Job Security and Productivity: Evidence From Academics

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Abstract: How does job security influence productivity? I create a dataset from the bibliographic records of the National Bureau of Economic Research working paper series and from hand collected data from individual curricula vitae to compare productivity of professors before and after tenure. This paper uses a fuzzy regression discontinuity design with fixed effects and finds that the number of papers produced drops immediately after tenure. Also, the pattern in productivity growth changes from increasing every year to having very little change in the years after tenure. Assuming researchers are similar pre- and post-tenure except for the new position, this finding is suggests that tenure causes the decrease in productivity. This gives credibility to the concern that tenured professors stop being productive.

Keywords: Lazy professors

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1 Introduction

"The juvenile sea squirt wanders through the sea searching for a suitable rock or hunk of coral to cling to and make its home for life. For this task, it has a rudimentary nervous system. When it finds its spot and takes root, it doesn't need its brain anymore so it eats it! (It's rather like getting tenure.)"
Consciousness Explained, by Daniel Denett

For firms to maximize efficiency, it is important to know what institutions motivate workers to work hard. Job security is a topic where the balance of benefits and costs are still relatively unknown. For example, employees with high job security may invest more in their companies out of loyalty or because they view their jobs as long term commitments. On the other hand, workers may take advantage of their job security and do as little work as possible. Job security can also be costly to the firm since dismissal of employees requires more time, effort, and compensation.

One limitation to the study of job security and employee effort is the difficulty in finding industries where job security changes internally. Previous studies have compared countries with differing levels of job security (OECD Employment Outlook). For example, job security in the United States is highly dependent on the economy and business conditions. Hence job security is something that can vary greatly depending on the economic climate. In times of economic growth, jobs are generally stable. However, in periods of recession, firms can easily dismiss employees to cut costs. Job security in Europe is perceived to be high relative to many other places in the world because of a system of indefinite contracts and is not affected as much by economic conditions. These contracts do not guarantee employment for life, but make it difficult for employers to dismiss employees. While it might seem sensible to compare employee effort or labor market performance between countries and attribute differences to different employment protection institutions, there are many other factors that could influence workers. One broad area to consider is cultural differences.

Another limitation to the study of job security and effort is the difficulty of finding a gauge of effort or productivity. While productivity can be measured in jobs such as supermarket cashiers by how fast they move through customers in a check-out line (Mas and Moretti 2009), it is more difficult to get accurate measures of productivity and effort in high level jobs where task are not as concrete. For example, it would be misleading to only measure a CEO's effort by how well his company performs since company performance is dependent on external factors like the economic climate.

There is one industry where both these limitations are addressed. In academics, researchers start as assistant professors and their employment status is determined almost entirely by their ability to do research. Research output can be measured by how many papers a professor produces. If a professor is promoted to a tenured position, he gets almost complete job security. Therefore, in academics there is both an observable shift in job security for each professor and also a quantitative measure of productivity that can be observed through time.

This paper analyzes the effect of academic tenure on professor research productivity. I use the bibliographic database of the National Bureau of Economic Researcher (NBER) and hand collected data from each NBER researcher's individual CV to create a measure of productivity that predicts the time of research effort more accurately than the date of publication in a journal. In total, I look at the academic careers of 934 researchers and papers produced from 1973 to 2008. To motivate the empirical tests, I present a graphical analysis showing discontinuities of productivity at tenure both in terms of value and growth rate. Using the fuzzy regression discontinuity design and controlling for fixed effects, this paper finds that the effect of tenure is twofold. First there is a noticeable drop in productivity immediately after tenure. The average drop is about 20% fewer papers than the predicted value if tenure was not granted. Second, the pattern of productivity growth flattens from an increase in productivity each year to almost no growth in productivity. To test whether the patterns that are observed are merely from some sort of momentum built up from papers produced in the past, I also consider an AR(1) process. The pattern of productivity remains the same as before. Finally, I assume various correlation patterns in the errors. The results are still statistically significant.

The findings do not necessarily give evidence regarding the quality of work, but do suggest that if the university wants to maximize the productivity of its professors, it would want to consider modifying the institution of tenure. The findings complement studies relating to private sector jobs. Ichono and Riphahn (2005) find that the average number of days of absence per week more than triples once the probability of being fired decreases. Hence this paper furthers the literature that suggests that job security has negative impact on productivity.

The paper is organized as follows. Section 2 provides background and motivation for the analysis by describing how productivity of professors relates to a broader question of labor market efficiencies. Section 3 builds up the empirical model. Section 4 describes the data. Section 5 presents the results. I apply the measure of productivity to discuss wages in section 6. Section 7 concludes.

2 Literature Review

This paper relates to an ongoing question of how job security and employment protection legislation (EPL) affects worker performance and the labor market. Intuitive arguments can go both ways. Workers can benefit from EPL by getting ample warning of future layoffs and thus facilitate their own job searches. Job security and EPL can also lead to higher worker satisfaction and a loyalty to the company which may result in the worker investing more time and effort into their companies. On the other hand, if it is difficult for a firm to layoff a worker, workers could have incentive to become unproductive and firms would suffer inefficiencies from having to keep these workers. Increased job security and EPL also has potential to increase the probability of long-duration unemployment for workers. Also the firm may try to balance out the costs of complying with EPL by instituting lower wages (OECD Employment Outlook).

In terms of the effects on the labor market, the OECD Employment outlook concludes that EPL strictness has little effect on unemployment. The effect on unemployment is less consistent and cross-country comparisons weakly suggest that EPL raises employment for "prime-age" men, but lowers employment for youths and "prime-age women".

Most empirical findings suggest that job security decreases employee effort. Ichino and Riphahn (2005) use data from 545 men and 313 women white collared workers and show that the number of days of absence per week increases significantly once employment protection is granted. One explanation of this can indeed be that job security results in more shirking. However, Ichino and Riphahn suggest two alternatives as well. One theory is that absenteeism increases over the first months because the worker has to learn what is acceptable in the firm. If work results in disutility, the worker will gradually learn how to work as little as possible. Another explanation is that in earlier months, the workers ability is unobservable and his individual output is the gauge that a supervisor uses to learn about the workers ability. This would also lead to a pattern of high effort in early months that declines with tenure. Similarly, Engellandt and Riphahn (2004) that workers with temporary contracts provide more effort than permanent employees. One main results is that the probability of a temporary worker working unpaid overtime exceeds that of the permanent worker by 60%.[1]

More specifically, this paper relates to a literature of productivity studies dominated by sociologists but that has more recently been studied by economists. Clemente (1973) notes that productivity studies have been performed on physicists, psychologists, biologists, political scientists, psychometricians, medical researchers, chemists, physiologists, sociologists,

[1]Other similar results mentioned by Engellandt and Riphahn (2004): Riphahn and Thalmaier (2001), Guadalupe (2003), Jimeno and Toharia (1996).

agricultural scientists, women scientists, and Nobel laureates.

As noted by Rauber and Ursprung (2007), although it is clear that research success is important in determining salary, tenure, academic rank, and the rank of employment, it is not as easy to pin down the determinants of research productivity over a life cycle and findings have been varied. Clemente (1973) finds that only age at first publication and publishing before PhD have important effects on research productivity. Levine and Stephan (1991) find that in general, scientists become less productive as they age. They also find that there are vintage effects on research. Human capital models suggest a quadratic (hump-shaped) pattern of productivity over a life cycle. While the models of Levin and Sharon (1991) support this hump shape, it is possible that that this could merely be an artifact of having squared terms in the model. Goodwin and Sauer (1995) suggest that a fifth order polynomial may fit the data better and show a pattern of productivity with the largest peak in research productivity early in the career and a second smaller peak 25-30 years in.

In this study I measure research productivity in terms of a count of NBER working papers. Early studies in this area have used journal publication counts (Zuckerman 1967, Clemente 1973, Jauch, Glueck and Osborn 1978). Since then, there has been a general trend of putting different weights on publications. For example Levine and Stephan (1989 and 1991) generate an author adjusted count where publications with coauthors only count as a fraction of a total publication, a journal quality count that weights publications by the journal impact in which they are published, and a hybrid adjustment that adjusts for both coauthors and journal impact factor. Another way to control for publication quality has been restricting the article count to those published in specific highly reputable journals (Goodwin and Sauer, 1995 and Coupe, Smeets, and Warznski 2006). However, even with adjusted weights on publications, there is still a problem of publication lag which in the 1980s averaged 15 to 24 months in economics journals, (Yohe 1980) and hasn't been closely studied since. Studies have tried to adjust by this by adding lags or forwards to different variables in the models (Coupe et al 2006, Levine 1991). This study presents a novel way to approach the problem of publication lag since scientists can immediately upload working papers when the first draft is finished instead of having to wait for a lengthy review process.

Finally this paper relates to a more general literature on promotion and productivity. Coupe et al (2006) find that tenure has a negative effect on research productivity due to lessened incentives after achieving this status. Similarly, CEOs that are offered special benefits or win specific awards are noted to under perform (Yermack 2006, Liu and Yermack 2007, Malmendier and Tate 2009). For researchers however, it remains to be seen if a decrease in quantity can be compensated by an increase in quality since once they attain tenure they have more opportunity to pursue risky projects.

3 Model

The basic source of identification in this paper is comparing the output rate of working papers to a researcher's academic status. This section identifies sources of omitted variables and develops various estimation methods to identify the effect of professor status on research productivity.

3.1 OLS Approach

Consider the following model where research productivity is a function of professor status:

$$y_{i,t} = \beta_0 + \beta_1 tenure_{i,t} + \epsilon_{i,t} \tag{1}$$

Where $y_{i,t}$ is a measure of research productivity and the independent variable is an indicator for whether the researcher is a tenured professor in a given year. In this context, β_0 identifies a baseline number of working papers produced by a researcher and β_1 indicates how the position of tenure changes the researcher's productivity.

The error term is actually the sum of three components:

$$\epsilon_{i,t} = \epsilon_i + \tilde{\epsilon_t} + \hat{\epsilon_{i,t}} \tag{2}$$

The first term captures a permanent component of the researcher such as ability or family background. The second error component captures time variant components in the academic world. Examples of this could be the introduction of a certain paper that sparks off a new area of research, the introduction of new tools that allow researchers to be more productive, or some indication of the demand for academic scientists. The third error term captures a time variant component of a researcher's ability. Examples of this could be the effects of aging, changes in motivation, or more specifically, life style changes such as marriage or pregnancy.

One area of concern in estimating equation (1) is measurement error in the tenure variable. Since not all researchers list the date of tenure on their CV, I define tenure as:

$$tenure_{i,t} = \begin{cases} 1 & if\ Vintage\ of\ PhD \geq 6 \\ 0 & if\ Vintage\ of\ PhD < 6 \end{cases} \text{ [2]} \tag{3}$$

[2] Although the regressions I run will use this definition of tenure, subsequent mentions of tenure in the model section will refer to the more accurate description which would be *tenure* $= 1$ if in fact the researcher is actually tenured. This is dependent on more than just the vintage of PhD and is discussed more in section 5.3.

This definition comes from the fact that many economics departments have a six year tenure track. However, there are also cases where a researcher does not enter a professor position immediately after attaining his PhD. It is clear that this definition of tenure is not completely accurate and the tenure variable in equation (1) is actually defined as: $tenure_{i,t} = tenure^{*}_{i,t} + e_{i,t}$. Assuming that this is a case of classical measurement error, *i.e* $cov(e_{i,t}, tenure^{*}_{i,t} = 0)$, the expected value of β_1 is:

$$E[\hat{\beta}_1] = \beta_1 - \frac{\beta_1 \sigma_{e^2_{i,t}}}{var(tenure_{i,t})} \tag{4}$$

If the variance of tenure is low or the standard deviation of the error term is high the error in our estimate of will be high.

In estimating equation (1), difficulties also come from each component of the error term because a researcher's status is not exogenous. The same factors that determine whether a professor has attained tenure are likely to affect the amount of working papers he or she produces every year.

Consider the case where a researcher's productivity is a function of tenure status and innate ability.

$$y_{i,t} = \beta_0 tenure_{i,t} + \beta_1 ability_i + \epsilon_{i,t} \tag{5}$$

where $corr(ability_i,\ tenure_{i,t}) \neq 0$ ability is time invariant, but where we can only observe the model:

$$y_{i,t} = \tilde{\beta}_0 tenure_{i,t} + \tilde{\epsilon}_{i,t}$$

Then the OLS estimate of β_0 is:

$$\begin{aligned}
\hat{\tilde{\beta}}_{OLS} &= (tenure'_{i,t} tenure_{i,t})^{-1} tenure_{i,t} y_{i,t} \\
&= (tenure'_{i,t} tenure_{i,t})^{-1} tenure_{i,t} (\beta_0 tenure_{i,t} + \beta_1 ability_i + \epsilon_{i,t}) \\
&= \beta_0 + \beta_1 (tenure'_{i,t} tenure_{i,t})^{-1} tenure'_{i,t} ability_i
\end{aligned}$$

And so,

$$E(\hat{\tilde{\beta}}_0) = \beta_0 + \beta_1 \frac{cov(ability_i,\ tenure_{i,t})}{var(ability_i)}.$$

In this context, the estimate of the effect of tenure will likely be biased upwards because a researcher with a strong ability for writing and producing papers is likely to achieve tenure faster than a researcher who isn't as strong in this area. The bias will also be affected by the variance in our sample. Given that NBER researchers are among the leading scholars in their respective fields and have similar levels of education, I expect that the variance in innate ability would be rather small. If this is the case, the estimate of the effect of tenure could be biased upwards as well. However, any other time-invariant component of a researcher that is correlated with tenure can also lead to bias in our model. This includes unobservable characteristics such as family background, cultural background, and work ethic. In the end, it is impossible for to pin down the direction and magnitude of the bias.

One solution to this problem is adding variables that serve as proxies for the omitted variables. A new function to estimate would be:

$$y_{i,t} = \beta_0 + \beta_1 tenure_{i,t} + \beta X_i + u_{i,t} \tag{6}$$

where X_i is a vector containing information such as institutions where individuals went to school, year of PhD, age, etc. Although this method will lessen the omitted variable bias from the e_i term in the error model, none of our proxies will completely control for ability or other time invariant individual effects. Furthermore, the inclusion of irrelevant variables will lead to a loss in efficiency.

The most effective way to address the problem of time invariant factors is to exploit the panel structure of the data. By observing the same individual over each year of his academic career, I can control for the time invariant factors that make the individual more productive. More specifically I use the fixed effects model: $y_{i,t} = \beta_0 + \beta_1 tenure_{i,t} + ID + \epsilon_{i,t}$, where y and $tenure$ are the same as in (1) and ID represents a dummy variable for each individual. I then Average over all time periods for each individual to get:

$$\begin{aligned}\overline{y_{i,t}} &= \beta_1 \overline{tenure_{i,t}} + ID + \epsilon_{i,t} \\ &= \frac{1}{N}\sum_{i=1}^{N} y_{i,t}\end{aligned}$$

Subtracting the averaged equation from the model gives me the demeaned equation:

$$y_{i,t} - \overline{y_{i,t}} = \beta_1(tenure_{i,t} - \overline{tenure_{i,t}}) + (\epsilon_{i,t} - \overline{\epsilon_{i,t}}) \tag{7}$$

The fixed effects model is powerful because it will control for all individual time invariant factors. However, discussed earlier, this only takes care of the error term e_i in (2) and our result is still biased because of the $\tilde{e_t}$ and $\hat{e_{i,t}}$ terms.

Consider the model where a researcher's productivity is a function of professor status and some time varying ability:

$$y_{i,t} = \beta_0 tenure_{i,t} + \beta_1 ability_t + \epsilon_{i,t} \tag{8}$$

where $cov(ability_t, tenure) \neq 0$. Again, only *tenure* is observed and OLS estimates of the coefficient on tenure will be:ed and OLS estimates of the coefficient on tenure will be:

$$\hat{\hat{\beta}}_{OLS} = \beta_0 + \beta_1 (tenure'_{i,t} tenure_{i,t})^{-1} tenure'_{i,t} ability_t$$

and

$$E(\hat{\hat{\beta}}_0) = \beta_0 + \beta_1 \frac{cov(ability_t, tenure_{i,t})}{var(ability_t)}.$$

This bias will come into play when there is some sort of event that affects the academic world, the productivity of researchers, and how long it takes researchers to attain tenure. Examples of this could be the introduction of new software or the technology that allows researchers to become much more productive and produce substantial work early on in their careers. Other examples of this could be the introduction of a paper or new field of research, giving all researchers in that time period a novel area to base their research on. If this shock results in professors getting tenured earlier, there will be an upward bias on the affect of tenure. Similarly, in time periods where an academic field is 'stuck', there will be a downward bias on the effect of tenure on productivity. Similarly, it is possible that events such as recessions and natural disasters will affect research productivity because they will either give researchers something to investigate, or cause them to allocate time away from their research. An effective way to address this type of bias is to add a dummy variable for each time period in (7) to arrive at:

$$(y_{i,t} - \overline{y_{i,t}}) = \beta_1 (tenure_{i,t} - \overline{tenure_{i,t}}) + T_t + (\epsilon_{i,t} - \overline{\epsilon}_{i,t}) \tag{9}$$

where variables are the same as in (7) except T represents a dummy variable for each year.

The $e_{i,t}$ bias comes into play when researchers decide how to allocate their time. For example, a visiting professor whose primary position is at a research institute or consulting firm may never attain tenure at the university level, but could still be a prolific publisher. In this circumstance, $cov(ability_{i,t}, tenure_{i,t}) < 0$, and so the effect attributed to tenure could be biased downwards. On the other hand, it is possible for researchers to allocate time away from research to get involved in politics or because they are chosen to serve as an advisor. In this case, the researchers reputation is likely to indicate that he or she has already attained tenure. Another example captured by the $e_{i,t}$ term is female professors who are pregnant or have recently given birth. They might expect to produce fewer papers during that time because they would allocate time away from research and into taking care of their child. However, it could also be the case that maternity leave allows the researcher to focus on her research instead of having to teach classes and actually results in more papers being produced. I would predict also that once a professor has tenure she would be more willing to take time to start a family because of the job security. Depending on how a researcher deals with maternity leave, the bias on the effect of tenure could be positive or negative.

One way to reduce the magnitude of $e_{i,t}$ is to add individual specific variables that change with time. I use the vintage of the researcher's PhD in hopes that it also captures some life-cycle changes. Because life-cycle patterns may not be linear, I also consider quadratic and cubic patterns. The resulting model is:

$$(y_{i,t} - \overline{y_{i,t}}) = \beta_1(tenure_{i,t} - \overline{tenure_{i,t}}) + T_t + \sum_{j=1}^{3} \gamma_j vintage_{i,t}^{j} + (\epsilon_{i,t} - \overline{\epsilon_{i,t}}) \tag{10}$$

Another concern in our model is selection bias. The first way this affects the model is in terms of external validity. The sample of NBER researchers is not a random sample that represents the population of all academic scientists and so I cannot draw strict conclusions to the entire population of workers in relating job security to worker effort. However, Levin 1991 compares 6 different fields and in only one of the fields, do the scientists express strikingly different life cycle productivity patterns.

More important is selection bias that affects internal validity. In estimating the model, the affect of tenure only comes from researchers who have achieved tenure; we do not observe the affect of tenure for researchers who recently achieved their PhD, never started on the tenure track, or choose to go into industry instead of academics. In this context we actually estimate two functions:

$$y_{1,i,t} = \beta_1 tenure_{1,i,t} + \epsilon_{i,t} \tag{11}$$

and

$$y_{2,i,t} = \begin{cases} 1 & if\ tenure_{1,i,t} > 0\ for\ some\ t \in T \\ 0 & otherwise \end{cases} \tag{12}$$

where (11) can only be observed if $y_{2,i,t} > 0$ for some $t \in T$ and $tenure_{1,i,t} = X'\beta + \epsilon_2$. In this case,

$$\begin{aligned} E(\epsilon_{i,t}|tenure_{1,i,t}, sample\ selection\ rule) &= E(\epsilon_{i,t}|tenure_{1,i,t}, y_{2,i,t} > 0) \\ &= E(\epsilon_{i,t}|tenure_{1,i,t}, \epsilon_2 > -X'\beta) \end{aligned}$$

If the conditional expectation of the error here is zero then our estimates will still be unbiased. However this is usually not the case. As discussed already, there are many factors that influence both how many papers are published and tenure. The resulting model is:

$$E(y_{i,t}|X_{1,i,t}, y_{2,i,t} > 0) = \beta_1 tenure_{1,i,t} + E(\epsilon_{i,t}|\epsilon_2 > X'\beta).$$

Making the assumption that the errors $e_{1,i,t}$ and e_2 are joint normal,

$$E(y_{1,i,t}|X_{1,i,t}, Y_{2,i,t} > 0) = \beta_1 tenure_{1,i,t} + \delta E(\epsilon_2|\epsilon_2 > -X_1'\beta_1). \tag{13}$$

Because of this, researcher productivity will be biased since the error term is conditioned on being above a certain threshold. The bias however could be either positive or negative. If researchers who are more likely to get tenure select into being researchers, then the expected bias should be upward. However, if researchers who are more likely to tenure select out of academics and are lured into the private sector, the bias should be down.

3.2 Fuzzy Regression Discontinuity

Perhaps the best way to estimate the effect of tenure on productivity is through a fuzzy regression discontinuity (FRD) design. In this design, I assume that a researcher does not have precise control over whether he or she attains the position of tenure in a given year. Even if a researcher is extremely productive, it is not in his power to change his or her status to a tenured professor. I also assume that a researcher immediately before tenure is identical to a researcher immediately after tenure and that all factors that may affect research productivity (excluding the award of tenure) are evolving smoothly. Therefore change in research productivity immediately after the award of tenure can be attributed to the promotion.

I consider the FRD design over the strict regression discontinuity. The probability of a promotion to tenure is likely to jump discontinuously at six years after PhD. However the probability of achieving tenure does not change from 0 to 1 upon holding a PhD for six years. As discussed earlier, this can be due to career choices of the researcher or the academic job market. More formally,

$$lim_{x\downarrow 6} Pr(tenure = 1|vintage_{i,t} = 6) \neq lim_{x\uparrow 6} Pr(tenure = 1|vintage_{i,t} = 6) \tag{14}$$

In this context, the effect of tenure on research productivity will be measured by the difference in papers immediately after and before the sixth year of holding a PhD divided by the difference the in the probability of being tenured immediately after and before the sixth year of holding a PhD. This can be expressed as:

$$\tau_{FRD} = \frac{lim_{x\downarrow 6}E(y_{i,t}|vintage_{i,t} = 6) \neq lim_{x\uparrow 6}E(y_{i,t}|vintage_{i,t} = 6)}{lim_{x\downarrow 6}Pr(tenure = 1|vintage_{i,t} = 6) \neq lim_{x\uparrow 6}Pr(tenure = 1|vintage_{i,t} = 6)} \tag{15}$$

and will give the resulting resulting function:

$$y_{i,t} = \alpha_l + \tau tenure_{i,t} + \sum_{j=1}^{n}\beta_{l,j}(vintage_{i,t} - 6)^j + \sum_{k=1}^{n}(\beta_{r,k} - \beta_{l,k})tenure_{i,t}(vintage_{i,t} - 6)^k + \epsilon_{i,t} \tag{16}$$

where subscripts of l and r represent values to the left and right of the cutoff point of $vintage = 6$. Hence, β_l indicates how the years since PhD affects research productivity before attaining tenure, and β_r indicates how a researcher's productivity is changed each year after attaining tenure. When considering a large range of years before and after tenure, a higher order model gives a more accurate fit since it is unlikely that the effect of time is completely linear. However, when I restrict the sample to look at years close to the cutoff point I will make the assumption that on smaller intervals I can assume the relationship to be linear.

$$y_{i,t} = \alpha_l + \tau tenure_{i,t} + \beta_l(vintage_{i,t} - 6) + (\beta_r - \beta_l)tenure_{i,t}(vintage_{i,t} - 6) + \epsilon_{i,t} \tag{17}$$

This type of model has several advantages over the models discussed previously. Before, I assumed that the effect of tenure is permanent and constant. However, it seems unlikely that the effect of tenure after forty years is the same as it is immediately upon award. The FRD design considers both the immediate impact of tenure on productivity, as well as how research productivity changes over time before and after tenure. Thus if a researcher decides to celebrate for a year after attaining tenure and not do any research but then continues his previous trend of research, the value of τ will be negative, but the β_r terms should be the same or greater than the β_l terms. If on the other hand, researchers after adopt a slower pattern of productivity after tenure, the β_r terms will be less than zero. Like before, this model can be adjusted to control for individual fixed effects.

3.3 Autocorrelation

Finally, I consider what would happen if a researcher's productivity in one year is impacted by the productivity in previous years. For example if a researcher finishes several projects in one year, the next year will perhaps look less productive since he will have more projects in early stages. On the other hand, some researchers may look more productive every year since they build off the momentum of previous projects. Specifically, I consider an autoregressive process of order 1 (AR(1)) applied to the FRD design:

$$
\begin{aligned}
y_{i,t} = & \\
& \rho_l y_{i,t-1} + (\rho_r - \rho_l) tenure_{i,t} y_{i,t-1} + \alpha_l + \tau tenure_{i,t} \\
& + \sum_{j=1}^{n} \beta_{l,j} (vintage_{i,t} - 6)^j + \sum_{k=1}^{n} (\beta_{r,k} - \beta_{l,k}) tenure_{i,t} (vintage_{i,t} - 6)^k + \epsilon_{i,t}
\end{aligned}
$$

where stability requires that, $|\rho_l| < 1$ and $|\rho_r| < 1$.

4 Data Description

The existing literature generally uses article publications in peer reviewed journals as a measure of research productivity. To control for publication lag, sometimes various factors are lagged by two years (Coupe et al. 2006). Existing literature also creates various measures of productivity adjusting for co-authorship of journal quality.

In this paper, I use the count of NBER working papers as a measure of individual research productivity. One advantage of using working papers instead of peer reviewed journal articles is a more accurate gauge of the time when work was done. Journal articles can take up to two years from initial submission to eventual publication while working papers can be uploaded immediately after being written. Since I am interested in the change in research productivity between two specific years, using the date an article was published is unreliable. One limitation to using NBER working papers is that individuals are selected into the NBER based on merit. This selection could happen a couple years after a researcher receives his PhD and so papers that are written early in the career may not show up.

The data was created in two steps. The first source of data is the bibliographic record of the NBER working paper series which was downloaded March 1, 2009 from the NBER website. [3] This keeps a record of all NBER working papers from 1973 onward. In total there are 15,238 papers. The data contains all authors, upload date, and a note of subsequent publication in an academic journal. Four measures of productivity were generated from this data. Papers1 attributes all authors of a paper one article count. Papers2 is adjusted for coauthors and defined in a given year as: $Papers2 = \sum_i^N \frac{paper_i}{authors_i}$ where $authors_i$ is how many coauthors there are for $paper_i$. M1 only counts articles that are subsequently published in a peer reviewed journal. M2 adjusts M1 for coauthors.

This data was then merged with individual data collected for all researchers listed as

[3] http://www.nber.org/policies.html/

part of the "NBER Family". [4] Individual level data was gathered from each researchers CV. I attempted to gather information from the most recent CV and include information about institutions of education, years of graduation, and dates of promotions. At the time of download, there were 1072 researchers. The dates of PhD range from 1941 to 2007 and come from over 68 different universities. After collecting all available data and performing the merge, the resulting sample consists of 934 researchers. Table 1 and 2 show the evolution of the number of researchers and papers in the NBER. The tables show that the NBER has grown substantially since 1973 from about 100 researchers to the over 1000 researchers affiliated with it now. The rate of papers being published has also increased almost every year from 25 papers in 1973 to 912 papers in 2008. Tables 3 and 4 give a more detailed view into the various institutions of education and the PhD vintage of the researchers in the sample. It should be noted that the majority of NBER researchers come from only a handful of schools. Table 5 gives summary statistics on the frequency and quantity of working papers produced by researchers in their various stages of PhD vintage.

I also create a balanced sample of researchers. This is a subset of the original database which only contains researchers who received their PhD between 1979 and 1989. I pick these dates so I can follow the same set of researchers from 0 to 20 years of PhD vintage. Summary statistics for the balanced sample are also reported. In total, the balanced sample contains 236 researchers. Table 6 is the same as table 5 except for the balanced sample of researchers.

5 Empirical Results

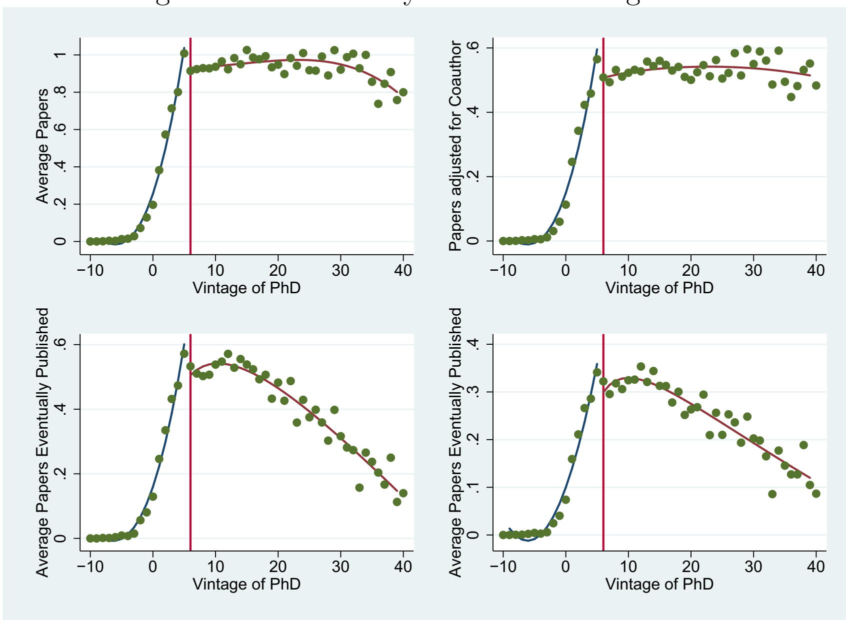
As discussed above, the total effect of tenure in (16) can be split into two components. The first is the immediate effect of promotion, τ, and the other is the long term consequences of tenure, β_r. If tenure merely has a one time effect, there should be a discontinuous jump in productivity immediately after promotion, but the trend afterwards should continue to evolve smoothly. If there are also long term consequences to tenure, the trend of productivity will also change discontinuously after the award of tenure.

5.1 Graphical Analysis

I begin with a simple graphical analysis of research productivity. Figure 1 plots four measures of research productivity against the vintage of PhD. The time starts from ten years before PhD and goes to 40 years after PhD. Throughout the rest of the analysis, the number of papers is measured for each researcher. For the graphical analysis however, each point in

[4] http://www.nber.org/vitae.html

Figure 1: Productivity and PhD Vintage -10-40



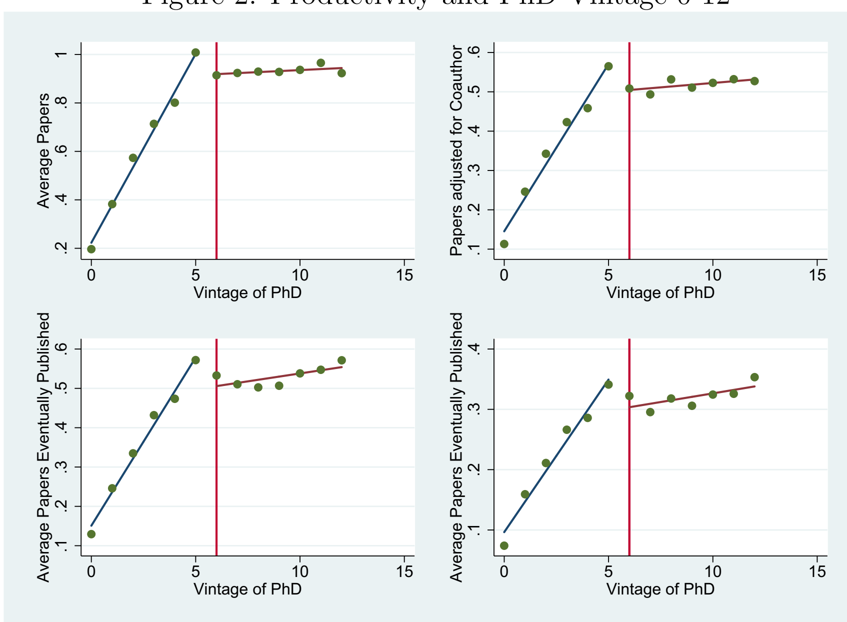
Note: This figure plots four measures of productivity against PhD Vintage ranging from -10 to 40. Each circle is the average productivity score for the given vintage year. Vertical line at $vintage = 6$ indicates the year of tenure. Continuous lines are fitted values of a fractional polynomial.

the figures is the average number of papers produced by a researcher in a given vintage year. The vertical line in the figures marks the 6th year after PhD. This represents a time where there is a discontinuous jump in the probability of being promoted to tenure. The continuous lines are the predicted number of papers. It is estimated separately for the data to the right and to the left of the vertical line and fitted to a high order polynomial.

Figure 2 is similar to Figure 1 except the vintage range is restricted between zero and twelve years after PhD. It is important to restrict the range even more than before since our first set of figures are more likely to capture life cycle effects of productivity that may not be related to tenure. Although any time related data will be biased by unobservable characteristics of life cycle changes, I hope that restricting the range of data will help lessen this. I also make the assumption that on smaller intervals, I can use a linear function to estimate predicted papers and so the continuous line is fitted to a linear function.

In the figures, productivity appears to be a smooth and continuous function of PhD vintage everywhere except the threshold that determines tenure. If the FRD design is valid, the only difference between an individual observed in year 5 of his PhD and an individual

Figure 2: Productivity and PhD Vintage 0-12



Note: This figure plots four measures of productivity against PhD Vintage ranging from 0 to 12. Each circle is the average productivity score for the given vintage year. Vertical line at $vintage = 6$ indicates the year of tenure. Continuous lines are from fitting a line to the data.

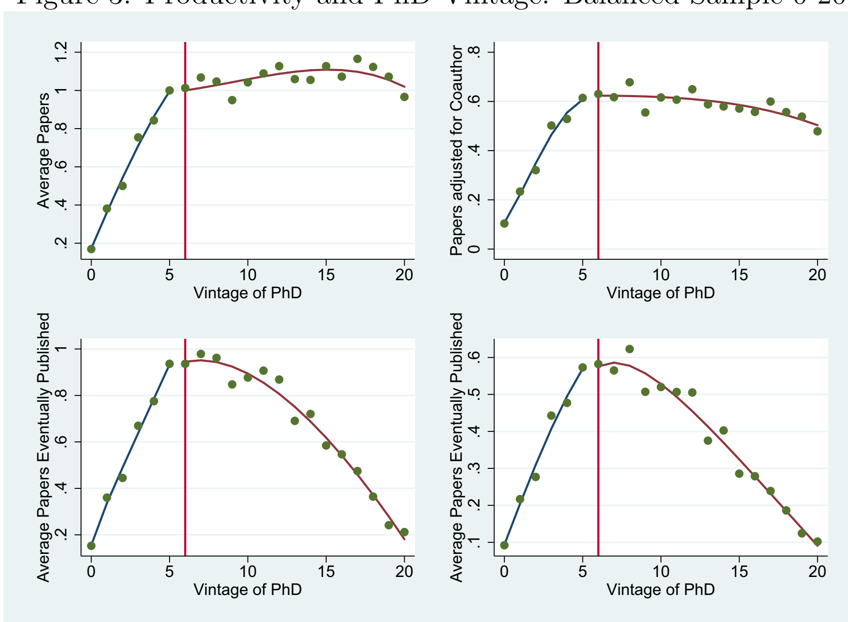
observed in year 6 of his PhD is the presence of tenure and so the discontinuity can be attributed to tenure. The size of the jump between year 5 and 6 is -.094 $papers1$ which represents a 9.3% drop in productivity from the previous year. If the trend of productivity were to continue in year 6, the size of the jump between the predicted value and actual value in year 6 is about -.24 which corresponds about a 20% decrease in papers1. The slope of the estimated function also changes on either side of the discontinuity. Before tenure, the slope of the graph indicates that each additional year of PhD corresponds to an additional .16 papers per year. However, the slope drops to about .01 after tenure.

The figures give credibility to the model in equation (16). Formally, the jump at tenure is τ and the change in slope after tenure is β_l in (16). Intuitively, the trend in productivity is not surprising. Immediately after attaining PhD it makes sense that paper count is low. Researchers have relatively little experience all on their own and need to develop their paper producing skills. Since universities only keep the best researchers, there should be an observed increase in productivity every year as individuals signal their worth to the universities.

For those that make it to tenure, there is no longer pressure to maintain the constant growth in publishing productivity since tenure and job security come hand in hand. This corresponds with the flattening that is observed in the figures after tenure. It would also make sense if researchers "took a breather" upon attaining tenure. This would corresponds with the sudden drop that is observed in the year immediately after tenure.

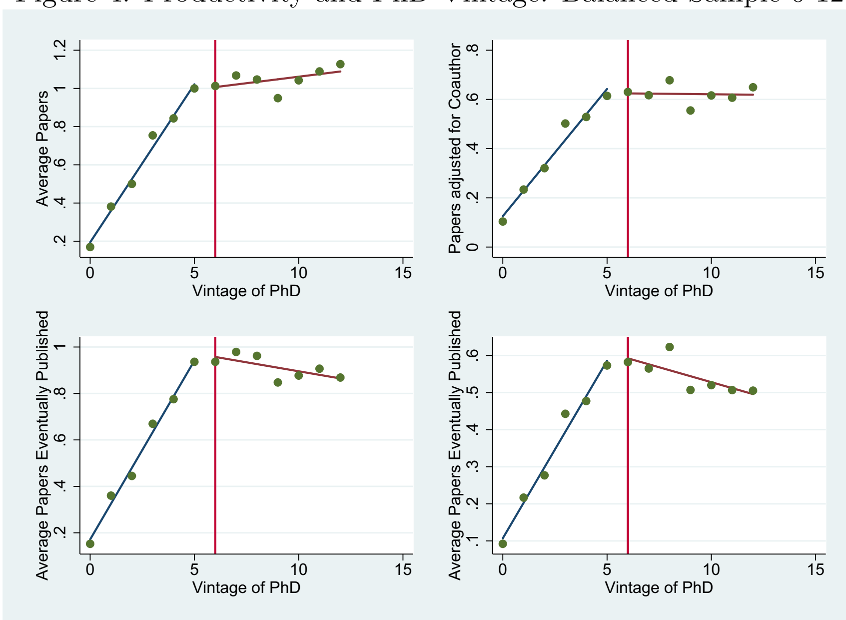
In the balanced sample, productivity also appears to be a continuous function of PhD vintage. Unlike the full sample, there doesn't appear to be a significant drop in productivity immediately after tenure. However, tenure is still clearly the spot where the function switches slope. Figures 3 and 4 plots the four measures of research productivity against the vintage of PhD for the balanced sample.

Figure 3: Productivity and PhD Vintage: Balanced Sample 0-20



Note: Graphs plot four measures of productivity against PhD vintage between -10 and 40. Each circle is the average productivity score for the given vintage year. Vertical line at $vintage = 6$ indicates the year of tenure. Continuous lines the predicted fitted to a fractional polynomial.

Figure 4: Productivity and PhD Vintage: Balanced Sample 0-12



Note: Graphs plot four measures of productivity against PhD vintage between 0 and 12. Each circle is the average productivity score for the given vintage year. Vertical line at $vintage = 6$ indicates the year of tenure. Continuous lines the predicted fitted to a first degree polynomial.

5.2 Regression Analysis

I now quantify the findings more precisely.

Table 7 reports the findings on a naively specified regression model. PhD vintage is restricted from -10 to 40 years. Column 1 reports the baseline estimate of the affect of tenure by fitting (1) to the data. This estimate indicates that tenure is associated with a positive increase in research productivity. Specifically, a tenured researcher can expect to produce .724 more papers in a given year than a non-tenured researcher.

Column 2 fits the data to (7). When controlling for individual fixed effects, the estimates do not change by much. The new estimate is that tenure increases productivity by .737 papers. Although the estimate seems robust to individual fixed effects, the estimate is not robust to the inclusion of a variety of controls.

Column 3 fits (9) to the data by including a dummy variables for each year. The general trend indicates that the absolute productivity of researchers has gone up with time. With the dummy variables for each year included the effect of tenure drops to an additional .457 papers each year. Column 4 is similar to column 3 but also controls for individual fixed effects. This drops the coefficient of tenure down to .4739.

Column 5 fits (10) to the data including up to a third order term for vintage. Again, adding variables drops coefficient of tenure. Column 6 controls (10) for individual fixed effects and column 7 controls for both individual fixed effects and adds year dummies. In both cases, the coefficient associated with tenure is much lower than what was predicted in the baseline case.

Although I predicted that tenure should have a negative impact on productivity, it is not surprising that this regression table consistently has positive values for tenure. In the baseline model, tenure merely captures the fact that researchers are always producing more than they were when they first started. This is supported by the fact that the effect of tenure drops with the inclusion of time reliant variables.

Table 8 reports the findings of the FRD design. Allowing the slope and intercept to change at the sixth year of PhD also reveals the true impact of tenure. For all columns of table 8, the constant minus tenure indicates the predicted drop in productivity immediately following tenure. In the figures, this is the drop at the vertical line. Column 1 fits the data to (16) using a second degree polynomial. The value -.295 associated with tenure suggests a 24.3% drop from the predicted value of papers. The interaction terms also indicate that after tenure, the trend in productivity changes from increasing and convex to decreasing and concave. Column two also controls for individual fixed effects. All estimates are significant at the 1% level.

Column 3 fits the data to (16) using a third degree polynomial. The value of -.3412 associated with tenure indicates a 27% drop from the predicted value of papers. The interaction terms also indicate that before tenure, the trend of productivity is rapidly increasing and begins to decline after tenure. Except for the cubic terms, all estimates are significant at the 1% level. Column 5 fits the data to (16) using a forth degree polynomial. The results are similar but estimates are no longer all statistically significant.

I assume that at a small interval the relationship between vintage and productivity can be estimated with a linear function. Column 7 fits the data of vintage 0 to 12 to (16) using a first degree polynomial. The value of -.239 associated with tenure corresponds to a 20% drop from the predicted value of papers. The interaction term also indicates a shift in the productivity trend.

Columns 2, 4, 6 and 8 control for individual fixed effects. Except for the case of the forth degree polynomial, controlling for fixed effects leads to a decrease in the magnitude in the effect of tenure. In column 2, all estimates are significant at the 1% level. In column 4, only the cubic terms are statistically insignificant, and all other estimates are significant at the 1% level. Similarly, trends of the forth degree polynomial are similar but not all estimates are statistically significant.

Table 9 runs the same models as regression table 7 except on the balanced sample. Although the value associated with tenure is initially positive, it turns negative and insignificant after adding terms for vintage and controlling for individual fixed effects. Table 10 runs the same models as table 8 except for the balanced sample. The results are similar to those in table 8 except the immediate impact of tenure on research productivity is only significant when fit to the first degree polynomial. This is similar to what is predicted from the figures. Recall that the figure for the balanced sample didn't have a visible discontinuity at the sixth year of PhD. It is possible that I no longer have statistically significant results because of the reduced sample. The balanced sample is more than eighty percent smaller than the sample restricted from PhD vintage of -10 to 40.

Table 11 show the results of the FRD designs with an AR1 process and fixed effects. Column 1 fits the data to a second degree polynomial. The value .3039 associated with lagged papers indicates that before tenure, producing papers in the year before is an indication of producing more papers in the next year. The value associated with the cross product of tenure and lagged papers indicates that after tenure, the growth in productivity attributed to papers produced in the past period decreases by .0819. One more lagged paper after tenure would indicate .222 more papers, about a 24% increase in papers. The coefficients suggest productivity grows at a rate of .16 papers each year before tenure but changes to .01 papers per year afterwards. The coefficient of tenure is also smaller in magnitude when compared to the corresponding coefficient in table 8. In this model, part of the decrease in productivity originally attributed to tenure is taken by lagged papers after tenure. All estimates are significant at the 1% level.

Column 2 fits the data to a third degree polynomial. The trends are similar. The cubic terms are not statistically significant and the squared terms are significant at the 5% level. All other terms are significant at the 1% level. Column 3 fits the data to a forth degree polynomial. The trends are also similar except fewer terms are statistically significant. Column 4 fits the data to a first degree polynomial. The patterns are the same as the previous regressions where there is quick growth in productivity before tenure, a drop in productivity immediately after tenure, and almost no growth in productivity after tenure. The coefficient of lagged papers after tenure is not statistically significant. This indicates that lagged papers has the same effect on productivity before and after tenure. All other coefficients are significant at the 1% level.

What is the effect of tenure? The results consistently show that tenure has an immediate negative effect on productivity and also leads to a change in the pattern of productivity.

5.3 Ability Bias

In table 8 I find that including fixed effects generally has a negative impact on the effect of tenure while the model predicted that ability bias would bias the estimate of productivity upwards since researchers with higher level of ability are more likely to be tenured faster. However, it could also be true that researchers with the highest levels of ability are lured away from academics by the private sector. In this case we would never observe individuals with high ability in tenured positions. Since the data here deals almost entirely of academic researchers, I disregard the selection problem for now and focus on the apparently absent upward ability bias. Recall omitting ability from (5) leads to a biased estimate of the impact of tenure. Specifically,

$$E(\hat{\hat{\beta}}_0) = \beta_0 + \beta_1 \frac{cov(ability_i,\ tenure_{i,t})}{var(ability_i)}.$$

.

The disagreement in what the model predicts and what is actually observed may be an artifact of how tenure is defined. In the model, tenure is given to all researchers upon reaching the sixth year of PhD and so a researcher's ability isn't actually correlated with the definition of tenure assigned in the model.

To correct for this, I create another measure of tenure.

$$tenure_{i,t} = \begin{cases} 1 & if\ Vintage\ of\ PhD \geq 6\ and\ researcher \\ & is\ associate\ or\ full\ professor \\ 0 & otherwise \end{cases}$$

I hope this captures some aspect of ability since a promotion to full professor early on in the academic career might indicate something about ability. Table 12 reports the results of fitting (16) to a first degree polynomial while using the new definition of tenure. Controlling for fixed effects changes decreases the impact of tenure by .0382. Thus as predicted, controlling for fixed effects alleviates a positive ability bias.

5.4 Serial Correlation

Motivated by Bertrand, Duflo, and Mullainathan (2004) and the fact that the standard errors in the models seem a bit optimistic, I consider the impact that serial correlation may have. First I consider the effect of within group variation by clustering the standard errors for each individual. More specifically, standard errors take the functional form:

$$SE = \frac{var(e)}{\sqrt{N}} \tag{18}$$

where N is the number of researchers multiplied by the number of panels. The low standard errors that are observed could come primarily from the fact that the data is structured in panel form. If errors between individuals are not correlated, extra information about one researcher, or an increase in N, shouldn't be able to lower the standard errors or everyone else. Clustering allows the errors in different time period to be correlated for the same researcher and also assumes that errors between individuals are not correlated. Intuitively this captures for the idea of the adage, "Once a lazy researcher, always a lazy researcher."

Table 13 presents the results of running the FRD fixed effects regressions while clustering the standard errors for each individual. Column 1 of table 13 shows the estimates of fitting (16) to a second degree polynomial with individual fixed effects and clustered standard errors. The standard errors are all higher compared to the estimate without clustering. However, all estimates are still significant at the 1% level. Column 2 of table 13 shows the estimates of fitting (16) to a third degree polynomial with individual fixed effects and clustering. When compared to the estimate without clustering, standard errors are higher for *tenure*, $tenure(vintage - 6)$, and for the constant. However the standard errors of the $(vintage - 6)$ and $(vintage - 6)^2$ terms both change from statistically insignificant to significant at the

10% level.

Column 3 of table 13 has similar results, where standard errors are only higher for the constant. $(vintage-6)^2$ moved form 10% statistical significance to 5% statistical significance. The standard errors of $(vintage-6)$ and $tenure(vintage-6)$ also drop but still do not lead to statistically significant estimates. Column 4 shows the linear case adjusted for clustering. Clustering gives higher standard errors for all estimates. However, all estimates are still significant at the 1% level.

Second, I consider a more specific error structure where the error term is first-order autoregressive. Specifically, the error term takes the form:

$$\epsilon_{i,t} = \rho\epsilon_{i,t-1} + z_{i,t} \tag{19}$$

where stability requires $|\rho| < 1$ and $z_{i,t}$ is an i.i.d. error term.

Table 14 presents the results of running the FRD fixed effects regressions while controlling for AR(1) serial correlation in the error term. Column 1 presents the estimates when the data is fitted to a second degree polynomial. All standard errors are higher than the comparable column in table 8. However, all estimates are still significant at the 1% level. Column 2 presents estimates when the data is fitted to a third degree polynomial. All standard errors are higher than the comparable column of table 8. The squared terms are no longer statistically significant but the terms $(vintage-6)$, $tenure(vintage-6)$, $tenure$ are still significant at the 1% level. Column 3 presents the results when fitted to a forth degree polynomial. When compared to table 8, Estimates of $(vintage-6)$ and $tenure(vintage-6)$ are no longer statistically significant but all other estimates are significant at the 5% level. Column 4 presents data fitted to the first degree polynomial. Standard errors are higher than in the comparable column in table 8. All estimates are significant at the 1% level.

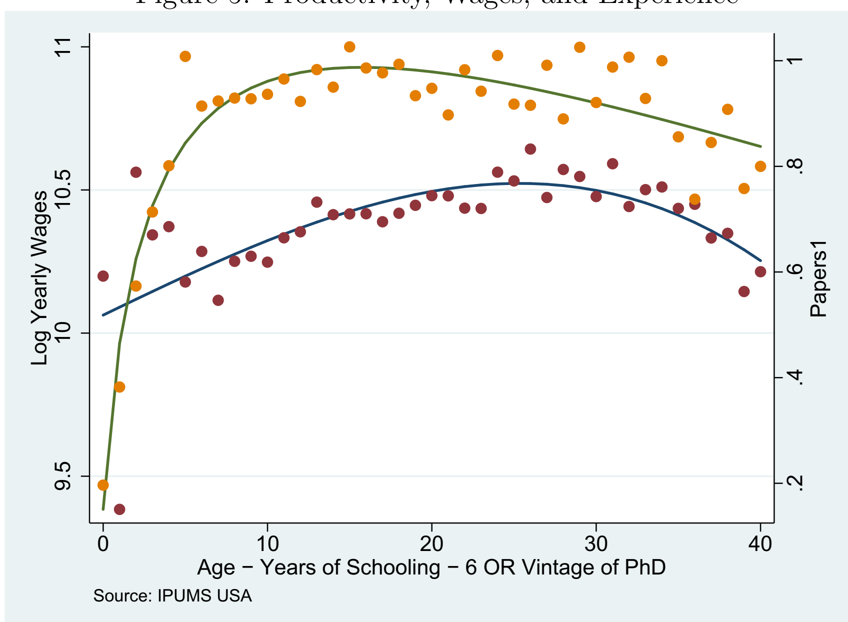
Both clustering and allowing an AR(1) form of serial correlation still gives similar results and except for the forth degree polynomial with AR(1) error specification, results are still statistically significant.

6 Exercise: Productivity, wages, and experience

This paper relates to a broader area in economics: The interaction between productivity and wages. Basic economic theory suggests that wage rates are determined by the value of the marginal product of labor. This section looks at how researcher productivity compares to the general trend of wages in the US.

Using IPUMS USA, I gather data from the 2000 census for white males, age 25-60. The total number of observations in the sample is 12,743. Figure 6 plots log wages and papers1 against experience. The lower line is a polynomial fit estimating the pattern in log wages over time. The higher line estimates productivity over time. When comparing log wages, experience is defined as age minus years in school minus six. When comparing papers1, experience is defined as PhD vintage.

Figure 5: Productivity, Wages, and Experience



Note: Figure plots log wages and raw paper count against experience. The bottom fitted curve is the trend in log wages. The top fitted curve is the trend in productivity.

The scaling on the figure is arbitrary, but the pattern is clear. The graph suggests that researchers reach their peak productivity within 5-15 years of experience. In general, wages reach their peak at around 28 years of experience.

The most compelling suspicion is that job security in academics leads to the difference in patterns of productivity and pay. In order to maintain their jobs and receive promotions, individuals in the private sector must maintain high levels of observable output. On the other hand, professors receive job security and reach the highest level of promotion relatively early on in their careers.

7 Conclusions

What are the patterns of productivity in academics? Most of the literature on academic productivity has focused on patterns in productivity over life cycles. In this paper I consider the impact of tenure. Using the NBER bibliographic database, I investigate whether researchers change their behavior and reduce productivity after job security is guaranteed. My sample consists of 934 academic researchers affiliated with the NBER observed between 1973 and 2009. I consider six years after PhD as the first year of tenure. Evidence indicates productivity drops in the year immediately after tenure. Also the pattern close to the institution of tenure changes from a positive trend to almost no change. I present additional evidence that these findings are robust to various forms of serial correlation in the errors.

These results complement the findings of Ichino and Riphahn (2005). Using data from a large Italian bank, the authors find that the average number of days of absence per week more than triples once the probability of being fired decreases. The results do not support the idea that productivity decreases over time because researchers have to learn about social norms in their jobs or because of some uncertainty about the researcher's ability early on in the career. In both of these cases, the data would show a constant decline in productivity instead of the discontinuity observed right after tenure.

The findings imply that if the university wanted to maximize productivity of its professors, it might want to consider changing the institution of tenure. However, the findings do not necessarily constitute evidence regarding the quality of work. For example, a researcher might have the ability to pursue riskier and longer term projects after attaining tenure. Although this would reflect itself in fewer papers, the work being done could be more influential than work done before tenure.

Perhaps professors, after more than 20 years of schooling and 6 years as assistant professors, where they could probably make more money in the private sector, have earned their freedom to be lazy for a season.

Table 1: Evolution of the number of researchers per year by position.

Year	Assistant	Associate	Full	Total Number of Professors
1973	49	30	20	103
1974	59	30	24	118
1975	62	28	33	128
1976	64	35	36	140
1977	69	32	45	150
1978	72	34	53	167
1979	71	40	64	177
1980	82	47	70	196
1981	94	48	79	218
1982	99	51	86	234
1983	106	53	99	261
1984	112	55	112	280
1985	124	56	128	303
1986	126	64	137	329
1987	141	58	160	352
1988	151	61	178	381
1989	141	77	189	403
1990	152	76	204	424
1991	160	83	217	451
1992	168	79	238	481
1993	167	92	249	510
1994	167	100	267	535
1995	183	101	283	563
1996	196	99	303	599
1997	191	112	324	627
1998	217	107	350	670
1999	241	100	376	714
2000	255	104	392	744
2001	266	122	412	790
2002	278	132	429	829
2003	278	141	452	857
2004	281	144	482	883
2005	278	160	501	908
2006	267	167	525	923
2007	243	176	558	934
2008	216	181	590	934
2009	216	178	593	934

Note: Only contains researchers who were affiliated with the NBER in march 2009.

Table 2: Evolution of the number papers per year

Year	Freq.	Percent
1973	25	0.16
1974	44	0.29
1975	46	0.3
1976	37	0.24
1977	51	0.33
1978	41	0.27
1979	73	0.48
1980	148	0.97
1981	209	1.37
1982	211	1.38
1983	178	1.17
1984	264	1.73
1985	251	1.65
1986	289	1.9
1987	343	2.25
1988	320	2.1
1989	495	3.25
1990	398	2.61
1991	508	3.33
1992	326	2.14
1993	365	2.4
1994	446	2.93
1995	481	3.16
1996	530	3.48
1997	525	3.44
1998	548	3.6
1999	639	4.19
2000	665	4.36
2001	650	4.27
2002	723	4.74
2003	798	5.24
2004	828	5.43
2005	907	5.95
2006	918	6.02
2007	915	6
2008	912	5.98
Total	15,240	100

Note: Total number of papers in the online bibliographic database of NBER working papers. Data was downloaded February, 1 2009.

Table 3: Distribution of PhD Institutions

PhD Institution	Count	Percent
Boston College	2	0.0021
Boston University	2	0.0021
Brown	5	0.0053
Caltech	3	0.0032
Carnegie-Mellon	15	0.0160
City University, London	1	0.0011
Columbia	26	0.0277
Cornell	4	0.0043
CUNY	12	0.0128
DELTA Paris	1	0.0011
Duke	9	0.0096
Goethe Universitat Frankfurt	1	0.0011
Graduate Institute of Internal Studies, Geneva	1	0.0011
Harvard	171	0.1825
HEC School of Management, Paris	1	0.0011
Indiana University	2	0.0021
Johns Hopkins	4	0.0043
KU Leuven	1	0.0011
London Business School	1	0.0011
London School of Economics	8	0.0085
MIT	158	0.1686
New York University	3	0.0032
North Carolina State University	1	0.0011
Northwestern	18	0.0192
Ohio State University	1	0.0011
Oxford	10	0.0107
Pennsylvania State University	3	0.0032
Princeton	59	0.0630
Purdue	1	0.0011
Queen's University	3	0.0032
Rice	1	0.0011
Rutgers	3	0.0032
Stanford University	63	0.0672

Distribution of PhD Institutions Continued		
State University of New York	2	0.0021
Stockholm University	1	0.0011
University College London	1	0.0011
University of Arizona	2	0.0021
University of British Columbia	3	0.0032
University of California, Berkeley	57	0.0608
University of California, Davis	2	0.0021
University of California, Los Angeles	18	0.0192
University of California, San Diego	2	0.0021
University of Chicago	83	0.0886
University of Florida	1	0.0011
University of Illinois	5	0.0053
University of Kentucky	1	0.0011
University of London	1	0.0011
University of Mannheim	1	0.0011
University of Maryland	3	0.0032
University of Michigan	22	0.0235
University of Minnesota	20	0.0213
University of North Carolina	4	0.0043
University of Pennsylvania	19	0.0203
University of Pittsburgh	1	0.0011
University of Rochester	14	0.0149
University of St. Gallen	1	0.0011
University of Texas, Austin	1	0.0011
University of Toronto	3	0.0032
University of Virginia	4	0.0043
University of Washington	3	0.0032
University of Western Ontario	3	0.0032
University of Wisconsin-Madison	19	0.0203
University of Wyoming	1	0.0011
Unknown	1	0.0011
Vanderbilt University	2	0.0021
Yale University	42	0.0448

Table 4: Years of Graduation

Grad Year	Count	Percent
1950	1	0.11
1955	1	0.11
1958	1	0.11
1960	1	0.11
1961	1	0.11
1962	1	0.11
1963	2	0.21
1964	4	0.43
1965	4	0.43
1966	2	0.21
1967	10	1.07
1968	10	1.07
1969	12	1.28
1970	12	1.28
1971	14	1.5
1972	8	0.86
1973	19	2.03
1974	15	1.61
1975	10	1.07
1976	12	1.28
1977	10	1.07
1978	17	1.82
1979	10	1.07
1980	19	2.03
1981	22	2.36
1982	16	1.71
1983	27	2.89
1984	19	2.03
1985	23	2.46
1986	26	2.78
1987	23	2.46
1988	29	3.1
1989	22	2.36

Distribution of year graduated, continued		
1990	21	2.25
1991	27	2.89
1992	30	3.21
1993	29	3.1
1994	25	2.68
1995	28	3
1996	36	3.85
1997	28	3
1998	43	4.6
1999	44	4.71
2000	30	3.21
2001	46	4.93
2002	39	4.18
2003	28	3
2004	26	2.78
2005	25	2.68
2006	15	1.61
2007	11	1.18

Table 5: Frequency of Working Papers: Full Sample

Vintage	Count	papers1	papers2	m1	m2	F(0)	F(1)	F(2)	F(3)	F(4)	F(5)	F(6)	F(7)	F(8)	F(9)	F(10+)
-10-1	831	0.0269	0.0121	0.0178	0.0084	701	88	25	6	4	4	0	1	1	0	1
		(0.0869)	(0.0466)	(0.0657)	(0.0383)											
0-5	906	0.5779	0.3385	0.3391	0.2080	303	101	84	79	70	61	45	31	18	30	84
		(0.7275)	(0.4518)	(0.5934)	(0.3787)											
6-10	851	0.8432	0.4648	0.4485	0.2716	231	94	73	77	74	50	52	35	34	25	106
		(0.9162)	(0.5824)	(0.7593)	(0.5148)											
11-15	668	0.8587	0.4788	0.4653	0.2826	189	76	63	54	51	32	37	32	29	18	87
		(0.9828)	(0.6196)	(0.7829)	(0.5309)											
16-20	508	0.8828	0.4766	0.4212	0.2447	119	66	54	48	30	41	29	23	12	22	64
		(0.9456)	(0.5792)	(0.7001)	(0.4653)											
21-25	380	0.8210	0.4555	0.3353	0.2009	111	50	33	28	30	19	17	22	12	13	45
		(0.9368)	(0.5757)	(0.6459)	(0.4190)											
26-30	261	0.8077	0.4711	0.2797	0.1795	74	31	32	17	21	19	11	12	9	7	28
		(0.9253)	(0.6253)	(0.6023)	(0.4291)											
31-35	167	0.8330	0.4786	0.1920	0.1230	45	20	20	15	13	11	10	6	7	4	16
		(0.9509)	(0.5842)	(0.4323)	(0.2919)											
>35	106	0.6507	0.3876	0.0868	0.0614	31	20	8	10	4	4	4	2	4	2	17
		(0.7637)	(0.4811)	(0.2047)	(0.1535)											

Notes: Vintage indicates the year since PhD with year 0 being the receipt of the PhD. Count is the number of individuals with experience equal to are between the ranges listed. papers1, papers2, m1, and m2 (defined in section 4) are the average number of working papers per period by active individual during each period. F(0), F(1), etc. indicate how many individuals put out 0,1, etc. working papers in each period. Standard deviation in parenthesis.

Table 6: Frequency of Working Papers: Balanced Sample

Vintage	Count	papers1	papers2	m1	m2	F(0)	F(1)	F(2)	F(3)	F(4)	F(5)	F(6)	F(7)	F(8)	F(9)	F(10+)
0-5	236	0.5974	0.3500	0.3506	0.2149	101	23	20	14	8	12	11	5	6	10	26
		(0.7585)	(0.4704)	(0.6180)	(0.3929)											
6-10	236	0.8889	0.4892	0.4729	0.2855	61	24	16	20	10	13	18	13	8	8	45
		(0.9929)	(0.6194)	(0.8088)	(0.5402)											
11-15	236	0.9062	0.5037	0.4893	0.2958	41	26	18	21	17	11	19	15	13	10	45
		(1.0677)	(0.6615)	(0.8283)	(0.5536)											
16-20	236	0.9255	0.4976	0.4358	0.2518	27	26	23	24	14	24	25	17	9	11	36
		(0.9960)	(0.5988)	(0.7245)	(0.4749)											

Notes: Vintage indicates the year since PhD with year 0 being the receipt of the PhD. Count is the number of individuals with experience equal to are between the ranges listed. papers1, papers2, m1, and m2 (defined in section 4) are the average number of working papers per period by active individual during each period. F(0), F(1), etc. indicate how many individuals put out 0,1, etc. working papers in each period. Standard deviation in parenthesis.

Table 7: OLS Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Constant$	0.2574	0.2426	-0.1347	-0.0114	0.3875	0.3537	-0.0289
	(0.0183)	(0.0104)	(0.0700)	(0.0291)	(0.0189)	(0.0115)	(0.0436)
$Tenure$	0.7248	0.7376	0.4577	0.4739	0.1420	0.1442	0.1799
	(0.0151)	(0.0155)	(0.0197)	(0.0169)	(0.0272)	(0.0272)	(0.0269)
$Vintage$					0.0578	0.0588	0.0336
					(0.0019)	(0.0019)	(0.0028)
$Vintage^2$					-0.0018	-0.0018	-0.0018
					(0.0001)	(0.0001)	(0.0001)
$Vintage^3$					0.0000	0.0000	0.0000
					(0.0000)	(0.0000)	(0.0000)
FE?	No	Yes	No	Yes	No	Yes	Yes
year dummies?	No	No	Yes	Yes	No	No	Yes
Observations	25107	25107	25107	25107	25107	25107	25107

Notes: Standard errors in parenthesis. Dependent variable is papers1: the raw count of working papers produced in a given year.

Table 8: Regressions for Fuzzy Regression Discontinuity Design

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
polynomial degree	2	2	3	3	4	4	1	1
constant	1.2155	1.1911	1.2629	1.2395	1.1067	1.0833	1.1543	1.1575
	(0.0351)	(0.0315)	(0.0504)	(0.0479)	(0.0738)	(0.0720)	(0.0409)	(0.0345)
tenure	-0.2957	-0.2936	-0.3412	-0.3407	-0.2085	-0.2096	-0.2399	-0.2387
	(0.0371)	(0.0371)	(0.0535)	(0.0535)	(0.0771)	(0.0769)	(0.0433)	(0.0433)
$(vintage-6)$	0.2170	0.2186	0.2479	0.2502	0.0954	0.0976	0.1636	0.1667
	(0.0092)	(0.0092)	(0.0253)	(0.0253)	(0.0584)	(0.0583)	(0.0089)	(0.0089)
$(vintage-6)^2$	0.0091	0.0091	0.0138	0.0139	-0.0263	-0.0261		
	(0.0006)	(0.0006)	(0.0036)	(0.0036)	(0.0143)	(0.0143)		
$(vintage-6)^3$			0.0002	0.0002	-0.0036	-0.0036		
			(0.0002)	(0.0002)	(0.0013)	(0.0013)		
$(vintage-6)^4$					-0.0001	-0.0001		
					(0.0000)	(0.0000)		
$tenure*(vintage-6)$	-0.2067	-0.2073	-0.2386	-0.2396	-0.0654	-0.0648	-0.1498	-0.1487
	(0.0099)	(0.0099)	(0.0265)	(0.0265)	(0.0600)	(0.0599)	(0.0118)	(0.0118)
$tenure*(vintage-6)^2$	-0.0091	-0.0091	-0.0138	-0.0139	0.0229	0.0225		
	(0.0006)	(0.0006)	(0.0037)	(0.0037)	(0.0144)	(0.0144)		
$tenure*(vintage-6)^3$			-0.0002	-0.0002	0.0038	0.0038		
			(0.0002)	(0.0002)	(0.0013)	(0.0013)		
$tenure*(vintage-6)^4$					0.0001	0.0001		
					(0.0000)	(0.0000)		
Fixed Effects?	No	Yes	No	Yes	No	Yes	No	Yes
Vintage Range	-10 to 40	-10 to 40	-10 to 40	-10 to 40	-10 to 40	-10 to 40	0 to 12	0 to 12
individuals	934.0	934.0	934.0	934.0	934.0	934.0	930.0	930.0
obs	25057	25057	25057	25057	25057	25057	10340	10340

Notes: Standard errors in parenthesis. Table shows the results of the FRD design regressions fit for various degree polynomials with and without fixed effects. Dependent variable is papers1.

Table 9: OLS Regressions: Balanced Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Constant$	0.6081	0.6081	0.7788	0.0741	0.1744	0.1744	0.6485
	(0.0615)	(0.0315)	(0.3852)	(0.2717)	(0.0797)	(0.0597)	(0.3132)
$Tenure$	0.4569	0.4569	0.2444	0.2412	-0.1117	-0.1117	-0.1297
	(0.0373)	(0.0373)	(0.0684)	(0.0701)	(0.0834)	(0.0834)	(0.0853)
$Vintage$					0.2256	0.2256	0.1987
					(0.0286)	(0.0286)	(0.0335)
$Vintage^2$					-0.0156	-0.0156	-0.0169
					(0.0030)	(0.0030)	(0.0034)
$Vintage^3$					0.0003	0.0003	0.0003
					(0.0001)	(0.0001)	(0.0001)
Fixed Effects?	No	Yes	No	Yes	No	Yes	Yes
Year Dummy?	No	No	Yes	Yes	No	No	Yes
observations	4956	4956	4956	4956	4956	4956	4956

Notes: Standard errors in parenthesis. Similar to table 7 except for balanced sample. Dependent variable is papers1.

Table 10: FRD regressions: Balanced Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
polynomial degree	2	2	3	3	4	4	1	1
constant	1.1216	1.1216	1.0989	1.0989	1.1052	1.1052	1.1873	1.1873
	(0.1467)	(0.1368)	(0.2808)	(0.2758)	(0.6691)	(0.6670)	(0.0896)	(0.0692)
tenure	-0.1271	-0.1271	-0.0560	-0.0560	-0.0818	-0.0818	-0.1803	-0.1803
	(0.1464)	(0.1464)	(0.2829)	(0.2829)	(0.6706)	(0.6706)	(0.0857)	(0.0857)
$(vintage - 6)$	0.1162	0.1162	0.0876	0.0876	0.0986	0.0986	0.1655	0.1655
	(0.0895)	(0.0895)	(0.3143)	(0.3143)	(1.0921)	(1.0921)	(0.0178)	(0.0178)
$(vintage - 6)^2$	-0.0070	-0.0070	-0.0165	-0.0165	-0.0106	-0.0106		
	(0.0125)	(0.0125)	(0.1006)	(0.1006)	(0.5716)	(0.5716)		
$(vintage - 6)^3$			-0.0009	-0.0009	0.0003	0.0003		
			(0.0095)	(0.0095)	(0.1185)	(0.1185)		
$(vintage - 6)^4$					0.0001	0.0001		
					(0.0084)	(0.0084)		
$tenure * (vintage - 6)$	-0.0920	-0.0920	-0.1136	-0.1137	-0.0845	-0.0845	-0.1519	-0.1519
	(0.0912)	(0.0912)	(0.3168)	(0.3168)	(1.0946)	(1.0946)	(0.0226)	(0.0226)
$tenure * (vintage - 6)^2$	0.0056	0.0056	0.0243	0.0243	0.0045	0.0045		
	(0.0126)	(0.0126)	(0.1008)	(0.1008)	(0.5721)	(0.5721)		
$tenure * (vintage - 6)^3$			0.0005	0.0005	0.0008	0.0008		
			(0.0095)	(0.0095)	(0.1185)	(0.1185)		
$tenure * (vintage - 6)^4$					-0.0001	-0.0001		
					(0.0084)	(0.0084)		
Fixed Effects?	No	Yes	No	Yes	No	Yes	No	Yes
Vintage Range	0-20	0-20	0-20	0-20	0-20	0-20	0-12	0-12
obs	4956	4956	4956	4956	4956	4956	3068	3068

Notes: Standard errors in parenthesis. Similar to table 8 except for balanced sample. Dependent variable is papers1.

Table 11: AR(1) FRD Regression

	(1)	(2)	(3)	(4)
polynomial degree	2	3	4	1
$constant$	0.9055	0.9172	0.7975	1.0558
	(0.0343)	(0.0499)	(0.0722)	(0.0389)
$papers1_{t-1}$	0.3039	0.3037	0.3023	0.1140
	(0.0148)	(0.0148)	(0.0148)	(0.0177)
$tenure * papers1_{t-1}$	-0.0819	-0.0817	-0.0804	-0.0250
	(0.0159)	(0.0160)	(0.0160)	(0.0198)
$tenure$	-0.2114	-0.2218	-0.1243	-0.2176
	(0.0397)	(0.0553)	(0.0771)	(0.0477)
$(vintage - 6)$	0.1610	0.1686	0.0504	0.1500
	(0.0095)	(0.0252)	(0.0572)	(0.0094)
$(vintage - 6)^2$	0.0066	0.0078	-0.0234	
	(0.0006)	(0.0036)	(0.0140)	
$(vintage - 6)^3$		0.0000	-0.0029	
		(0.0001)	(0.0013)	
$(vintage - 6)^4$			-0.0001	
			(0.0000)	
$tenure * (vintage - 6)$	-0.1529	-0.1611	-0.0234	-0.1340
	(0.0101)	(0.0263)	(0.0589)	(0.0121)
$tenure * (vintage - 6)^2$	-0.0067	-0.0078	0.0201	
	(0.0006)	(0.0036)	(0.0141)	
$tenure * (vintage - 6)^3$		0.0000	0.0031	
		(0.0001)	(0.0013)	
$tenure * (vintage - 6)^4$			0.0001	
			(0.0000)	
FE	Yes	Yes	Yes	Yes
Vintage Range	-10-40	-10-40	-10-40	0-12
obs	24823	24823	24823	10241

Notes: Standard errors in parenthesis. Table shows the results of running the FRD design with an AR(1) process.

Table 12: FRD Regression: Checking ability bias

	(1)	(2)
$constant$	0.9844155	1.021564
	(0.0496)	(0.0383)
$tenure$	-0.0625006	-0.1020401
	(0.0537)	(0.0539)
$vintage - 6$	0.1343495	0.1420112
	(0.0102)	(0.0102)
$tenure * (vintage - 6)$	-0.1196266	-0.1196544
	(0.0140)	(0.0139)
Fixed Effects?	No	Yes
Vintage Range	0-12	0-12
Number of Observations	6337	6337

Notes: Standard errors in parenthesis. Table shows the effect of controlling for fixed effects when the definition of tenure relies on more than just vintage of PhD. Dependent variable is papers1.

Table 13: FRD regressions with fixed effects and clustered standard errors

	(1)	(2)	(3)	(4)
polynomial degree	2	3	4	1
constant	1.1911	1.2395	1.0833	1.1575
	(0.0445)	(0.0574)	(0.0760)	(0.0377)
tenure	-0.2936	-0.3407	-0.2096	-0.2387
	(0.0482)	(0.0583)	(0.0762)	(0.0475)
$(vintage - 6)$	0.2186	0.2502	0.0976	0.1667
	(0.0107)	(0.0233)	(0.0512)	(0.0096)
$(vintage - 6)^2$	0.0091	0.0139	-0.0261	
	(0.0005)	(0.0028)	(0.0113)	
$(vintage - 6)^3$		0.0002	-0.0036	
		(0.0001)	(0.0010)	
$(vintage - 6)^4$			-0.0001	
			(0.0000)	
$tenure * (vintage - 6)$	-0.2073	-0.2396	-0.0648	-0.1487
	(0.0139)	(0.0266)	(0.0559)	(0.0146)
$tenure * (vintage - 6)^2$	-0.0091	-0.0139	0.0225	
	(0.0006)	(0.0030)	(0.0115)	
$tenure * (vintage - 6)^3$		-0.0002	0.0038	
		(0.0001)	(0.0010)	
$tenure * (vintage - 6)^4$			0.0001	
			(0.0000)	
FE	Yes	Yes	Yes	Yes
Vintage Range	-10 to 40	-10 to 40	-10 to 40	0 to 12
obs	25057	25057	25057	10340

Notes: Standard errors in parenthesis. Similar to table 8 except with clustering of errors by researcher. The dependent variable is Papers1.

Table 14: FRD regressions controlling for AR(1) serial correlated errors

	(1)	(2)	(3)	(4)
polynomial degree	2	3	4	1
constant	1.2201	1.2082	1.0677	1.1420
	(0.0300)	(0.0434)	(0.0631)	(0.0383)
tenure	-0.3234	-0.3061	-0.1885	-0.2278
	(0.0433)	(0.0596)	(0.0840)	(0.0511)
$(vintage - 6)$	0.2286	0.2187	0.0655	0.1587
	(0.0129)	(0.0341)	(0.0760)	(0.0140)
$(vintage - 6)^2$	0.0100	0.0082	-0.0366	
	(0.0009)	(0.0055)	(0.0208)	
$(vintage - 6)^3$		-0.0001	-0.0048	
		(0.0003)	(0.0022)	
$(vintage - 6)^4$			-0.0002	
			(0.0001)	
$tenure * (vintage - 6)$	-0.2196	-0.2128	-0.0396	-0.1425
	(0.0140)	(0.0363)	(0.0792)	(0.0169)
$tenure * (vintage - 6)^2$	-0.0100	-0.0080	0.0336	
	(0.0009)	(0.0055)	(0.0208)	
$tenure * (vintage - 6)^3$		0.0001	0.0050	
		(0.0003)	(0.0022)	
$tenure * (vintage - 6)^4$			0.0002	
			(0.0001)	
FE	Yes	Yes	Yes	Yes
Vintage Range	-10-40	-10-40	-10-40	0-12
obs	24123	24123	24123	9401

Notes: Standard errors in parenthesis. Similar to table 8 but controlling for AR(1) serial correlation. The dependent variable is papers1.

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