion of the size of the university proxied by the number of accepted students in the given year.[15] Specification (9) is estimated both without and with controls; and, for the whole sample, and pay in the prior period was more ($X_{1,t-1} - \bar{X}_{1,t-1} > 0$) or less ($X_{1,t-1} - \bar{X}_{1,t-1} < 0$) than average; Table 6 presents the results.

Table 6: Asymmetric bargaining model: regression results for VCs

	All	Below Ave	Above Ave	All	Below Ave	Above Ave
ϕ	-0.110***	-0.445***	-0.003	-0.220***	-0.541***	-0.076***
	(0.000)	(0.000)	(0.874)	(0.000)	(0.000)	(0.002)
Controls	No	No	No	Yes	Yes	Yes
n	1132	522	610	1131	522	609
R^2	0.049	0.155	0.000	0.165	0.295	0.151

Regression results for when specification (9) both without and with controls, and for the whole sample ('All'), for when lagged pay was below the lagged average ('Below Ave') and when it was above average ('Above Ave').

When estimating (9) on the whole sample, one can see a reversion to the mean with estimates of ϕ from (9) of negative 0.110 and 0.220 for regressions without and with controls; this suggests that pay below (above) the mean average this year will lead to higher (lower) pay in the subsequent year for the VC. When estimating (9) on the sample with those below and above average pay, one can see that this reversion to mean is asymmetric. Analysing the model including controls, the revision to mean for those below average pay is estimated to be over seven times greater than the revision back for those above mean pay. In this respect, the results suggest a stronger reversion to the mean from below than from above.

Table 7 presents similar results to those from Table 6, now considering more subsamples across the distribution of VC pay. There is a strong revision to the mean for those in the top 10% of pay, and to a lesser extent those in the bottom 10% of pay; this result is intuitive and represents regression to the mean for outliers. For salaries between the 10^{th} and 25^{th} percentile, however, there is limited evidence of benchmarking, with a statistically insignificant estimate of ϕ. The strongest reversion to the mean outside of the top outliers are for those institutions paying salaries in the second quartile. This suggests that there is a growing population chasing the average salary (those in the second quartile), but that there is a subsample of institutions who consistently pay lower than average (between the 10^{th} and the 25^{th} percentile). For those vice-chancellors with above average pay (but outside of the top 10%), the prior period average is not a statistically significant determinant of their pay change this period.

Performing an analysis of variance ('ANOVA') from the specifications presented in Table 6 with control variables and for the whole sample, it is estimated that 49% of the variance in annual real pay changes explained by the model is attributable to the difference in prior pay compared to the prior mean of salaries; of the remaining variables, 28% is explained by the year of the change, and 10% by the size of the institution. Focusing on the specification only including those institutions below mean pay, 68% of the variance in annual real pay changes explained by the model is attributable to the difference in prior pay compared to the prior

[15] Note that we did not include this size proxy into our analysis in Section 4 above, as the number of acceptances was taken as a performance variable.

Table 7: Asymmetric bargaining model: regression results for VCs

	$x < 10$	$10 < x < 25$	$25 < x < 50$	$50 < x < 75$	$75 < x < 90$	$90 > x$
ϕ	-0.253***	-0.071	-0.631***	-0.104	-0.088	-1.060***
	(0.003)	(0.610)	(0.006)	(0.565)	(0.743)	(0.000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
n	107	168	283	282	174	117
R^2	0.513	0.223	0.192	0.203	0.197	0.706

Regression results for specification (9) estimated by percentile for institutions ('x') by salaries. Therefore, the first column indicates the bottom 10% of real salaries, the second column between the 10^{th} and 25^{th} percentile, and so on.

mean of salaries; this compares to 8% for the specification including only those institutions with above average pay. By including into (9) changes in performance variables, it is possibly to directly compare the importance of performance and benchmarking in annual pay decisions; to do this, we include lagged changes in all annual performance indicators in Section 4 (note this exclude scores from research assessment processes as these are not performed annually). Looking at the whole sample, 64% of the explained sum of squares from the model is attributable to our benchmarking variable compared with only 2% from performance variables; this split is 71% and 2% respectively for the specification only including those institutions with lagged below average pay, and 25% and 5% with lagged above average pay. It is clear, therefore, that benchmarks contributes substantial more to VC pay changes than the performance of an institution, especially for those universities with below average chief executive pay.

To test if this relationship is common in labour markets, and specifically to academia, we perform the same methodology for academic pay; results are presented in Table A20. The results provide two key observations: first, there is a skew in the distribution of academic staff pay, with 78% of institutions paying below the mean average pay; and second, there is an asymmetry in benchmarking of pay, but the asymmetry works against those above average. That is, those above average regress to the mean quicker than those below average. This is the opposite of what happens to those vice-chancellors paid more than the average salary for executive pay and suggests a very different relationship in the two labour markets.

5.2 Asymmetric benchmarking simulation results

To consider the role of asymmetric benchmarking further, consider the following model:

$$X_{i,t} = \begin{cases} (1+\nu)\, X_{i,t-1} + \phi_a \left(X_{1,t-1} - \bar{X}_{1,t-1}\right) + \varepsilon_{i,t}, & X_{1,t-1} - \bar{X}_{1,t-1} > 0 \\ (1+\nu)\, X_{i,t-1} + \phi_b \left(X_{1,t-1} - \bar{X}_{1,t-1}\right) + \varepsilon_{i,t}, & X_{1,t-1} - \bar{X}_{1,t-1} < 0 \end{cases} \tag{10}$$

where parameters ϕ_a and ϕ_b dictate how salaries revert to mean from both above and below the average, respectively. We simulate the above model with a starting set of salaries for 130 institutions (the average number of institutions each year of the empirical data is 130.4), with a normal distribution with a mean of £235,311 and standard deviation of £58,339 (the values in the first year of the survey). We fix the salary increment (ν) at zero, and set $\phi_a = 0.125$ and $\phi_b = 0.620$, values obtained from estimating (9) with control variables and without taking natural logarithms in pay changes and deviations of pay from the lagged average. Finally, the error term of annual VC pay is normally distributed with a mean of zero and a standard deviation of £40,460, the standard deviation in the changes of pay in the first year of the THE pay survey. If we simulate the model 100 times over ten time periods, we get average inflation of VC pay of 44.85% (compared with 41.19% in the empirical data). That is, the simple asymmetric benchmarking model when calibrated to opening data values, tracks inflation in salaries well; however, it does not predict the variance in closing salaries, where the simulation gets a value of £54,132 compared to £67,367 in the data. The model suggests that those with below average wages catch up to the mean quickly, whereas those with above average wages will revert to the mean, but much slower. With such a model, there is a tightening of the distribution of salaries, with each observation reverting to the mean average. This tightening of the distribution, however, is not seen in the data.[16]

Table A21 in the Appendix presents the pay of vice-chancellors by year (and its growth) at different percentiles of the distribution. As can be seen, the bottom 10 percentile of salaries have seen the lowest growth in real pay over the decade of just 12%. Beyond those in the lower tail, the remaining below average salaries has seen the greatest salary increases; the 25^{th} and 50^{th} percentiles have grown at 23% and 21% respectively. The higher end of salaries have increased at a similar, but slightly lower rate: growth of 17% and 18% at the 75^{th} and 90^{th} percentile. This is supportive of the asymmetric benchmarking hypothesis with some institutions consistently paying below and above average salaries in the two tails of the distribution, with those institutions in the middle of the distribution (in the second quartile), growing their chief executive salaries the largest.

5.3 Why asymmetric benchmarking?

Despite the empirical evidence of an asymmetric benchmarking behaviour from universities in Table 6 and 7, and support from the simulations exercises above, there is no clear reason why this behaviour should be present in the market. In this section, we consider the literature, data and further simulations to consider how and why this asymmetric benchmarking behaviour is observed.

One argument would be that these universities want to pay more than the average either because the institution is better than average and/or, they want to send a signal to the market of this. Indeed, Carpenter & Sanders (2004) support this concept and further suggest that paying employees more provides a signal that the level of human capital is higher within that organisation. Another argument would say that certain executives have higher power in the market, and can therefore maintain their high salary relative to the others.[17] In such a case, their pay changes act as a positive externality for all executives in the market, as their salary changes drive up the average, of which those with less power can take advantage (DiPrete et al. 2010). A third argument is that these VCs, and the remuneration committees setting their wages may internally look at different market segments against which to compare wages. Indeed, in 2013 when commenting on the relatively high pay of their VC, the University of Warwick cited that the pay was comparable with other Russel Group institutions (Grove 2013); that is, the salary was compared against a more favourable segment of the market than the population average. Faulkender & Yang (2010), Bizjak

[16]Figure A1 in Appendix A presents a series of simulations varying the value of each calibrated parameter in the model. It can be seen that higher values of φ_b, ν and variation in both the opening distribution of salaries in the individual pay (ε) lead to higher overall inflation; higher values of φ_a does the reverse.

[17]Gritsko et al. (2013) construct a game theoretic model of CEO pay to illustrate that only a small proportion of higher paying firms compensating higher performing CEOs can lead to an 'arms-race' type behaviour, as competition amongst firms filters through the market.

et al. (2011) and Laschever (2013) demonstrate the remuneration committees are more likely to chose higher-paying-CEO firms for benchmarking purposes, holding all else constant. A fourth argument is that higher paid VCs and their remuneration committees may look externally for benchmarking purposes, analysing beyond the UK and/or beyond Higher Education. Faulkender & Yang (2010) demonstrate that it is common for remuneration committees to select benchmark CEOs outside the specific industry, especially if this CEO is highly paid.[18] Finally, it is common in macroeconomic models to maintain the Keynesian belief that wages are sticky downwards, that is, there is an aversion to pay reductions; this aversion would stop those above average to regress downwards. For example Shue & Townsend (2017) show that there is a downward nominal rigidity in CEO pay.

We consider this behaviour further through simulations of a theoretical model applying the empirical observation that $x\%$ of institutions chase the y^{th} percentile of salaries, with $x > y$, as identified in Crystal (1992), Bizjak et al. (2008) and Faulkender & Yang (2010). We consider this with a model which starts with a spread of executive pay values in the opening period with mean and standard deviation as in the first year of vice-chancellor pay in our data. Each institution in the simulation is then randomly assigned to one of three groups: an independent, median-chasing, and aspirational group. Those institutions in the independent group set pay based on a increment (ν) from the previous period for the institution, plus some error (ε); those in the 'median-chasing' group set pay at the previous period's median pay value plus an increment (ν), plus an error; and finally, those in the 'aspirational' group set pay to the 90^{th} percentile from the previous period plus an increment (ν), plus an error term. We allow the weight of the median chasing group to be represented by x_1 and that of the aspiration group by x_2 and the percentile this group is chasing by y_2 (note using this terminology, $y_1 = 50$). In the benchmark calibration, we use the results of Crystal (1992) to have 65% of institutions chasing the median and 35% chasing the 75^{th} percentile of the distribution. This is consistent with the evidence from Tables 7 and A21 which demonstrate that there are institutions which consistent pay below and above average salaries; Table A21 in particular shows that the real pay increase of the bottom 10% is the lowest of anywhere in the distribution, and that although the rises for those in the middle of the distribution are higher than those in the upper-tail, the top 25% still see substantial increases in pay and show little evidence of reverting back to the median. The starting distribution of salaries is calibrated to match the starting year of our dataset, and the error in each institution's annual pay is calibrated to match the standard deviation of the pay rises in the first year of our dataset.

With an annual increment of (ν) of 2% (representing an inflationary increase in salaries) the mean inflation rate of the ten year simulation is 42.37% (compared with 41.19% in the empirical data) and the standard deviation of the final period salaries £108,490 (compared with £67,367 in the empirical data). The key to the simulations is that there is more than one group chasing a target point in the distribution. Were there only the independent group and the median chasing group, those in the latter category would get to the median in the second period of the simulation, and all institutions would add an increment and error each period; as the error has an expected value of zero, expected period inflation is simply the increment.

Inflation can become explosive in the simulations if those chasing a higher point in the distribution are more than double that of the remaining distribution. For example, say 25% of institutions chase the 90^{th}

[18] Although this behaviour in remuneration committees would explain levels of inflation in VC pay and an asymmetric use of benchmarking behaviour, it is still an open question as to why the committees would do this in the first place. Weale (2018) documents that 47% of VCs are on their own remuneration committees, and a further 42% are allowed to attend the committee's meetings.

percentile; next period, these institutions chasing the 90^{th} percentile will be doing so based the outcome of the error term for the 40^{th} ((100-90)/25) 'luckiest' institution, who is expected to have a positive error term. That is, the 50^{th} luckiest institution would be expected to have neither good luck or bad luck ($\varepsilon = 0$) and any institutions above this should have a positive distribution for the error ($\varepsilon > 0$) which results in those in the chasing group each period inflating their salary above the increment (ν). More broadly, when x% of institutions are chasing the top $z = (100 - y)^{th}$ in the distribution, if $x > z/2$, then next period the target point will be an institution that got a positive error in the prior period, and this drives up inflation in the model. The calibration of the model in our benchmark simulation does not have this (35% of institutions chase the top 25% percentile of the distribution) and therefore inflation is not explosive.[19]

Although the allocation of between the independent, median chasing and aspiration group is based on an old study (Crystal 1992), it reconciles well with descriptive statistics (Table A21) and the results from the stimulation are reassuringly in line with the empirical observations. In reality, it would seem logical to hypothesise that there is a distribution of target points in the distribution of chief executive pay; although the mean or median may be an attraction for many, others may look at more nuanced points in the distribution. The results from the simulations (and the sensitivity around these in Figure A2) demonstrate that such behaviour can lead to empirically consistent changes in pay independent from performance, consistent with the results from Tables 4, 5 and 6. The key to these models is that the setting of each institution's VC pay acts as an externality to those universities targeting some point in the distribution of salaries (DiPrete et al. 2010); this then can lead to a ratcheting effect, and a race to the top. This assumes that 'too many' institutions chase points in the distribution than arithmetic would allow. This behaviour can be explained through aspirational or signalling motives (signalling to the market that the institution is in the top x% of institutions by paying in the top x% of institutions) and through bias in the ways in which salaries are set through remuneration committees.

6 Conclusion

We have analysed the relationship between performance and pay for university vice chancellors in the UK, using a comprehensive dataset including 154 institutions over a ten years and several performance indicators related to both teaching and research. There is a correlation between the levels of pay and the reputation and standing of the university; however, there is no statistically significant association between a change in pay being correlated with a change in performance. That is, high performing institutions pay higher wages, but there is limited evidence that these institutions are high performing because they pay higher wages; in fact, the performance of universities across a wide range of measures is very stable, with performance of a specific institution maintaining over time. Instead, we find strong evidence of benchmarking behaviour in UK universities, with salaries of vice-chancellors being set against some point in the distribution of their peers. Although there are a minority of institutions who pay relatively lower remuneration packages to their VCs, those with below average pay are estimated to have large increases in salaries to bring them up to average. Those already with above average pay, have a different aspiration for their salary levels, and these increase the average in the distribution for all, acting as an externality on pay. We found clear evidence for

[19]Figure A2 in Appendix A illustrates sensitivity of the results to changing all calibrated parameters one at a time. As is illustrated, larger increments (ν), target percentiles (y_1 and y_2), the proportion of those chasing these percentiles (x_1 and x_2) and more error in the annual institutional pay increases (ε) leads to higher rates of inflation.

an 'asymmetric benchmarking' behaviour whereby those institutions below average pay regress to the mean, whereas those with above average pay do not; this behaviour leads to an increasing of the distribution of pay and can explain the inflation of VC salaries over the sample period.

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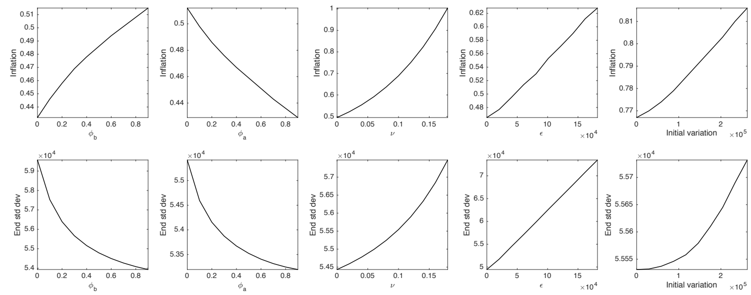
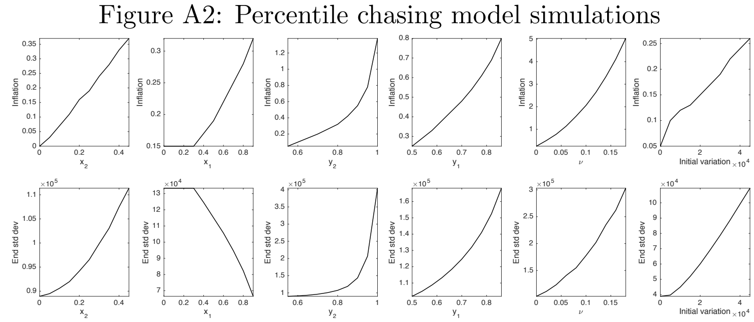
A Simulation results

Figure A1: Asymmetric benchmarking model simulations



Simulations of the asymmetric benchmarking model (10) varying each parameter in turn, using $\nu = 0.0$, $\phi_a = 0.125$, $\phi_b = 0.620$, $\varepsilon = 40,460$ for the benchmark calibration with the starting distribution of salaries given by $N(235311, 58339)$ as per the data for the first year in our sample. The model is simulated over ten periods, and the y-axis in the top row provides the inflation of pay between the start and the end point and the second row illustrates the standard deviation of pay in the final period.

Figure A2: Percentile chasing model simulations



Simulations of the percentile chasing model discussed in Section 5.3 varying each parameter in turn, using $\nu = 0.0$, $x_1 = 0.65$, $y_1 = 0.5$, $x_2 = 0.3$, $y_2 = 0.75$, and $\varepsilon = 40,460$ for the benchmark calibration with the starting distribution of salaries given by $N(235311, 58339)$ as per the data for the first year in our sample. The model is simulated over ten periods, and the y-axis in the top row provides the inflation of pay between the start and the end point and the second row illustrates the standard deviation of pay in the final period.

Table A1: Descriptive statistics pay over time

	Mean	Median	StdDev	Min	Max	n
2007	250,448	240,278	51,536	133,149	415,456	106
2008	272,330	254,816	69,145	136,040	708,707	106
2009	295,322	275,874	74,374	142,810	648,193	103
2010	290,557	276,223	65,361	165,907	548,009	105
2011	282,790	273,442	57,369	161,018	461,293	108
2012	279,309	272,263	54,972	161,512	450,759	102
2013	282,946	272,626	59,793	163,454	501,380	103
2014	287,355	275,060	70,278	157,031	639,412	105
2015	301,792	288,006	79,766	140,416	607,784	105
2016	299,837	292,934	71,724	168,538	699,230	107
	284,246	273,862	67,272	133,149	708,707	1,050

Descriptive statistics illustrating vice-chancellor pay - including salary, pension and benefits and in 2017 prices – over time.

Table A2: Descriptive statistics pay over time by country

	England	NI	Scotland	Whales
2007	252,348 (94)	257,956 (2)	235,829 (9)	188,418 (1)
2008	275,972 (91)	259,366 (2)	256,764 (10)	222,357 (3)
2009	296,548 (89)	274,756 (2)	307,807 (9)	235,188 (3)
2010	292,657 (92)	278,997 (2)	281,644 (9)	245,606 (2)
2011	283,462 (93)	268,725 (2)	290,098 (10)	246,966 (3)
2012	281,203 (89)	249,831 (2)	271,821 (10)	244,516 (1)
2013	287,057 (89)	226,666 (2)	264,798 (10)	247,034 (2)
2014	292,637 (90)	234,006 (2)	263,104 (10)	245,296 (3)
2015	306,824 (90)	259,308 (2)	280,001 (10)	251,792 (3)
2016	302,797 (93)	277,886 (2)	277,773 (10)	294,439 (2)
	287,033 (910)	258,750 (20)	272,898 (97)	243,995 (23)

Mean average vice-chancellor pay - including salary, pension and benefits and in 2017 prices – over time.

Table A3: Descriptive statistics pay over time: differences

	Mean	Median	StdDev	Min	Max
2008	20,536	14,936	40,460	-122,733	293,250
2009	20,669	18,113	68,586	-363,303	424,091
2010	-4,254	2,628	62,991	-398,594	170,205
2011	-5,246	-3,832	44,715	-342,385	149,001
2012	-5,296	-3,820	24,639	-152,906	47,844
2013	5,686	1,942	29,924	-93,856	214,340
2014	4,922	334	34,076	-97,001	257,109
2015	15,031	6,752	52,394	-203,576	313,224
2016	-2,329	1,894	64,537	-323,209	358,953
	5,532	3,877	50,235	-398,594	424,091

Descriptive statistics illustrating vice-chancellor pay - including salary, pension and benefits and in 2017 prices – over time in looking at the difference in salary compared with the prior period.

Table A4: Descriptive statistics performance variables: levels and differences

		mean	p50	sd	min	max
Levels	Applications	7906.36	767.5	11989.84	5	64280
	Acceptances	1571.26	345	2028.41	5	9835
	AppAccRatio	4.71	3.95	4.24	0.02	54
	CUG	607.6	598	153.55	269	1000
	Gaudian	59.32	58.4	13.23	28.9	100
	REF	2.86	2.62	1.16	0.49	6.61
Differences	Applications	212.65	5	1385.5	-9375	10305
	Acceptances	47.39	5	290.79	-3130	2910
	AppAccRatio	-0.05	0	2.96	-44.18	38.82
	CUG	12.37	12	32.97	-115	148
	Gaudian	0.26	0.1	4.22	-13.2	18.3
	REF	-0.47	0.24	1.33	-3.63	1.28

Descriptive statistics of performance variables, looking in the top half at levels of the variables and the bottom half changes in variables.

Table A5: Descriptive statistics academic staff pay over time

	Mean	Median	StdDev	Min	Max	n
2007	47,945	47,480	3,248	40,936	66,910	98
2008	48,778	48,461	2,780	41,869	62,068	108
2009	51,713	51,566	2,895	45,255	64,087	107
2010	51,410	51,597	3,004	44,409	61,292	64
2011	50,901	50,867	2,851	44,106	62,155	107
2012	50,194	50,039	2,989	41,954	61,040	88
2013	49,487	49,524	3,505	30,932	61,079	106
2014	49,302	49,146	3,185	38,753	65,577	108
2015	49,879	49,571	3,380	38,692	66,555	108
	49,900	49,740	3,300	30,932	66,910	894

Descriptive statistics illustrating academic staff pay (in 2017 prices) over time with numbers of observations in parentheses..

Table A6: Descriptive statistics academic staff pay over time by country

	England	NI	Scotland	Whales
2007	47,992 (88)	45,851 (2)	48,446 (7)	44,477 (1)
2008	48,840 (93)	48,398 (2)	49,442 (10)	44,894 (3)
2009	51,855 (50)	51,288 (2)	51,399 (9)	48,543 (3)
2010	51,408 (94)	50,936 (2)	51,854 (10)	49,715 (2)
2011	50,953 (86)	. (0)	51,189 (10)	48,330 (3)
2012	50,206 (89)	. (0)	52,043 (1)	47,374 (1)
2013	49,785 (91)	48,184 (2)	49,459 (10)	41,399 (3)
2014	49,403 (93)	47,593 (2)	49,169 (10)	47,774 (3)
2015	50,044 (93)	47,805 (2)	49,494 (10)	47,425 (3)
	49,993 (781)	48,579 (14)	50,128 (77)	46,654 (22)

Mean average academic staff pay - including salary, pension and benefits and in 2017 prices – over time with numbers of observations in parentheses.

Table A7: Descriptive statistics academic staff pay over time: differences

	Mean	Median	StdDev	Min	Max
2008	1176	1405	2256	-17865	4246
2009	3133	2908	1672	-939	8828
2010	22	27	995	-2769	3217
2011	-874	-730	982	-3409	3517
2012	-773	-787	861	-6903	1917
2013	-443	-265	1635	-10111	4764
2014	-132	-343	1968	-2739	19175
2015	631	651	831	-2236	3521
	468	142	1992	-17865	19175

Descriptive statistics illustrating academic staff pay (in 2017 prices) over time looking at the difference in salary compared with the prior period.

Table A8: Correlation coefficients: levels

	allapp	allacc	appaccrati	CUG	Guardian	RVC	RAll	change	female	inpost	whales	scotland	ni	special	million	university	group	guildhe	russell
allapp	1																		
allacc	0.9521	1																	
appaccrati l	0.2221	0.1348	1																
	0	0																	
overallscore	0.3239	0.0886	0.523	1															
	0	0.0026	0																
averagetea e	0.2653	0.0618	0.4931	0.9158	1														
	0	0.0619	0	0															
Rsalarypen n	0.5401	0.4918	0.0568	0.4817	0.4526	1													
	0	0	0.0405	0	0														
Raallpay	0.2174	0.1253	0.1743	0.3418	0.3145	0.3324	1												
	0	0	0	0	0	0													
change	0.0182	0.0199	-0.0256	0.0096	0.0009	0.0986	0.0493	1											
	0.5097	0.4721	0.3546	0.7516	0.9798	0.0004	0.1088												
female	-0.0674	-0.0544	-0.0657	0.0088	-0.0056	-0.0625	0.0319	0.031	1										
	0.0145	0.0489	0.0174	0.7705	0.8681	0.024	0.3002	0.261											
inpost	0.0159	-0.0047	0.1363	-0.011	0.0246	-0.0009	-0.0879	-0.3048	-0.0493	1									
	0.5763	0.8693	0	0.7229	0.4777	0.9749	0.0053	0	0.0832										
whales	-0.0123	0.008	-0.0289	-0.0454	-0.1103	-0.0445	-0.1061	0.0266	0.0915	-0.0671	1								
	0.4664	0.6465	0.098	0.1229	0.0008	0.1081	0.0004	0.3355	0.0009	0.0184									
scotland	0.0958	0.0688	0.0601	0.0527	0.0836	0.0171	0.0398	0.0027	0.1146	-0.0476	-0.0184	1							
	0	0.0001	0.0006	0.0733	0.0115	0.5368	0.1865	0.9225	0	0.0944	0.2745								
ni	0.1307	0.1286	0.0216	0.0311	-0.0353	-0.0165	-0.0285	-0.0109	-0.0583	0.005	-0.0082	-0.0142	1						
	0	0	0.2169	0.2911	0.2868	0.5528	0.3456	0.6926	0.0347	0.8601	0.6278	0.4004							
special	0.0698	0.0306	0.0788	0.1371	0.1713	0.0401	0.2997	0.0321	-0.0382	-0.0539	-0.01	-0.0174	-0.0077	1					
	0	0.0797	0	0	0	0.1474	0	0.2448	0.167	0.0583	0.5521	0.3023	0.6473						
million	0.2412	0.2935	0.0139	-0.4874	-0.4281	-0.0386	-0.1463	0.0515	0.0546	-0.0214	-0.0298	0.1452	-0.0229	-0.0281	1				
	0	0	0.4258	0	0	0.1634	0	0.0618	0.048	0.4522	0.0774	0	0.1743	0.0956					
university e	0.2944	0.3944	-0.0026	-0.1989	-0.1794	0.0213	-0.0495	-0.0223	0.0499	0.01	0.0983	-0.0467	-0.0207	-0.0254	-0.0755	1			
	0	0	0.8828	0	0	0.4422	0.1009	0.42	0.0708	0.7262	0	0.0056	0.219	0.1316	0				
group	0.2155	0.1762	0.0854	0.4064	0.4059	0.1553	0.1963	0.0405	-0.0346	-0.0349	-0.0244	0.0381	-0.0188	0.1215	-0.0684	-0.0619	1		
	0	0	0	0	0	0	0	0.1427	0.2104	0.2209	0.1476	0.0238	0.2652	0	0	0.0002			
guildhe	-0.0113	-0.0015	-0.0037	-0.1583	-0.1973	-0.1559	-0.0967	0.0198	0.0874	-0.0489	-0.0137	-0.0237	-0.0105	-0.0129	-0.0384	-0.0347	-0.0315	1	
	0.5015	0.9328	0.8322	0	0	0	0.0013	0.4731	0.0015	0.0857	0.4169	0.1591	0.5322	0.4435	0.0229	0.0395	0.062		
russell	0.5549	0.4166	0.1628	0.5549	0.4858	0.4516	0.217	-0.0048	-0.0864	-0.0424	-0.0266	0.0284	0.1433	0.1088	-0.0746	-0.0675	-0.0612	-0.0343	1
	0	0	0	0	0	0	0	0.8608	0.0017	0.1365	0.1144	0.0924	0	0	0	0.0001	0.0003	0.0419	

Correlation coefficient matrix between pay, performance and control variables. The order of variables are: our performance variables ('allapp' - 'Guardian'); followed by our pay variables ('RVC' - 'Rall'); followed by variables representing characteristics of the VC ('change', 'female' and 'inpost'; followed by geographical indicators and university group indicators.

Table A9: Correlation coefficients: REF levels

	researchquy	RVC	Rall	female	inpost	whales	scotland	ni	special	million	university e	group	guildhe	russell
researchqu y	1													
rsalarypenn	0.2499	1												
	0													
rallpay	0.1562	0.3842	1											
	0.0035	0												
female	-0.0909	-0.032	0.0567	1										
	0.0884	0.5179	0.2536											
inpost	-0.0684	0.0038	-0.0657	-0.059	1									
	0.2065	0.9396	0.1949	0.2404										
whales	0.0136	-0.053	-0.1096	0.0691	-0.0476	1								
	0.798	0.284	0.0259	0.1584	0.3434									
scotland	0.0283	0.0167	0.039	0.0972	0.023	-0.0173	1							
	0.5937	0.7352	0.429	0.0471	0.6479	0.5713								
ni	0.0462	-0.011	-0.0295	-0.0585	0.0026	-0.0077	-0.0128	1						
	0.3832	0.8235	0.5504	0.2326	0.9593	0.8024	0.6766							
special	0.1265	0.0476	0.2938	-0.0449	-0.0633	-0.0094	-0.0157	-0.0069	1					
	0.0166	0.3357	0	0.3595	0.2076	0.7589	0.6089	0.8211						
million	-0.3275	-0.0249	-0.1298	0.0692	-0.0293	-0.028	0.1529	-0.0207	-0.0253	1				
	0	0.6146	0.0083	0.1577	0.5598	0.36	0	0.5001	0.4082					
universitye	-0.1116	0.0511	-0.0367	0.0221	0.0055	0.0948	-0.0418	-0.0185	-0.0227	-0.0676	1			
	0.0348	0.3012	0.4567	0.6518	0.9124	0.0019	0.1718	0.5459	0.4589	0.0271				
group	0.3014	0.1704	0.2088	-0.0388	-0.0434	-0.0228	0.0417	-0.0168	0.1235	-0.0615	-0.0551	1		
	0	0.0005	0	0.4285	0.3873	0.4558	0.1738	0.5827	0.0001	0.0443	0.0718			
guildhe	-0.175	-0.1561	-0.0944	0.0783	-0.0597	-0.013	-0.0216	-0.0096	-0.0117	-0.035	-0.0313	-0.0285	1	
	0.0009	0.0015	0.0552	0.1101	0.2348	0.6719	0.4803	0.755	0.7019	0.2538	0.3068	0.3524		
russell	0.3906	0.445	0.2239	-0.0702	-0.0297	-0.0249	0.0324	0.1449	0.111	-0.0671	-0.06	-0.0546	-0.031	1
	0	0	0	0.1521	0.554	0.4165	0.2908	0	0.0003	0.0284	0.0498	0.0743	0.311	

Correlation coefficient matrix between pay, performance and control variables. The order of variables are: our performance variables (‘allapp’ - ‘Guardian’); followed by our pay variables (‘RVC’ - ‘Rall’); followed by variables representing characteristics of the VC (‘change’, ‘female’ and ‘inpost’; followed by geographical indicators and university group indicators.

Table A10: The impact of performance on pay: full results

	Specification (5): Dependent variable $\ln(X_{1,i,t})$							Specification (6): Dependent variable $\Delta[\ln(X_{1,i,t})]$					
	App	Acc	AppAccR	CUG	Guardian	REF		App	Acc	AppAccR	CUG	Guardian	REF
$\ln(Y_{i,t})$	0.528	0.193	0.025	0.093	0.046	0.488	$\Delta[\ln(Y_{i,t})]$	-0.039	-0.033	0.01	-0.104	0.001	-0.192
	(0.000)	(0.000)	(0.668)	(0.346)	(0.613)	(0.000)		(0.331)	(0.372)	(0.766)	(0.273)	(0.986)	(0.338)
$\ln(Y_{i,t-1})$	-0.391	-0.052	0	0.205	0.187	0.008	$\Delta[\ln(Y_{i,t-1})]$	0.065	0.016	0.018	0.081	0.076	-0.066
	(0.000)	(0.328)	(0.996)	(0.034)	(0.041)	(0.883)		(0.15)	(0.662)	(0.601)	(0.322)	(0.301)	(0.426)
change	0.046	0.05	0.059	0.067	0.038	0.259	change	0.044	0.044	0.043	0.048	0.031	0.200
	(0.033)	(0.015)	(0.011)	(0.000)	(0.068)	(0.000)		(0.002)	(0.002)	(0.002)	(0.003)	(0.076)	(0.004)
female	-0.003	0	-0.017	-0.027	-0.014	0.017	female	-0.002	-0.001	-0.002	0.003	-0.001	0.045
	(0.849)	(0.98)	(0.354)	(0.079)	(0.427)	(0.612)		(0.885)	(0.904)	(0.886)	(0.816)	(0.957)	(0.320)
inpost	0.001	0.003	0.003	0.004	0.006	0.006	inpost	0.003	0.003	0.003	0.003	0.004	0.005
	(0.328)	(0.039)	(0.06)	(0.005)	(0.000)	(0.055)		(0.006)	(0.006)	(0.006)	(0.007)	(0.006)	(0.216)
whales	0.061	0.012	0.023	-0.074	-0.032	-0.192	whales	0.031	0.027	0.028	0.034	0.047	-0.183
	(0.214)	(0.804)	(0.675)	(0.102)	(0.55)	(0.034)		(0.380)	(0.446)	(0.425)	(0.408)	(0.297)	(0.153)
scotland	0.063	0.079	0.086	-0.012	-0.01	0.014	scotland	-0.003	-0.004	-0.004	-0.002	-0.002	-0.039
	(0.011)	(0.001)	(0.001)	(0.586)	(0.673)	(0.752)		(0.847)	(0.817)	(0.791)	(0.911)	(0.935)	(0.554)
ni	-0.139	-0.158	-0.065	-0.146	-0.15	-0.153	ni	-0.017	-0.019	-0.018	-0.009	-0.020	0.115
	(0.011)	(0.003)	(0.261)	(0.001)	(0.004)	(0.128)		(0.619)	(0.596)	(0.604)	(0.82)	(0.638)	(0.500)
special	0.037	0.081	0.083	-0.019	-0.043	-0.067	special	-0.03	-0.03	-0.03	-0.048	-0.029	0.042
	(0.466)	(0.098)	(0.135)	(0.656)	(0.449)	(0.391)		(0.354)	(0.364)	(0.365)	(0.198)	(0.566)	(0.727)
million	0.033	0.009	0.146	0.086	0.061	0.098	million	0.011	0.01	0.011	0.004	0.007	-0.006
	(0.097)	(0.64)	(0.000)	(0.000)	(0.005)	(0.011)		(0.372)	(0.403)	(0.388)	(0.796)	(0.689)	(0.916)
unialliance	0.039	0.012	0.197	0.071	0.071	0.089	unialliance	0.009	0.008	0.008	0.013	0.018	0.08
	(0.082)	(0.575)	(0.000)	(0.000)	(0.001)	(0.018)		(0.516)	(0.556)	(0.554)	(0.413)	(0.315)	(0.159)
group	0.141	0.158	0.285	0.070	0.102	0.079	group	0	-0.001	-0.001	0	-0.01	-0.056
	(0.000)	(0.000)	(0.000)	(0.003)	(0.000)	(0.074)		(0.980)	(0.957)	(0.952)	(0.984)	(0.588)	(0.417)
guildhe	-0.076	-0.099	-0.051	-0.045	-0.152	0.021	guildhe	0.01	0.01	0.011	0.01	-0.005	-0.023
	(0.035)	(0.004)	(0.194)	(0.221)	(0.000)	(0.774)		(0.667)	(0.663)	(0.65)	(0.757)	(0.87)	(0.827)
russell	0.221	0.248	0.421	0.203	0.243	0.204	russell	0.007	0.006	0.006	0.001	0.007	-0.068
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		(0.585)	(0.644)	(0.632)	(0.959)	(0.669)	(0.295)
2008	0.137	0.058	0.079				2008						
	(0.000)	(0.039)	(0.016)										
2009	0.133	0.123	0.151	0.063			2009	0.011	-0.006	-0.003			
	(0.000)	(0.000)	(0.000)	(0.010)				(0.592)	(0.748)	(0.887)			
2010	0.087	0.121	0.139	0.046			2010	-0.073	-0.083	-0.084	-0.071		
	(0.003)	(0.000)	(0.000)	(0.066)				(0.000)	(0.000)	(0.000)	(0.000)		
2011	0.106	0.109	0.136	0.025	-0.017		2011	-0.092	-0.094	-0.096	-0.091		
	(0.000)	(0.000)	(0.000)	(0.312)	(0.49)			(0.000)	(0.000)	(0.000)	(0.000)		
2012	0.147	0.099	0.114	-0.005	-0.038		2012	-0.093	-0.097	-0.095	-0.079	0.008	
	(0.000)	(0.000)	(0.000)	(0.84)	(0.117)			(0.000)	(0.000)	(0.000)	(0.000)	(0.667)	
2013	0.1	0.075	0.101	-0.012	-0.026		2013	-0.054	-0.066	-0.067	-0.061	0.032	
	(0.001)	(0.008)	(0.001)	(0.652)	(0.296)			(0.006)	(0.000)	(0.000)	(0.003)	(0.091)	
2014	0.099	0.083	0.112	-0.026	-0.019	-0.066	2014	-0.065	-0.073	-0.073	-0.056	0.027	
	(0.001)	(0.003)	(0)	(0.32)	(0.432)	(0.033)		(0.000)	(0.000)	(0.000)	(0.005)	(0.141)	
2015	0.153	0.145	0.185	0.012	0.024		2015	-0.024	-0.03	-0.030	-0.02	0.075	
	(0.000)	(0.000)	(0.000)	(0.662)	(0.333)			(0.195)	(0.10)	(0.114)	(0.309)	(0.000)	
2016	0.188	0.153	0.189	0.012	0.015		2016	-0.082	-0.09	-0.088	-0.08	0.005	
	(0.000)	(0.000)	(0.000)	(0.64)	(0.534)			(0.000)	(0.000)	(0.000)	(0.000)	(0.810)	
n	1219	1218	1218	925	717	213	n	1064	1063	1063	792	591	97
R^2	0.469	0.464	0.323	0.357	0.391	0.439	R^2	(0.079)	(0.077)	(0.077)	(0.07)	(0.064)	(0.194)

Regressions from specifications (5) and (6) for the six different measures of performance (as labelled in the first heading row). For each result, the coefficient is reported with the p-value associated with this coefficient reported in parentheses underneath.

Table A11: The impact of pay on performance: full results

	Specification (7): Dependent variable $\ln(Y_{i,t})$							Specification (8): Dependent variable $\Delta[\ln(Y_{i,t})]$					
	App	Acc	AppAccR	CUG	Guardian	REF		App	Acc	AppAccR	CUG	Guardian	REF
$\ln(X_{1,i,t})$	0.68	0.676	0.024	0.051	0.044	0.159	$\Delta[\ln(X_{1,i,t})]$	-0.024	-0.046	0.015	-0.036	-0.002	-0.053
	(0.001)	(0.001)	(0.784)	(0.187)	(0.331)	(0.009)		(0.582)	(0.291)	(0.738)	(0.094)	(0.963)	(0.419)
$\ln(X_{1,i,t-1})$	0.894	0.964	-0.048	0.122	0.12	0.132	$\Delta[\ln(X_{1,i,t-1})]$	-0.022	0.046	-0.072	0.011	0.021	-0.026
	(0.000)	(0.000)	(0.596)	(0.003)	(0.012)	(0.045)		(0.591)	(0.258)	(0.097)	(0.580)	(0.462)	(0.757)
$\ln(X_{2,i,t})$	-1.089	-2.513	1.416	-0.193	-0.302	-0.073	$\Delta[\ln(X_{2,i,t})]$	0.321	0.257	0.109	0.003	0.019	-0.196
	(0.285)	(0.008)	(0.001)	(0.325)	(0.299)	(0.770)		(0.154)	(0.241)	(0.642)	(0.977)	(0.924)	(0.573)
$\ln(X_{2,i,t-1})$	1.142	1.709	-0.544	0.043	-0.246	0.539	$\Delta[\ln(X_{2,i,t-1})]$	-0.176	0.017	-0.075	-0.201	-0.152	-0.529
	(0.253)	(0.066)	(0.191)	(0.821)	(0.408)	(0.037)		(0.322)	(0.92)	(0.687)	(0.027)	(0.392)	(0.094)
change	0.114	0.083	0.031	-0.024	-0.001	-0.076	change	0.009	-0.031	0.034	-0.002	-0.019	0.014
	(0.210)	(0.328)	(0.406)	(0.154)	(0.970)	(0.070)		(0.593)	(0.071)	(0.063)	(0.792)	(0.131)	(0.744)
female	-0.131	-0.153	0.023	0.067	0.047	-0.010	female	0.01	0.013	-0.006	-0.007	-0.002	-0.026
	(0.069)	(0.023)	(0.45)	(0)	(0.002)	(0.663)		(0.489)	(0.355)	(0.688)	(0.293)	(0.847)	(0.329)
inpost	0.018	0.004	0.014	0	0.001	-0.003	inpost	0.002	0.001	0	0.001	0.001	0.002
	(0.007)	(0.546)	(0.000)	(0.787)	(0.367)	(0.215)		(0.216)	(0.646)	(0.784)	(0.321)	(0.385)	(0.392)
whales	-0.251	0.004	-0.253	-0.005	-0.099	0.115	whales	-0.032	-0.053	0.016	-0.016	0.003	-0.051
	(0.24)	(0.985)	(0.005)	(0.898)	(0.017)	(0.04)		(0.484)	(0.236)	(0.730)	(0.453)	(0.913)	(0.496)
scotland	0.036	-0.087	0.121	0.096	0.116	0.032	scotland	0.016	-0.035	0.044	0.000	0.000	-0.025
	(0.745)	(0.39)	(0.008)	(0.000)	(0.000)	(0.288)		(0.497)	(0.112)	(0.064)	(0.984)	(0.988)	(0.489)
ni	0.677	0.712	-0.03	-0.007	-0.111	0.074	ni	-0.017	-0.048	0.024	-0.017	-0.012	-0.012
	(0.007)	(0.002)	(0.778)	(0.866)	(0.043)	(0.283)		(0.758)	(0.383)	(0.676)	(0.519)	(0.782)	(0.904)
special	0.446	0.182	0.259	0.103	0.245	0.054	special	0.004	-0.003	-0.005	-0.021	-0.063	-0.016
	(0.039)	(0.364)	(0.004)	(0.008)	(0.000)	(0.355)		(0.928)	(0.931)	(0.909)	(0.269)	(0.056)	(0.831)
million	0.636	0.66	-0.028	-0.211	-0.174	-0.099	million	-0.004	0.001	-0.014	0.000	0.009	-0.072
	(0.000)	(0.000)	(0.415)	(0.000)	(0.000)	(0.000)		(0.793)	(0.940)	(0.386)	(0.974)	(0.402)	(0.021)
unialliance	0.938	0.97	-0.037	-0.023	-0.01	0.029	unialliance	-0.009	-0.012	-0.007	0.009	-0.012	-0.034
	(0.000)	(0.000)	(0.305)	(0.156)	(0.603)	(0.258)		(0.571)	(0.45)	(0.677)	(0.288)	(0.306)	(0.283)
group	0.652	0.454	0.188	0.292	0.263	0.146	group	0.012	-0.001	0.002	-0.009	-0.008	-0.110
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		(0.474)	(0.956)	(0.891)	(0.295)	(0.512)	(0.001)
guildhe	0.351	0.413	-0.057	-0.158	-0.142	-0.143	guildhe	0.008	-0.008	0.005	-0.012	0.001	-0.004
	(0.020)	(0.003)	(0.364)	(0.000)	(0.000)	(0.001)		(0.785)	(0.773)	(0.871)	(0.419)	(0.948)	(0.941)
russell	0.887	0.542	0.329	0.313	0.265	0.129	russell	-0.015	-0.005	-0.020	-0.013	-0.019	-0.117
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		(0.367)	(0.768)	(0.237)	(0.101)	(0.118)	(0.000)
2009	-0.070	-0.042	-0.031	0.017			2009						
	(0.519)	(0.679)	(0.499)	(0.406)									
2010	-0.057	-0.177	0.114	0.054			2010	0.113	-0.026	0.134	0.028		
	(0.651)	(0.132)	(0.030)	(0.023)				(0.000)	(0.291)	(0.000)	(0.021)		
2011	-0.066	-0.235	0.163	0.062	-0.007		2011	-0.007	-0.023	0.019	-0.03		
	(0.612)	(0.052)	(0.003)	(0.011)	(0.834)			(0.798)	(0.404)	(0.502)	(0.028)		
2012	-0.119	-0.286	0.163	0.13	-0.048		2012	-0.126	-0.067	-0.053	0.027	-0.007	
	(0.308)	(0.009)	(0.001)	(0.000)	(0.115)			(0.000)	(0.020)	(0.084)	(0.067)	(0.719)	
2013	-0.124	-0.241	0.114	0.146	-0.006		2013	-0.046	0.027	-0.067	-0.008	0.058	
	(0.284)	(0.025)	(0.018)	(0.000)	(0.826)			(0.078)	(0.286)	(0.015)	(0.543)	(0.003)	
2014	-0.05	-0.187	0.134	0.191	-0.009	0.154	2014	-0.023	0.006	-0.022	-0.004	0.010	
	(0.647)	(0.064)	(0.003)	(0.000)	(0.74)	(0.000)		(0.365)	(0.809)	(0.394)	(0.757)	(0.582)	
2015	-0.038	-0.149	0.101	0.198	0.048		2015	-0.061	0.01	-0.051	-0.04	0.059	
	(0.711)	(0.124)	(0.020)	(0.000)	(0.046)			(0.005)	(0.651)	(0.025)	(0.000)	(0.001)	
n	783	782	782	686	585	224	n	577	576	576	506	405	104
R^2	0.494	0.467	0.279	0.765	0.643	0.716	R^2	(0.191)	(0.075)	(0.193)	(0.164)	(0.181)	(0.26)

Regressions from specifications (7) and (8) for the six different measures of performance (as labelled in the first heading row). For each result, the coefficient is reported with the p-value associated with this coefficient reported in parentheses underneath.

Table A12: Sensitivity: The impact of performance on pay: more lags

	Specification (5): Dependent variable $\ln(X_{1,i,t})$					
	App	Acc	AppAccR	CUG	Guardian	REF
$\ln(Y_{i,t})$	0.505	0.132	0.066	-0.02	0.05	0.214
	(0)	(0.035)	(0.329)	(0.883)	(0.647)	(0.584)
$\ln(Y_{i,t-1})$	-0.213	0.152	0	0.139	0.121	0.598
	(0.07)	(0.06)	(0.998)	(0.388)	(0.379)	(0.031)
$\ln(Y_{i,t-2})$	0.046	0.02	-0.056	0.225	0.061	
	(0.708)	(0.808)	(0.488)	(0.106)	(0.663)	
$\ln(Y_{i,t-3})$	-0.194	-0.161	0.03	0.023	0.034	
	(0.011)	(0.008)	(0.652)	(0.824)	(0.762)	
n	968	967	967	694	496	97
R^2	0.465	0.453	0.305	0.376	0.407	0.426
	Specification (6): Dependent variable $\Delta[\ln(X_{1,i,t})]$					
	App	Acc	AppAccR	CUG	Guardian	REF
$\Delta[\ln(Y_{i,t})]$	-0.04	-0.021	-0.011	0.027	-0.039	-0.192
	(0.337)	(0.616)	(0.783)	(0.817)	(0.697)	(0.338)
$\Delta[\ln(Y_{i,t-1})]$	0.1	0.036	-0.019	0.153	0.142	-0.066
	(0.048)	(0.371)	(0.627)	(0.157)	(0.133)	(0.426)
$\Delta[\ln(Y_{i,t-2})]$	-0.138	-0.009	-0.056	0.072	0.044	
	(0.004)	(0.821)	(0.142)	(0.472)	(0.649)	
$\Delta[\ln(Y_{i,t-3})]$	0.029	-0.066	0.036	-0.015	0.047	
	(0.531)	(0.08)	(0.321)	(0.859)	(0.62)	
n	820	819	819	569	385	97
R^2	0.056	0.049	0.049	0.065	0.072	0.194

Regressions from specifications (5) and (6) for the six different measures of performance (as labelled in the first heading row). For each result, the coefficient on the performance variable is reported with the p-value associated with this coefficient reported in parentheses underneath. Results extend those from Table 4 by including more lagged independent variables in the specification. Note there are fewer REF assessment periods limiting further analysis with this performance measure.

Table A13: Sensitivity: The impact of pay on performance: more lags

	App	Acc	AppAccR	CUG	Guardian	REF
	Specification (7): Dependent variable $\ln(Y_{i,t})$					
$\ln(X_{1,i,t})$	0.343	0.317	0.026	0.13	0.083	0.082
	(0.395)	(0.381)	(0.868)	(0.051)	(0.273)	(0.179)
$\ln(X_{1,i,t-1})$	0.613	0.551	0.061	0.068	0.049	0.107
	(0.151)	(0.15)	(0.707)	(0.33)	(0.538)	(0.33)
$\ln(X_{1,i,t-2})$	0.58	0.538	0.042	0.004	0.012	0.042
	(0.126)	(0.114)	(0.771)	(0.954)	(0.869)	(0.597)
$\ln(X_{1,i,t-3})$	0.835	0.916	-0.082	-0.026	0.051	
	(0.011)	(0.002)	(0.514)	(0.635)	(0.423)	
$\ln(X_{2,i,t})$	-1.528	-3.694	2.165	-0.039	-0.378	0.032
	(0.42)	(0.03)	(0.003)	(0.905)	(0.384)	(0.928)
$\ln(X_{2,i,t-1})$	-0.44	0.712	-1.153	-0.589	-0.216	-0.068
	(0.859)	(0.749)	(0.223)	(0.165)	(0.702)	(0.889)
$\ln(X_{2,i,t-2})$	1.274	0.565	0.709	0.243	0.098	0.722
	(0.529)	(0.756)	(0.359)	(0.494)	(0.831)	(0.014)
$\ln(X_{2,i,t-3})$	0.279	1.436	-1.157	-0.016	-0.3	
	(0.857)	(0.302)	(0.051)	(0.956)	(0.438)	
n	392	392	392	349	337	106
R^2	0.509	0.505	0.307	0.78	0.669	0.723
	Specification (8): Dependent variable $\Delta[\ln(Y_{i,t})]$					
	App	Acc	AppAccR	CUG	Guardian	REF
$\Delta[\ln(X_{1,i,t})]$	0.099	0.068	0.031	0.001	0.038	-0.053
	(0.147)	(0.374)	(0.729)	(0.977)	(0.51)	(0.419)
$\Delta[\ln(X_{1,i,t-1})]$	0.037	0.036	0.001	0.04	0.021	-0.026
	(0.591)	(0.64)	(0.992)	(0.319)	(0.713)	(0.757)
$\Delta[\ln(X_{1,i,t-2})]$	0.056	0.018	0.038	0.035	0.03	0
	(0.3)	(0.762)	(0.594)	(0.282)	(0.523)	(0)
$\Delta[\ln(X_{1,i,t-3})]$	0.004	0.021	-0.017	-0.036	0.045	
	(0.927)	(0.668)	(0.767)	(0.171)	(0.226)	
$\Delta[\ln(X_{2,i,t})]$	0.361	-0.197	0.558	0.024	0.05	-0.196
	(0.174)	(0.508)	(0.11)	(0.881)	(0.863)	(0.573)
$\Delta[\ln(X_{2,i,t-1})]$	-0.192	0.141	-0.333	-0.239	-0.249	-0.529
	(0.464)	(0.63)	(0.333)	(0.131)	(0.37)	(0.094)
$\Delta[\ln(X_{2,i,t-2})]$	0.02	-0.148	0.169	0.066	-0.476	0
	(0.925)	(0.54)	(0.553)	(0.634)	(0.045)	(0)
$\Delta[\ln(X_{2,i,t-3})]$	-0.431	-0.023	-0.408	-0.048	-0.291	
	(0.09)	(0.936)	(0.22)	(0.786)	(0.308)	
n	270	270	270	240	230	104
R^2	0.246	0.186	0.083	0.266	0.17	0.26

Regressions from specifications (7) and (8) for the six different measures of performance (as labelled in the first heading row). For each result, the coefficient on the performance variable is reported with the p-value associated with this coefficient reported in parentheses underneath. Results extend those from Table 5 by including more lagged independent variables in the specification. Note there are fewer REF assessment periods limiting further analysis with this performance measure.

Table A14: Sensitivity: The impact of performance on pay: fixed effects panel

	Specification (5): Dependent variable $\ln(X_{1,i,t})$					
	App	Acc	AppAccR	CUG	Guardian	REF
$\ln(Y_{i,t})$	-0.019	-0.01	-0.017	-0.08	-0.082	-0.056
	(0.622)	(0.784)	(0.608)	(0.319)	(0.228)	(0.756)
$\ln(Y_{i,t-1})$	0.018	0.051	-0.037	0.215	0.132	0.011
	(0.64)	(0.129)	(0.241)	(0.003)	(0.056)	(0.828)
n	1219	1218	1218	925	717	213
R^2 witihin	0.021	0.207	0.012	0.166	0.09	0.225
R^2 between	0	0.284	0.002	0.158	0.163	0
R^2 overall	0.213	0.215	0.215	0.133	0.109	0.023
	Specification (6): Dependent variable $\Delta[\ln(X_{1,i,t})]$					
	App	Acc	AppAccR	CUG	Guardian	
$\Delta[\ln(Y_{i,t})]$	-0.033	-0.027	0.016	-0.041	0.036	
	(0.494)	(0.517)	(0.681)	(0.697)	(0.647)	
$\Delta[\ln(Y_{i,t-1})]$	0.087	0.016	0.028	0.064	0.104	
	(0.091)	(0.696)	(0.458)	(0.478)	(0.209)	
n	1064	1063	1063	792	591	
R^2 witihin	0.072	0.072	0.071	0.064	0.048	
R^2 between	0.03	0.052	0.049	0.005	0.02	
R^2 overall	0.083	0.08	0.08	0.068	0.061	

Regressions from specifications (5) and (6) for the six different measures of performance (as labelled in the first heading row). For each result, the coefficient on the performance variable is reported with the p-value associated with this coefficient reported in parentheses underneath. Results similar to those from Table 4 now using fixed effects panel. Note there are fewer REF assessment periods limiting further analysis with this performance measure.

Table A15: Sensitivity: The impact of pay on performance: fixed effects panel

	Specification (7): Dependent variable $\ln(Y_{i,t})$				
	App	Acc	AppAccR	CUG	Guardian
$\ln(X_{1,i,t})$	0.004	0.02	-0.021	-0.006	-0.014
	(0.932)	(0.629)	(0.633)	(0.813)	(0.653)
$\ln(X_{1,i,t-1})$	0.011	0.08	-0.07	0.011	-0.018
	(0.822)	(0.058)	(0.113)	(0.646)	(0.567)
$\ln(X_{2,i,t})$	0.576	0.385	0.166	-0.194	-0.037
	(0.011)	(0.051)	(0.423)	(0.105)	(0.848)
$\ln(X_{2,i,t-1})$	-0.401	-0.095	-0.235	-0.2	-0.128
	(0.054)	(0.601)	(0.216)	(0.066)	(0.484)
n	783	782	782	686	585
R^2 witihin	0.004	0.072	0	0.036	0.001
R^2 between	0.004	0.127	0.044	0.03	0.118
R^2 overall	0.398	0.204	0.298	0.676	0.2
	Specification (8): Dependent variable $\Delta[\ln(Y_{i,t})]$				
	App	Acc	AppAccR	CUG	Guardian
$\Delta[\ln(X_{1,i,t})]$	-0.03	-0.056	0.026	-0.02	0.022
	(0.414)	(0.244)	(0.622)	(0.413)	(0.621)
$\Delta[\ln(X_{1,i,t-1})]$	-0.038	0.015	-0.053	0.004	0.041
	(0.291)	(0.74)	(0.292)	(0.88)	(0.264)
$\Delta[\ln(X_{2,i,t})]$	0.337	0.138	0.199	-0.08	0.05
	(0.082)	(0.582)	(0.464)	(0.557)	(0.836)
$\Delta[\ln(X_{2,i,t-1})]$	0.009	-0.061	0.07	-0.298	-0.12
	(0.954)	(0.758)	(0.746)	(0.005)	(0.585)
n	577	576	576	506	405
R^2 witihin	0.175	0.046	0.149	0.137	0.124
R^2 between	0.036	0.022	0.053	0.04	0.056
R^2 overall	0.329	0.079	0.201	0.156	0.173

Regressions from specifications (7) and (8) for the six different measures of performance (as labelled in the first heading row). For each result, the coefficient on the performance variable is reported with the p-value associated with this coefficient reported in parentheses underneath. Results similar to those from Table 5 now using fixed effects panel. Note there are fewer REF assessment periods limiting further analysis with this performance measure.

Table A16: Sensitivity: The impact of performance on pay: random effects panel

	Specification (5): Dependent variable $\ln(X_{1,i,t})$				
	App	Acc	AppAccR	CUG	Guardian
$\ln(Y_{i,t})$	0.097	0.062	0.012	0.052	0.031
	(0.009)	(0.059)	(0.715)	(0.476)	(0.625)
$\ln(Y_{i,t-1})$	0.04	0.085	-0.009	0.276	0.236
	(0.282)	(0.008)	(0.772)	(0)	(0)
n	1219	1218	1218	925	717
R^2 witihin	0.375	0.344	0.032	0.249	0.237
R^2 between	0.372	0.332	0.019	0.257	0.29
R^2 overall	0.195	0.207	0.213	0.126	0.097
	Specification (6): Dependent variable $\Delta[\ln(X_{1,i,t})]$				
	App	Acc	AppAccR	CUG	Guardian
$\Delta[\ln(Y_{i,t})]$	-0.038	-0.032	0.007	-0.093	-0.003
	(0.332)	(0.385)	(0.831)	(0.32)	(0.967)
$\Delta[\ln(Y_{i,t-1})]$	0.059	0.017	0.013	0.088	0.074
	(0.185)	(0.637)	(0.695)	(0.275)	(0.306)
n	1064	1063	1063	792	591
R^2 witihin	0.076	0.075	0.074	0.065	0.056
R^2 between	0.063	0.086	0.086	0.03	0.06
R^2 overall	0.081	0.079	0.078	0.067	0.058

Regressions from specifications (5) and (6) for the six different measures of performance (as labelled in the first heading row). For each result, the coefficient on the performance variable is reported with the p-value associated with this coefficient reported in parentheses underneath. Results similar to those from Table 4 now using random effects panel. Note there are fewer REF assessment periods limiting further analysis with this performance measure.

Table A17: Sensitivity: The impact of pay on performance: random effects panel

	Specification (7): Dependent variable $\ln(Y_{i,t})$				
	App	Acc	AppAccR	CUG	Guardian
$\ln(X_{1,i,t})$	0.081	0.071	0.025	0.031	0.031
	(0.103)	(0.096)	(0.546)	(0.213)	(0.314)
$\ln(X_{1,i,t-1})$	0.085	0.13	-0.028	0.046	0.028
	(0.091)	(0.003)	(0.512)	(0.068)	(0.373)
$\ln(X_{2,i,t})$	0.616	0.381	0.336	-0.029	0.176
	(0.009)	(0.061)	(0.101)	(0.819)	(0.363)
$\ln(X_{2,i,t-1})$	-0.298	-0.036	-0.115	-0.058	0.084
	(0.171)	(0.845)	(0.543)	(0.612)	(0.647)
n	783	782	782	686	585
R^2 witihin	0.097	0.16	0.024	0.126	0.149
R^2 between	0.181	0.219	0.001	0.03	0.182
R^2 overall	0.391	0.199	0.292	0.668	0.18
	Specification (8): Dependent variable $\Delta[\ln(Y_{i,t})]$				
	App	Acc	AppAccR	CUG	Guardian
$\Delta[\ln(X_{1,i,t})]$	-0.028	-0.051	0.017	-0.027	-0.002
	(0.433)	(0.232)	(0.709)	(0.201)	(0.948)
$\Delta[\ln(X_{1,i,t-1})]$	-0.035	0.044	-0.072	0.013	0.017
	(0.306)	(0.277)	(0.093)	(0.525)	(0.553)
$\Delta[\ln(X_{2,i,t})]$	0.313	0.273	0.112	0.003	-0.021
	(0.097)	(0.209)	(0.63)	(0.978)	(0.916)
$\Delta[\ln(X_{2,i,t-1})]$	-0.054	0.02	-0.057	-0.209	-0.158
	(0.714)	(0.908)	(0.754)	(0.02)	(0.369)
n	577	576	576	506	405
R^2 witihin	0.178	0.067	0.185	0.146	0.156
R^2 between	0.044	0.143	0.214	0.142	0.171
R^2 overall	0.328	0.068	0.185	0.15	0.16

Regressions from specifications (7) and (8) for the six different measures of performance (as labelled in the first heading row). For each result, the coefficient on the performance variable is reported with the p-value associated with this coefficient reported in parentheses underneath. Results similar to those from Table 5 now using random effects panel. Note there are fewer REF assessment periods limiting further analysis with this performance measure.

Table A18: Sensitivity: The impact of performance on pay: three year time periods

	Specification (5): Dependent variable $\ln(X_{1,i,t})$				
	App	Acc	AppAccR	CUG	Guardian
$\ln(Y_{i,t})$	0.528	0.193	0.025	0.093	0.046
	(0)	(0)	(0.668)	(0.346)	(0.613)
$\ln(Y_{i,t-1})$	-0.391	-0.052	0	0.205	0.187
	(0)	(0.328)	(0.996)	(0.034)	(0.041)
n	1219	1218	1218	925	717
R^2	0.469	0.464	0.323	0.357	0.391
	Specification (6): Dependent variable $\Delta[\ln(X_{1,i,t})]$				
	App	Acc	AppAccR	CUG	Guardian
$\Delta[\ln(Y_{i,t})]$	-0.039	-0.033	0.01	-0.104	0.001
	(0.331)	(0.372)	(0.766)	(0.273)	(0.986)
$\Delta[\ln(Y_{i,t-1})]$	0.065	0.016	0.018	0.081	0.076
	(0.15)	(0.662)	(0.601)	(0.322)	(0.301)
n	1064	1063	1063	792	591
R^2	0.079	0.077	0.077	0.07	0.064

Regressions from specifications (5) and (6) for the six different measures of performance (as labelled in the first heading row). For each result, the coefficient on the performance variable is reported with the p-value associated with this coefficient reported in parentheses underneath. Results similar to those from Table 4 now using three year time periods. Note there are fewer REF assessment periods limiting further analysis with this performance measure.

Table A19: Sensitivity: The impact of pay on performance: three year time periods

	Specification (7): Dependent variable $\ln(Y_{i,t})$				
	App	Acc	AppAccR	CUG	Guardian
$\ln(X_{1,i,t})$	0.68	0.676	0.024	0.051	0.044
	(0.001)	(0.001)	(0.784)	(0.187)	(0.331)
$\ln(X_{1,i,t-1})$	0.894	0.964	-0.048	0.122	0.12
	(0)	(0)	(0.596)	(0.003)	(0.012)
$\ln(X_{2,i,t})$	-1.089	-2.513	1.416	-0.193	-0.302
	(0.285)	(0.008)	(0.001)	(0.325)	(0.299)
$\ln(X_{2,i,t-1})$	1.142	1.709	-0.544	0.043	-0.246
	(0.253)	(0.066)	(0.191)	(0.821)	(0.408)
n	783	782	782	686	585
R^2	0.494	0.467	0.279	0.765	0.643
	Specification (8): Dependent variable $\Delta[\ln(Y_{i,t})]$				
	App	Acc	AppAccR	CUG	Guardian
$\Delta[\ln(X_{1,i,t})]$	-0.024	-0.046	0.015	-0.036	-0.002
	(0.582)	(0.291)	(0.738)	(0.094)	(0.963)
$\Delta[\ln(X_{1,i,t-1})]$	-0.022	0.046	-0.072	0.011	0.021
	(0.591)	(0.258)	(0.097)	(0.58)	(0.462)
$\Delta[\ln(X_{2,i,t})]$	0.321	0.257	0.109	0.003	0.019
	(0.154)	(0.241)	(0.642)	(0.977)	(0.924)
$\Delta[\ln(X_{2,i,t-1})]$	-0.176	0.017	-0.075	-0.201	-0.152
	(0.322)	(0.92)	(0.687)	(0.027)	(0.392)
n	577	576	576	506	405
R^2	0.191	0.075	0.193	0.164	0.181

Regressions from specifications (7) and (8) for the six different measures of performance (as labelled in the first heading row). For each result, the coefficient on the performance variable is reported with the p-value associated with this coefficient reported in parentheses underneath. Results similar to those from Table 5 now using three year time periods. Note there are fewer REF assessment periods limiting further analysis with this performance measure.

Table A20: Asymmetric bargaining model: regression results for academic staff

	All	Below Ave	Above Ave	All	Below Ave	Above Ave
Coefficient	-0.147***	-0.170***	-0.190***	-0.170***	-0.178***	-0.362***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Controls	No	No	No	Yes	Yes	Yes
n	874	687	187	845	665	180
R^2	0.078	0.078	0.045	0.480	0.652	0.469

Similar analysis as 6 now presenting results for academic staff.

Table A21: VC salary distribution and growth rates

		Percentile				
Year	Mean	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}
2007	233,385	162,682	195,300	232,249	270,332	306,166
2008	255,569	175,241	219,846	249,128	286,668	332,171
2009	267,138	192,064	231,241	265,782	307,275	349,890
2010	271,867	197,244	236,484	270,677	308,394	354,986
2011	268,207	176,885	232,121	265,461	305,716	363,921
2012	269,553	175,526	233,885	265,778	305,113	341,259
2013	268,605	187,540	227,615	264,269	312,318	348,877
2014	274,731	181,663	234,006	269,415	307,903	383,852
2015	271,452	178,338	233,684	275,194	309,675	352,576
2016	279,079	182,582	240,768	281,274	316,278	361,152
			Growth rates			
2008	9.51	7.72	12.57	7.27	6.04	8.49
2009	4.53	9.60	5.18	6.68	7.19	5.33
2010	1.77	2.70	2.27	1.84	0.36	1.46
2011	-1.35	-10.32	-1.84	-1.93	-0.87	2.52
2012	0.50	-0.77	0.76	0.12	-0.2	-6.23
2013	-0.35	6.84	-2.68	-0.57	2.36	2.23
2014	2.28	-3.13	2.81	1.95	-1.41	10.03
2015	-1.19	-1.83	-0.14	2.15	0.58	-8.15
2016	2.81	2.38	3.03	2.21	2.13	2.43
	19.58	12.23	23.28	21.11	17.00	17.96

Real vice-chancellor pay over time for different parts of the distribution; the top half of the table gives the actual numbers, whereas the bottom half gives the growth rates.

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