The Selection of Skills into Sectors: Evidence from the Market for Economists

Boehm, Michael J. and Watzinger, Martin

London School of Economics, Department of Economics, London, University of Munich, Department of Economics

June 2010

The Selection of Skills into Sectors: Evidence from the Market for Economists

Michael Boehm* and Martin Watzinger**

June 2010

PRELIMINARY AND INCOMPLETE: COMMENTS WELCOME

Abstract We study the selection of skills into sectors in an environment with (1) exogenous variation in the attractiveness of sectors and (2) good measurability of skills. More concretely, we examine how the selection into leading economics PhD programs varies with the business cycle and we measure PhD's skills by their publication success. Our results strongly support a selection story: cohorts applying for a PhD- and graduating from a PhD during recession achieve a substantially better publication record if they stay in academia after graduating.

JEL Classification Numbers : J24, J44, I29

Keywords : Sectoral Selection, Skill Composition, Business Cycle, Careers

* London School of Economics, Department of Economics, London

** University of Munich, Department of Economics, Akademiestr. 1, D-80799 Munich, Germany. Phone: +49 89 2180 3953, Fax: +49 89 2180 3954,

We thank Dirk Jenter, Paul Oyer, Andrea Prat, Luis Garicano, Joern-Steffen Pischke, Radha Iyengar, Daniel Metzger and Monika Schnitzer for helpful suggestions. Rafael Winterhalter and Marco-Alexander Schwarz provided invaluable research assistance. Furthermore we want to thank the SFB-TR 15 of the German Research Foundation for financial assistance and J-Stor for providing their Data for Research interface. The authors still argue who of them is responsible for all the errors and omissions.

1 Introduction

There has been a growing interest in labor economics about the effect of macroeconomic conditions on microeconomic outcomes. For example, recent studies have found a substantial and long-lasting impact of recessions on employment, earnings and health outcomes of workers. Yet, the effect of the business cycle on the selection of skill into sectors has not been studied empirically because of the difficulty in measuring individual skills (see also Kim, Morse, and Zingales 2009). In most sectors the observable output depends on the input of several individuals, which makes the task of measuring individual productivity impossible to perform. One sector, however, where individual skills can be readily measured via publication success is academic research.

In this paper, we study the impact of the business cycle at application and graduation on the skill allocation in the academic labor market. This is done by relating the research productivity of economists graduating from top 30 US universities to the change in the unemployment rate during the last 50 years. We identify the causual effect of the business cycle on the skill allocation because the overall unemployment rate is arguably exogenous to the labor market for economists.

The results may help us to understand how quickly and how persistently the skill allocation responds to (temporary) changes in the relative attractiveness of knowledge intensive sectors. For example, they shed light on the potential effect of the recent attractiveness of the financial and consulting sector on the distribution of skilled individuals (e.g Philippon and Reshef 2009). More directly, they provide evidence on the potential effectiveness of some late initatives by the US Congress to increase R&D spending for basic research to increase the supply of scientists (e.g. Goolsbee (1998) and Freeman and van Reenen (2009)).

We find that cohorts who applied for the PhD program during economically bad times publish significantly better on average than boom cohorts. However, a significantly smaller fraction of them is publishing at all. For example, during the first 10 years after graduation, the average PhD student admitted at the 90% quantile of increase in unemployment rate (+1.8%) publishes the impact-equivalent of one single-authored ‘Economica’ article more than the average PhD student admitted when unemplyoment change was at the 10% quantile (-1.0%). The probability that the economist who applied in the recession publishes at all is reduced by 2.9%, compared to an average of 36%. The effect at graduation has the same sign and magnitude for the average research productivity while the propensity to publish appears unaltered by macroeconomic variation at graduation. In the following we consider subsamples of graduates from tier 1 universities and a subsample of PhDs who have at least one publication. In both groups the results become much stronger. Furthermore we conduct extensive robustness checks which confirm our findings.

Taking our estimates literally, we expect the cohort of graduate students who applied for the PhD during the recession of 2008 (3.46% increase in unemployment) to produce on average 16 percent more publication output than a cohort applying in an average year (0% unemployment change). On average they are however 3% less likely to publish at all. Finally, we expect assistant professors who graduated during 2008 to be around 17 percent more productive than assistant professors graduating in an average year.

To arrive at our results, we construct a new dataset of PhD cohorts' publication success from publicly available sources. The dataset consists of graduation years and degree granting universities of 13624 PhDs since 1955. We match each person with all their publications available on JStor. Thus we can calculate the likelihood to publish and the average performance for each economist. Finally, we aggregate each yearly cohort and match macroeconomic conditions at application to the PhD and at graduation obtained from Datastream. In the analysis we use standard OLS regressions to quantify the influence of labor market conditions at application and at graduation on economists' probability to publish and on their productivity.

We interpret our two main results, the better average publication success and lower propensity to publish of "recession economists", in terms of a selection hypothesis: Suppose every individual has a distinct skill for the private sector and for research. Undergraduate students choose their sector of occupation according to their relative skill advantage and their relative career prospects in these sectors. During recession the carreer prospects in the private sector are reduced. This induces individuals with high private sector skill, who would not have applied during a boom, to apply for PhD programs. Because the number of places in graduate education is fixed, they then crowd out graduate students with lower expected academic and private sector ability who would have taken the places in a boom. After the five years of graduate program have passed, students can decide again if they want to enter the private sector. "Recession economist" have a higher average private sector ability and therefore leave academia by a larger proportion. This explains their lower propensity to publish. If a "recession economist", who would have entered the private sector in a boom, decides to stay in academia he outperforms his "boom collegues" because his academic ability was higher in the first place. This explains the higher average publication success of boom cohorts. Our reasoning is similar for cohorts of PhD economists who face a recession at graduation. Given that the number of assistant professor positions does not increase during recessions, we expect them on average to be of higher academic- as well as private sector skill and thus to publish more successfully.

Our results are related to two ongoing research debates. First, we contribute to a recent literature which analyzes the impact of the initial macroeconomic situation on microeconomic outcomes in the labor market. For example, Oreopoulos, Wachter, and Heisz (2008) show that university graduates who enter the labor market during recessions experience substantial short-term earnings losses which fade only after 8-10 years, but that more highly skilled graduates suffer less because they switch to better firms quickly.[1] Our study complements their findings by focusing on the composition of skills within sectors for highly able individuals. In two related articles, Paul Oyer studies the effect of the first job placement for highly skilled indiviuals by the example of MBAs (Oyer 2008) and economics PhD graduates' (Oyer 2006). In order to get exogenous variation, he instruments the first placement using the state of the macroeconomy. He finds that, despite their potentially higher job mobility, MBAs' lifetime earnings and PhD graduates' publication success are substantially negatively affected by adverse macroeconomics conditions. Our results complement his findings by showing that recessions also change the composition of applicants, not only the compositions of job offers.

The second literature we contribute to is concerned with the determinants of scientific productivity and their potential implications for policy makers.[2] As mentioned above, our study is most closely related to the papers that examine the impact of science funding on research productivity. Funding increases, like recessions, raise the attractiveness of the academic sector relative to the private sector. Goolsbee (1998) shows that up to 50% of

[1] In other articles, Till von Wachter and different coauthors examine the effect of recessions on the long term employment, earnings and health outcomes of workers in the US and in Germany (von Wachter, Song, and Manchester 2008, Oreopoulos, Wachter, and Heisz 2008, Schmieder, von Wachter, and Bender 2009, Sullivan and von Wachter 2009).

[2] Some recent studies have exploited exogenous shocks to cooperations between scientists in order to better understand the importance of peer effects (e.g. Waldinger 2009, Azoulay, Zivin, and Wang 2008). Other studies suggest that new communication technologies have changed the production and the dissemination of research (e.g. Kim, Morse, and Zingales 2006, Ellison 2007).

a spending increase goes into higher salaries for scientists and engineers. Suggesting that the supply of such knowledge workers is relatively inelastic, he argues that a large fraction of government research funding may in fact be ineffective and only constitute a windfall gain for scientists. To the contrary, our results imply that, although the quantity does not change, the quality of researchers should increase swiftly and substantially with more funding. Along these lines, Freeman and van Reenen (2009) assert that, at least in the long run, not only the number of scientists but also the selection of talent into science will increase due to higher salaries.

The remainder of the paper proceeds as follows. The next section describes how we assembled our novel dataset of PhD economists' publication success. Section 3 analyzes the effect of the labor market conditions at application and at graduation on the average research success of PhD cohorts. This effect is separated into the probability to publish and the publication success of those who do so in section 4. Section 5 interprets our results in the context of the selection of skills into sectors and provides strong secondary evidence that supports this interpretation. Section 6 concludes.

2 Data

To analyse the effect of macroeconomic variation on the research productivity of economists we collect a new dataset of individual productivity for a large sample of economists in North America from 1955 to 2004. We aggregate the individiduals to university year cohorts and match these with the change in unemployment for the year of application and the year of graduation.

2.1 Economist Sample Selection and Publication Data

We assemble a database of names, graduation years and PhD granting institutions of all economists who graduated from North American Universities since 1955 from the American Economic Association's (AEA) yearly "List of Doctoral Dissertations in Economics". This annual list was published in the Papers and Proceedings issue of the "American Economic Review" until 1986 and in the "Journal of Economic Literature" thereafter. Due to the sheer amount of processed data we employed Optical Character Recognition (OCR) programs and regular expression to convert the data into a computer-readable format. In a next step, we matched the information on PhD graduates to publication data from Jstor's "Data for Research" (DfR) database with the help of a Java program. Specifically, we entered the names and given names of all researchers contained in our database and extracted all recorded publications with journal title, page count and the number and identity of co-authors in the 10 years after their graduation. To be as specific as possible, we restricted our search to articles classfied as "research articles" and published in English language in the fields of economics, business and finance.

The restriction to articles published ten years after graduation (as in Oyer 2006), has three reasons: First, it improves the specifity of the data processing, because economists with the same name who were born in different decades are not matched but kept as different persons. Second, the quality of an economist is arguably best revealed in the first decade after PhD graduation. Academic researchers are highly motivated (incentivized) in this period because their tenure decision depends on the publication record of these first years. Finally, graduates from more recent years would be disadvantaged if we would not restrict the timeframe. Currently Jstor provides full publication data up to the year 2004, so the last individuals we can rightfully analyse using our ten year requirement are those who graduated in 1994.

One drawback of our study is that our recorded publications only entail articles in journals that are listed in JStor. Most noteably, it leaves out Elsevier publications such as the "Journal of Econometrics", the "Journal of Monetary Economics" or the "Journal of Financial Economics". Because we do not believe that either recession or boom cohorts systematically prefer or dislike Elsevier journals, this should be of no issue. In total we use 74 journals including all other major publications in economics and finance. For a list and ranking of the first 40 please refer to table 12. For a detailed discussion of our automated data processing method please refer to Appendix A. In a last step we supplemented the information with the respective tier of the degree granting university according to the NSF.[3]

2.2 Data Processing: Research Productivity, Subsamples & Aggregation

To be able to compare the oeuvre of different economists over time, we calculate a consistent measure of productivity for all researcher in our sample. We multiply each publication of an author by its weight according to a dynamic journal ranking and divide it by the number of coauthors of the paper. We then sum up all these contributions within ten years of graduating from the PhD to obtain a productivity measure for every individual in our sample.

Comparing the value of publications over the decades is difficult because the relative impact of economics journals has changed substantially over time (Kim, Morse, and Zingales (2006)). To account for this, we use for each journal in each decade a specifically calculated relative weight assembled from various sources: For the 1960s through the 1980s we use the ranking from Laband and Piette (1994). For the 1990s and 2000s we use the equivalent ranking published in Kalaitzidakis, Mamuneas, and Stengos (2003) and the recursive discounted ranking pubblished on the "ideas" webpage respectively.[4] For the 1950s we were not able to find a journal ranking and thus decided to extrapolate our 1960s ranking back to articles published in the 1950s. In total we collect impact factors of 74 ranked journals in economics, business and finance for five decades. Table 12 in appendix C provides a table of the dynamic ranking of the top fourty journals used in this study.

For further analysis we take three further steps: First we consider separately graduates

[3]The National Research Council rankings of economics graduate programs divide programs into tiers. The top three tiers include:

- Tier 1 (ranked 1-6): Chicago, Harvard, MIT, Princeton, Stanford and Yale
- Tier 2 (ranked 7-15): Columbia, Michigan, Minnesota, Northwestern, Pennsylvania, Rochester, California-Berkeley, UCLA, and Wisconsin-Madison
- Tier 3 (ranked 16-30): Illinois-Urbana, Boston University, Brown, Cornell, Duke, Iowa, Maryland, Michigan State, New York University, North Carolina, Texas-Austin, Virginia, California-San Diego, University of Washington, and Washington University-St. Louis

Source: http://www.vanderbilt.edu/AEA/gradstudents/

[4]Refer to http://ideas.repec.org/top/top.journals.rdiscount.html. Note, however, that the ranking on the website is updated continuously and thus is not exactly the same as we use in this study.

who publish in one of the ranked journals between year three and year ten after graduation. In the remainder refer to those as group who “publishes”. The three year requirement is intended to sort out graduates who just publish their dissertation but do not conduct further research after the PhD. It turns out that our results are virtually the same if we drop the requirement (see appendix B.3). Second we build subsamples according to the university tier. This is done in order to keep the education and research environment as comparable as possible in the analysis and to compare the effect of our variables of interest on different groups.

Eventually, we do perform one more manipulation of the data, which is innocuous for our results, but which is arguably more appealing from an econometric perspective. We group our graduates’ publication performances and the indicators of whether they publish or not into university-graduation year averages. This reduces the number of our observations from 13,624 individuals who graduated from tier one, two and three universities between 1955 to 1994 to 1,068 cohort means. The grouping entails no loss of information (because we do not use any explanatory or control variables that vary below the university-year level) but the calculation of standard errors becomes significantly easier.[5]

2.3 Macro Data and Timing

One main aim of our study is to relate the publication success of economists to the state of the macroeconomy at the point in time when they decide to enter the PhD program, which we label “at application” in the following.

To impute the application date we subtract the median duration of a PhD from the graduation date and then use the change in unemployment in the preceding year as an indicator for the state of the macroeconomy at application. The median duration of a PhD stayed almost constant with five to six years since the 1970s (see table 1).

For example if a graduate student obtained his doctorate in 2009, he is likely to have started the program either in August 2003 or August 2004 and must have applied either in the fall of 2002 or 2003. At this time, the eventual graduate student finishes his undergraduate degree and decides if he should enter the private labor market or not. Because he is

[5]Angrist and Pischke (2008, 312-315) argue that grouping has advantages from a statistical perspective because the cohort averages should be close to normally distributed even with modest group sizes and there is no need for clustering standard errors on the group level anymore.

Year	1977	1986	1996	1997	2001
	5.7	6.3	5.3	5.25	5.5
	Median years of registered time to PhD	Median years of registered time to PhD	Time to degree	median time-to-degree	Time to degree
Source	Hansen (1991)	Hansen (1991)	NSF*	Stock and Siegfried (2006)	NSF*

*NSF duration data includes masters degress, therefore we subtract 1.5 years

Table 1: Duration of a PhD

a new entrant, the best opportunities for him arise if new jobs are created in the economy. Consequently we proxy the outside option at application for the student who graduates in 2009 with the change in the unemployment rate from summer 2002 to summer 2003. For robustness we also use the change in GDP for this period.

One advantage of this approach is that unemployment data is available for a long period of time. Other potential proxies for the outside option, like job creation numbers and job openings for university graduates or measures of financial services activity are mostly only available starting in the 1970s or later.[6] As we have only 39 years covered (1955-1994) shortening the time period to (1970-1994) would result in a loss of 40% of our underlying data. Furthermore, unemployment change is a continuous variable and therefore more information is preserved compared to, for example, mere recession indicators.[7]

Of course, we cannot be sure that the median number of years is a good measure for the duration of the PhD for the considered graduate.[8] In addition, the overall change in the unemployment rate for the United States might not be the best proxy for the job opportunities of university graduates. As mentioned above, more specialized indicators are generally not available for longer time periods.

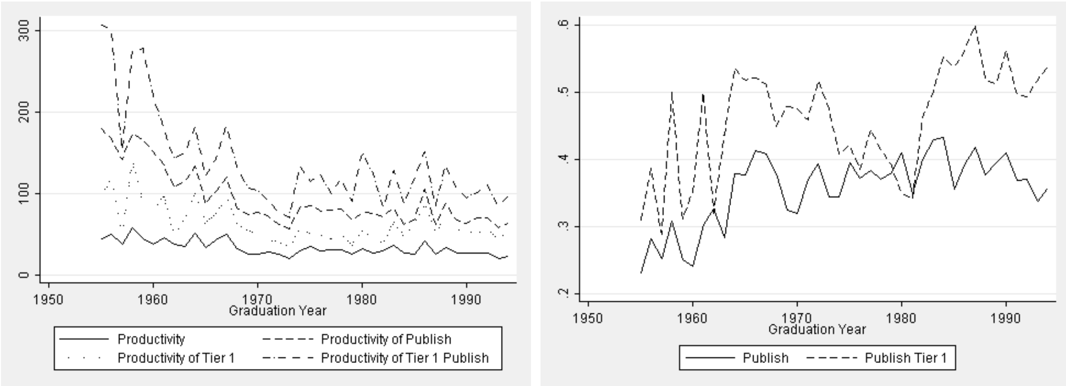
2.4 Descriptive statistics

In this section we summarize the PhD cohorts' average productivity, the average probability to publish and the macroeconomic variation first by graphical exposition and then using

[6]We are indebted to Paul Oyer for sharing his data on financial services activity.

[7]We redid our analysis using NBER recession indicators to arrive at the same qualitative results, however the estimates were not significant.

[8]There is micro data on the duration available with the National Science Foundation Survey of earned doctorates but access is limited to on site use.



(a) performance

(b) probability to publish

Figure 1: Research Productivity over Time

summary statistics. The average probability to publish here is simply the probability that a graduate publishes in between years three and ten after finishing his doctorate.

Panel (a) in figure 1 depicts the average productivity of the PhD cohorts for every year in our analysis. More specifically, it distinguishes between the average productivity of all the graduates, of the tier one subsample, and of those graduates that ”publish” among these two groups. As expected, we see that the performance measures move together to a substantial degree and that the performance of academics from the elite universities is highest. Panel (b) in figure 1 graphs the probability to publish for the full sample and the tier on subsample over the years. Again, the graph for the two groups move together and the probability of publishing is higher for the tier one graduates.

Table 2 provides further summary statistics of our dependent variables. We see that on average only 36 percent of the full sample and 44 percent of the tier one subsample publish in a ranked journal from year three to year ten after graduation (“publish”). Productivity is expressed in publication points. In order to translate those in terms of articles in a certain journal, one has to take into account that the importance of journals changes over time. For example an American Economic Review (AER) article in the 1990s was worth 100 publication points.[9] Therefore the average ten year productivity of a university-year cohort in the full sample is about the equivalent of a third of an AER article in the 1990s. The average productivity of an economist graduating from a tier 1 university is about double, i.e. approximately the equivalent of two thirds of an AER article in the 1990s. If we

[9]Please refer for a more detailed interpretation to appendix C.

	mean	sd	min	max	p10	p90	p50
Productivity	33.17	9.09	19.70	57.47	24.96	47.13	30.90
Publish	0.36	0.05	0.23	0.43	0.27	0.41	0.37
Productivity of Publish	93.69	35.29	56.32	179.37	61.74	157.89	80.06
Productivity of Tier 1	62.97	23.50	33.93	139.50	41.97	96.13	54.27
Publish Tier 1	0.46	0.08	0.29	0.60	0.33	0.55	0.48
Productivity of Tier 1 Publish	138.64	60.33	70.12	306.21	84.93	246.64	122.02
Observations	40						

Table 2: 10 year Productivity Distribution

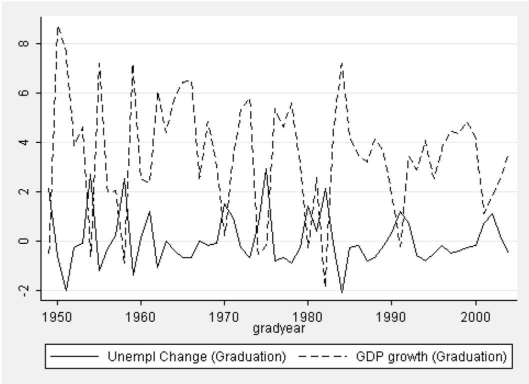


Figure 2: Unemployment Change and GDP Growth

only consider economists who do publish, then an economist from tier 1 to 3 universities publishes about one and a tier 1 economist produces on average 1.4 AER articles in the 1990s.

Finally, the high fraction of graduates that never publish already suggests that research economists' productivity is highly skewed with a few "superstars" publishing a multiple of what the average graduate achieves. Appendix B.2 describes the extent to which this is the case and uses methods, such as quantile regressions and restricted samples, to check the accuracy of our results in the main text, which turn out robust.

With respect to our independent variable figure 2 plots the change in the unemployment rate and GDP growth from 1949 to 2004 and table 3 provides descriptive statistics about these variables at application to the PhD and at graduation for the cohorts from 1955 to 2004. GDP change and unemployment change move more or less in lockstep.

	mean	sd	min	max	p10	p90	p50
Unempl Change (Graduation)	-0.00	0.97	-2.10	2.90	-0.85	1.30	-0.20
Unempl Change (Application)	0.01	1.11	-2.10	2.90	-1.00	1.80	-0.25
GDP growth (Graduation)	3.40	2.20	-1.94	7.20	-0.22	6.24	3.52
GDP growth (Application)	3.52	2.50	-1.94	8.74	-0.39	6.84	3.66
Observations	50						

Table 3: Summary Statistics of the Macro-Variables

3 Macroeconomic Conditions and PhD Cohorts' Average Research Productivity

3.1 Graphical Relationship and Empirical specification

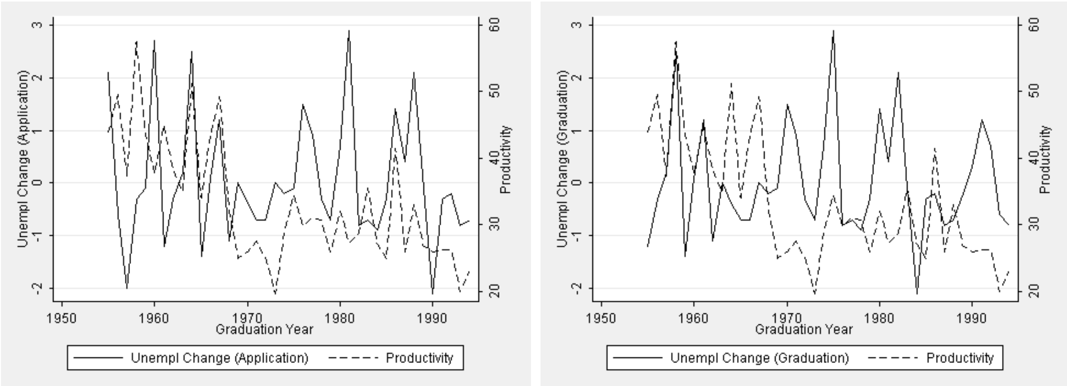
To get an initial sense of the degree to which the macroeconomic conditions at application and at graduation are related to the average performance of a cohort, we plot in figure 3 the average productivity of our full sample over time.

Productivity is compared to the change in unemployment at application and at graduation on the left- and the right-hand side, respectively. Graph 3(a) shows that the unemployment rate at application moves quite closely together with our productivity measure of cohort quality. The relationship of average performance with unemployment at graduation shown in panel 3(b) seems about equally pronounced. Hence, by just looking at the graphs of averages, we can see that our conjecture that productivity differences of cohorts should relate to the business cycle at application as well as at graduation may have some merit.

We now more formally analyse the relationship between the macroeconomy and the productivity of the corresponding PhD cohorts. To do this, let q_{it}, the performance of a cohort of PhD students from university i who graduate in year t, be determined by the following equation:

$$q_{it} = \beta x_t + \gamma y_t + controls_{it} + \epsilon_{it} \tag{1}$$

The first regressor x_t represents our measure for the macroeconomic situation when the cohort applied for the PhD while y_t represents the same measure at graduation



(a) At Application (b) At Graduation

Figure 3: Change in Unemployment and Average Research Productivity

from the PhD. In the following, this is mainly the change in the unemployment rate and, for robustness checks, the growth of GDP.

Furthermore, in each regression we include dummies for the university and the decade of graduation as well as the full set of interaction terms. The university dummies adjust for differences in PhD education between universities and the decade dummies control for different levels of competition and structural changes in the field of economics over time. This is appropriate because the standards of publication have changed considerably over time (e.g. Ellison (2002a) and Ellison (2002b)).

In further regressions we also control for linear and quadratic time trends and the number of graduates per university and year to check for robustness.

3.2 Regression Results

The OLS regression results of estimating our main specification of equation (1) along with several robustness checks, are displayed in table 4.

Regression (1) is our preferred specification: Here we regress the average academic productivity of each cohort on unemployment change at application and graduation. To control for the changing research environment we use university and decade dummies. In order to have our standard errors reflect the microdata, we weigh the observations by the number of underlying graduates.[10]

[10]This is done because smaller (lower tier) universities with only one or two underlying graduates

	(1)	(2)	(3)	(4)	(5)	(6)
Unempl Change	2.281***	1.656*		2.443***	4.307*	4.071
(Graduation)	(3.15)	(1.76)		(3.04)	(1.97)	(1.45)
Unempl Change	1.509**	0.985		1.514**	5.316**	7.703***
(Application)	(2.16)	(1.10)		(2.13)	(2.53)	(2.94)
GDP growth			-0.711**			
(Graduation)			(-2.12)			
GDP growth			-0.641**			
(Application)			(-2.02)			
Adj. R-Squared	0.515	0.380	0.512	0.514	0.371	0.320
N	1068	1068	1068	1068	234	234

Note: Regressions (1) and (3) are OLS with observations weighted by cohort size. In regression (2) observations are not weighted by cohort size. In column (4) a linear and quadratic time trend is added. Regression (5) and (6) restrict the sample to tier 1 weighted and unweighted by cohort size, respectively. t statistics are in parentheses. *, ** , *** indicates significance at the 1%, 5% and 10 % level.

Table 4: Effect of Macroeconomic Conditions on Research Productivity

The second cell in column (1) reports that the coefficient on x_t is positive and significant at the five percent level. More specifically, high unemployment change at application leads to above average research productivity of the resulting cohort. Hence, column one provides support for our hypothesis that cohorts who apply during a recession are on average of higher quality than boom cohorts. We can interpret this result causally under the assumption that the unemployment change at application is exogenous to all other factors influencing a cohort's publication success.

Further, the effect is also of an economically significant magnitude: taking our linear regression model seriously, a cohort on the 90% quantile of unemployment change at application is expected to achieve 4.22 publication points more than a cohort at the 10% quantile. This is around thirteen percent of the average publication success of 33.17 or the equivalent of one single-authored "Economica" publication in the 1990s for every economist in the university-year cohort.[11]

would otherwise obtain the same weight in this regression as observations from the larger (higher tier) universities with up to 56 graduates in Harvard in the year 1971 (see Angrist and Pischke (2008, 313-314)).

[11]Referring to table 3, the difference between the 10 and the 90 percent quantile of unemployment change in our data is 2.8. Multiplying this by the parameter estimate of 1.509 gives a difference in average productivity between "boom" and "recession" cohorts of 4.22 publication points. Referring to table 12, this is about the number of publication points one gets assigned for an article in

To check this result for robustness we estimate several variants of the model. In regression (2) we do not weigh the observations according to the underlying number of graduates. The direction of the effect remains the same, but it is less strong and the significance disappears. This may be the case because some observations with only very few underlying graduates receive "undue" weight. In regression (3) we use GDP change instead of unemployment change as the measure of our macroeconomic variation. Of course, the sign of the coefficient reverses but the interpretation is unchanged. Recession cohorts (when unemployment change is high and GDP change is negative) are significantly better than boom cohorts. In specification (4) a linear and a quadratic time trend are employed in addition to the decade dummies to control for potential time trends. The results of this potentially more robust model are identical to our preferred specification (1).

Regressions (5) and (6) reestimate the model on the subsample of graduates from tier one universities. Our hypothesized quality effects might be best measured on this subsample because graduates from lower ranked universities are less likely to publish in general. Even if there is a quality change of these cohorts when they are from a recession, we may have a somewhat harder time measuring it because some of the graduates could be too far below the publication threshold. Graduates from the leading universities are more likely to be able to publish throughout the whole business cycle, therefore we can more easily measure variation in publication quality conditioned on unemployment change.

The results are as expected. The direction and significance for the tier one subsample are the same as in the full sample, but the size of the parameter roughly quadruples. The economic significance of the effect is also larger. A cohort applying on the 90% quantile of unemployment change achieves on average 14.8 publication points more than a cohort applying on the 10% quantile. This is about 24% of their average of 62.97 publication points and the equivalent of one single-authored "Journal of Labor Economics" article in the 1990s.[12]

"Economica" during the 1990s. From table 2, we also find that the "average" PhD graduate achieves 33.17 publication points.

[12]Note that the last column does not weigh the observations by the underlying number of grad-

Finally, table 4 also reports the effect of the macroeconomic condition at graduation on the performance of PhD cohorts. Cohorts graduating in a recession perform on average better than cohorts graduating in a boom. The effect has the same magnitude as the effect at application and is significant in all but one specification. Its economic size is also of a similar magnitude as the effect at application: If one compares the cohort that graduated at the 10% quantile of unemployment change with the cohort at the 90% quantile, then the latter achieves on average 5.13 publication points more. This is again around 15% of the mean and equivalent to a bit more than one single-authored "Economica" in the 1990s in terms of articles.

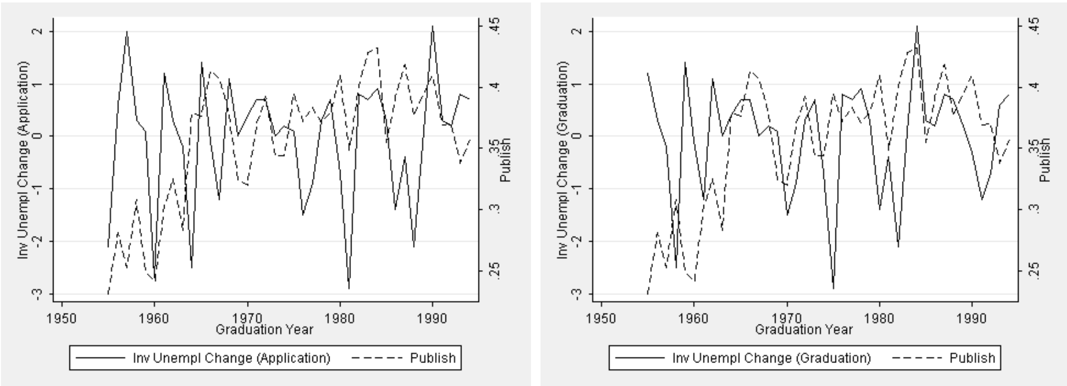
4 Propensity to Publish and Productivity of Those Who Do

In this section, we separate the positive effect of recessions on the quality of PhD economists into two components. The propensity publish after graduation and the productivity conditional on publishing at least one piece.

In the previous section we found that recession cohorts turn out to be more academically productive on average. At this point, we would like to know, however, if this is due to the fact that recession researchers are more likely to publish or that they publish more given that they publish (i.e. extensive versus intensive margin effects). In general, the likelihood to publish may be driven by two effects. On the one hand, there may be a quality effect where more able individuals are more likely to publish. On the other hand, there may be an outside option (or preference) effect such that members of some cohorts are more likely to choose the academic career path after the PhD and thus publish.

In the following, we find that, despite appearing more able, recession cohorts at application have a lower propensity to publish while the macroeconomic conditions

uates. Contrary to the regression in column (2) for the full sample, this does not change much our results in the tier one subsample because these cohorts are relatively large and do not differ too much in size. Consequently there are only few small observations that receive undue weight.



(a) At Application (b) At Graduation

Figure 4: Change in Unemployment and Propensity to Publish

at graduation have no effect on the likelihood to publish. In section 5 we argue that the former result may reflect the fact that outside options (in other sectors) have a stronger influence on whether someone publishes than ability differences. Further, we will argue that the previous sections' estimates thus rather constitute a lower bound for the quality differences between boom and recession cohorts.

4.1 Graphical Relationship and Empirical Specification

Figure 4 depicts the fraction of economists who publish every year together with the inverse of the change in unemployment at application to the PhD (panel 4(a)) and at graduation (panel 4(b)). We depict the inverse of the unemployment change in order to facilitate the visual inspection. Although not as clearly as in the graphs of the last section, we can see that the fraction of graduates who publish moves together with negative unemployment change. More graduates from boom cohorts seem to publish. It is much harder to find any visual relationship between the propensity to publish and the macroeconomic sitution at graduation.

The empirical specification is the same as in equation 1, except that we substitute our measure of academic productivity of each university-graduation year cohort by the fraction p_{it} that publishes in a ranked journal between years three and ten after graduation.[13]

$$p_{it} = \beta x_t + \gamma y_t + controls_{it} + \epsilon_{it} \tag{2}$$

4.2 Regression Results

Table 5 estimates equation 2 for our preferred specification and several other specifications in oder to check for robustness of the relationship. The regression models in the different panels are the same as in table 4. Our preferred weighted full sample model is presented in the first column. It is followed by the non-weighted model, the model with GDP growth as the proxy for the macroeconomy and the model with linear and quadratic time trends. Regressions (5) and (6) restrict the sample to tier one graduates with and without weighing, respectively.

The second cell in column (1) reports that the effect of the unemployment change at application on the propensity to publish is negative and significant. A one percent higher unemployment rate is associated with a 1.03 percent lower probability to ever publish. Cohorts that applied for the PhD during recession are thus significantly less likely to ever publish than boom cohorts.

In order to get an idea about the size of the effect, consider a cohort on the 10% quantile of unemployment change at application versus one at the 90% quantile. The fraction who publish in the former (the boom cohort) is 2.9% higher than in the latter. This is about 8% of the mean likeliness to publish (see table 2).

The alternative specifications for the full sample regression in columns (2) to (4) reinforce this interpretation. The mean estimates for the tier one subsample are of the same magnitude as in the full sample, but the coefficients are not statistically significant on any common level.

To sum up: although the difference is not large in magnitude, it is statistically significant and it may reflect the fact that outside options (in other sectors) have a stronger influence on whether someone publishes than ability differences. Moreover,

[13]Note that the dependent variable here is bounded between zero and one. Had we not constructed university-graduation year averages and were we thus to estimate this equation on the underlying microdata, our specification would be called a linear probability model.

	(1)	(2)	(3)	(4)	(5)	(6)
Unempl Change	0.00227	-0.000557		0.00275	0.00215	0.00832
(Graduation)	(0.54)	(-0.10)		(0.59)	(0.27)	(0.87)
Unempl Change	-0.0103**	-0.0149***		-0.00800*	-0.00979	-0.00804
(Application)	(-2.54)	(-2.70)		(-1.96)	(-1.28)	(-0.90)
GDP growth			0.000901			
(Graduation)			(0.47)			
GDP growth			0.00464**			
(Application)			(2.53)			
Adj. R-Squared	0.421	0.253	0.421	0.428	0.404	0.284
N	1068	1068	1068	1068	234	234

Note: Regressions (1) and (3) are OLS with observations weighted by cohort size. In regression (2) observations are not weighted by cohort size. In column (4) a linear and quadratic time trend is added. Regression (5) and (6) restrict the sample to tier 1 weighted and unweighted by cohort size, respectively. t statistics are in parentheses. *, ** , *** indicates significance at the 1%, 5% and 10 % level.

Table 5: Propensity to become an academic

our estimate for the difference in academic productivity at application from section 3 should thus constitute a lower bound for the underlying academic ability differences between recession and boom cohorts.

Table 5 also reports the effect of the macroeconomic conditions at graduation on the fraction of graduates who publish. In none of the different specifications do we find a significant effect. Further, the magnitude of the coefficient estimates is very low and their signs are changing over the different specifications.

We conclude that, according to our data, the macroeconomic situation at graduation has no effect on the propensity to publish. This may seem surprising because one would expect that during a recession more graduates would try to stay in academia and thus not only would a recession cohort's average productivity be higher as in table 4, but also the fraction of individuals who publish. In section 5 we show that this effect may be offset by a lower amount of academic jobs available during recession.

4.3 Productivity of Those Who Publish

To complete our regression analysis, we examine the productivity of those who do publish. One should keep in mind that, according to our results so far, those who publish are not a random selection of each graduating class. Also, we expect that the effect of macroeconomic conditions at application is even stronger in the "publish" subsample. The reason is that, although recession cohorts feature a larger fraction of graduates who don't publish, their average performance is higher. If we eliminate those who do not publish, the effect should increase further.

We run regression 1 for the subsample of the graduates who publish. Table 6 reports the results. Both, unemployment change at application and at graduation, are now highly significant and the parameter estimates for the effect more than double. If we compare cohorts at the 10% and 90% quantile of unemployment change at application, the 90% quantile cohort has on average 11 publication points more, which is about 12% of the mean. This corresponds to a single-authored "Rand Journal of Economics" publication in the 1990s for every economist in the university-year cohort.

The remaining columns of table 6 reinforce this impression. One interesting thing to note is that the effect at application is statistically and economically stronger for the tier 1 subsample. A cohort at the 90% quantile of unemployment change is 34 publication points better than a cohort at the 10% quantile. This is about 25% of the mean and in publication points it is about a third of a single-authored AER article in the 1990s.

5 Interpretation and Discussion

We can causally interpret our estimation results from the previous two sections because the business cycle is arguably exogenous to these microeconomic outcomes. However, we cannot test our hypothesis of the selection of skills into sectors directly. In this section we provide ecoomic theory and secondary evidence that we think is convincing enough to confidently endorse the selection hypothesis.

Section 5.1 shows that the number of spaces in academia is relatively stable over

	(1)	(2)	(3)	(4)	(5)	(6)
Unempl Change	4.607***	3.746*		4.447***	6.797*	6.909
(Graduation)	(2.98)	(1.86)		(2.59)	(1.83)	(1.47)
Unempl Change	3.884***	3.274*		3.522**	12.27***	18.20***
(Application)	(2.59)	(1.70)		(2.32)	(3.44)	(4.12)
GDP growth			-1.543**			
(Graduation)			(-2.16)			
GDP growth			-1.774***			
(Application)			(-2.61)			
Adj. R-Squared	0.477	0.409	0.474	0.477	0.422	0.476
N	950	950	950	950	226	226

Note: Regressions (1) and (3) are OLS with observations weighted by cohort size. In regression (2) observations are not weighted by cohort size. In column (4) a linear and quadratic time trend is added. Regression (5) and (6) restrict the sample to tier 1 weighted and unweighted by cohort size, respectively. t statistics are in parentheses. *, ** , *** indicates significance at the 1%, 5% and 10 % level.

Table 6: Effect of the Macroeconomy on the Productivity Those Who Publish

the business cycle while the number of people who seek to enter it is countercyclical. This creates a "better" selection of academic cohorts during recession. Section 5.2 formalizes this notion using a modification of the Roy (1951) model. In section 5.3 we discuss how our paper relates to the well-known article by Paul Oyer (2006).

5.1 The Business Cycle's Relationship with Application Numbers, Program Sizes, and Academic Positions for Graduates

A core channel for our selection hypothesis is the conjecture that more individuals would like to enter academia (graduate programs or assistant professorships, respectively) in economically bad times. Given that there is a (relatively) stable number of spaces in academia, the selectivity of academic positions should be higher during recession. Unfortunately, meaningful application numbers or ability measures of entry cohorts into economics PhD programs (such as average GRE results) are unavailable to us. The institutions we have contacted requesting such data were not able to provide us with it due to confidentiality reasons.

However, there exists some secondary evidence for our hypothesized channel. In a recent study, Bedard and Herman (2008) find that male science undergraduates become on average 15% more likely to enrol in a doctoral program if the unemployment rate rises by 1%. They locate the main effect at the students with a GPD above 3.75, i.e. the very strongest students of their respective cohorts. This is in line with our theory at application.

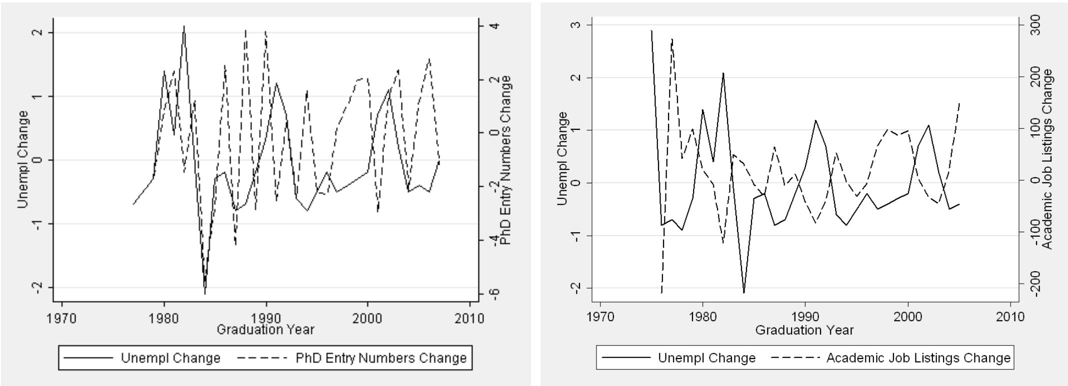
Gallet, List, and Orazem (2005) show for the years 1995 and 1997 that PhDs from lower ranked institutions search more for business jobs if the job market is weak. At the same time institutions only hire from the top PhD programs. In a related sector, Fougere and Pouget (2003) find that the applications per spaces ratio in the French public sector rises strongly in economically hard times. These pieces of evidence support our theory at graduation that during weak job markets more individuals seek employment in academia.

The second component of our selection hypothesis states that the number of spaces in academia should be relatively stable over the business cycle. Figure 5 plots the change in unemployment together with the change in the number of entrants into economics PhD programs and the number of academic jobs listed on the American Economic Association's (AEA) website.[14] Panel 5(a) suggests that the number of students admitted to graduate programs in economics is not systematically related to the business cycle. This impression is confirmed when calculating correlations between the two variables, which we do not report here.[15]

In panel 5(b), we see that the number of new jobs offered for economists who graduate with a PhD is clearly procyclical. More academic jobs are offered in times when the general unemployment rate falls and vice versa. This result is confirmed by a more formal statistical analysis (we find that the relationship is highly significant) and by Oyer (2006) who analyses the same data. This does not necessarily have

[14]The former data is from the NSF.

[15]Note that the change in the number of PhD entrants, which is in fact very stable, appears to be fluctuating a lot in the figure because of the scale of its axis. On average, each program takes on about 35 students and the yearly deviations from the mean are mostly below 4 students.



(a) PhD Entry Numbers (NSF Data) (b) AEA Academic Job Listings

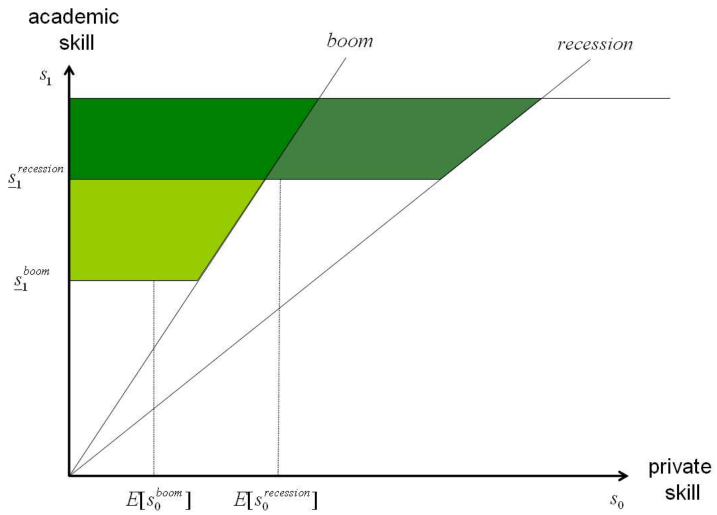
Figure 5: Unemployment Change and Change in “Academic Spaces”

to imply that less economists obtain academic positions during recession, as they might exert increased effort of search and a higher willingness to fill less attractive positions that may not be filled in good years. Thinking of publishing as an indicator of whether someone holds an academic position, in our data we find that recession economists are as likely to publish as boom cohorts. Nonetheless, the data supports our hypothesis that the competition for academic positions becomes fiercer during recession.

5.2 A Modified Roy (1951) Model with Quantity Constraints

The above results suggest that the number of positions available in academia does not increase with higher demand during economically hard times and that they might in fact decline. Further, more students and PhD graduates seem to be willing to take up academic positions during recession. Figure 5.2 presents a modification of the well-known Roy (1951) model of the selection of skills into different sectors into which we introduce quantity constraints in the academic sector. This modified model is able to bring together our above findings and the regression results from the main part of the paper (sections 3 and 4):

Peoples’ skills (or talent) in the population of potential applicants for an eco-



nomics PhD are distributed in two dimensions - academic and private sector skill.[16] During recession, the cutoff line of people who would prefer academia to private sector employment moves to the right compared to a boom, i.e. additional candidates would like to do a PhD.[17] If, as in the graph, the number of spaces in PhD programs are the same during recession as during boom and selection committees base their admission decision on (expected) academic skill, the lowest academic skill that can still enter the PhD will rise from $\underline{s}_1^{boom}$ to $\underline{s}_1^{recession}$. Also, the average private sector skill rises from $E[s_o^{boom}]$ to $E[s_o^{recession}]$. More generally, the distribution of skills of recession cohorts will first-order stochastically dominate that of boom cohorts in both sectors.

The model thus predicts that economists who applied for the PhD during recession will be of higher academic as well as private sector skill. If, at graduation, the economy is not in recession anymore and the cutoff line moves to the left, a higher fraction of them will choose private sector employment than of a boom cohort. Also, because of their higher ability, they will in general publish more than the members of a boom cohort. We find both of these predictions hold true in our empirical analysis of the

[16]For ease of exposition, the distribution of skills is uniform in the graph. However, our predictions should be robust to any specific distributional assumption.

[17]The threshold doesn't have to be a straight line as in the original Roy model where it represents the relative price for the two tasks. Instead, we only need that it is monotonic and that in a recession it (weakly) moves to the right.

effect of the business cycle at application.

Moreover, we can use the model to make predictions about the effect of the business cycle at graduation. Now the underlying population is all the economics PhD graduates in a given year. If the economy is in recession, additional economists, who would otherwise have chosen private sector employment, will try to find academic employment. Given that the number of academic positions doesn't increase (or in fact decreases), only the best of them will get an academic job. This leads to a more able cohort of young assistant professors in the respective year and it should be reflected in more academic output. Our regression results confirm this prediction. Further, as everyone who graduates from a top 30 university and secures an academic job should be able to write at least some publications in ranked journals (there are 74 different ones in our dataset), we do not expect boom or recession cohorts at graduation to differ much in their likeliness to publish. This is again consistent with our data.

To summarize, we believe that the business cycle drives the selection of skills into economics PhD programs and into academic versus private sector employment after graduation. This hypothesis is consistent with our empirical evidence and with a convincing theory based on the Roy model.

Finally, note that if we run a standard Heckman selection regression (1976) on data generated by a model with quantity constraints in one sector as in figure 5.2, we will virtually always obtain a positive estimate for the correlation between the two skills. This is the case because, under quantity constraints, individuals of higher skills in both sectors replace individuals of lower skills systematically with the business cycle. We have run such a misspecified Heckman regression on our data and, unsurprisingly, obtained a positive correlation between the two skills.

5.3 Comparison to Paul Oyer's (2006) Paper

Before we conclude, we should more explicitly relate our study to the well-known paper by Paul Oyer (2006) which inspired our work. Oyer studies how their initial academic placement affects economics PhDs' long term outcomes, including publication success. Because an economist's first placement is strongly affected by his unobserved ability, Oyer instruments it using the rate of unemployment or the number of AEA job listings in the respective year. This identification strategy is sensible because the first stage estimates show that initial job placement is significantly correlated with the state of the macroeconomy, i.e. negatively correlated with the unemployment rate.

Given the results of our paper, however, Oyer's instrument should be correlated with the expected ability of individuals who decide to pursue academic jobs. We found that, during recession, more academically able individuals select themselves into the academic career than during a boom. Therefore, Oyer's parameter estimates for the impact of the first placement on academic productivity should be downward biased and in fact his effect should be stronger. Indeed, they do not turn out robustly positive and significant in his paper (see table 6 in Oyer (2006)). By the same token, our estimates of the unemployment rate's impact at graduation on productivity in table 4 may constitute a lower bound of the difference in academic skill between boom and recession cohorts.[18]

More generally, there is a conceptual difference between the focus of the two papers. Oyer exploits how the favorability of the selection into institutions, which are (vertically) ranked, changes with the business cycle. We study how individuals (horizontally) select themselves into sectors depending to the macroeconomic conditions. Oyer focuses on the changes in demand for economists while we focus on the supply decision by economists over the cycle.

6 Conclusion and Implications

This paper has investigated the effect of adverse labor market conditions at application on the long term research productivity of economics PhDs in the United States. We have also studied the effect on PhDs' probability to publish and the effect of the macroeconomy at graduation. We find that recession cohorts at application as well

[18]This is the case because, according to Oyer's study, boom cohorts have the advantage of (relatively) better initial academic placements and their effect on publications.

as at graduation publish significantly better than boom cohorts, but that those who apply in a recession are less likely to publish at all. Our results suggest that the quality of skills selected into academia varies with the business cycle and thus with the relative attractiveness of the private sector versus academia.

Given the severity of last year's financial crisis and the large extent to which people flooded graduate schools with applications in response, our paper suggests that an exceptionally able selection of students may graduate from these cohorts. Further, we provide a rationale for countercyclical funding of education by the government that goes beyond mitigating the adverse impact of recessions on individuals. If it is the aim of the government to get more high-ability individuals into science and academia, it may in fact be efficient to specifically target recession cohorts with extra funding and to provide additional spaces in graduate programs for them.

References

Angrist, J. D., and J.-S. Pischke (2008): *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton University Press.

Azoulay, P., J. S. G. Zivin, and J. Wang (2008): "Superstar Extinction," Mimeo.

Bedard, K., and D. A. Herman (2008): "Who goes to graduate/professional school? The importance of economic fluctuations, undergraduate field, and ability," *Economics of Education Review*, 27(2), 197–210.

Ellison, G. (2002a): "Evolving Standards for Academic Publishing: A q-r Theory," *Journal of Political Economy*, 110(5), 994–1034.

——— (2002b): "The Slowdown of the Economics Publishing Process," *Journal of Political Economy*, 110(5), 947–993.

——— (2007): "Is Peer Review in Decline?," NBER working paper.

Fougere, D., and J. Pouget (2003): "Who Wants to Be a ŚFonctionnaireŠ? The Effects of Individual Wage Differentials and Unemployment Probabilities on the Queues for Public Sector Jobs," *Mimeo*.

Freeman, R. B., and J. van Reenen (2009): "What if Congress Doubled R&D Spending on the Physical Sciences?," Mimeo.

Gallet, C. A., J. A. List, and P. F. Orazem (2005): "Cyclicality and the Labor Market for Economists," *Southern Economic Journal*, 72(2), 284–304.

Goolsbee, A. (1998): "Does Government R&D Policy Mainly Benefit Scientists and Engineers?," *The American Economic Review*, 88(2), 298–302.

Hansen, W. L. (1991): "The Education and Training of Economics Doctorates: Major Findings of the Executive Secretary of the American Economic Association's Commission on Graduate Education in Economics," *Journal of Economic Literature*, 29(3), 1054–1087.

Heckman, J. J. (1976): "The Common Structure of Statistical Models of Truncation, Sample Selection and Limited Dependent Variables and a Simple Estimator for Such Models," pp. 120–137.

Kalaitzidakis, P., T. P. Mamuneas, and T. Stengos (2003): "Rankings of Academic Journals and Institutions in Economics," *Journal of the European Economic Association*, 1(6), 1346–1366.

Kim, E. H., A. Morse, and L. Zingales (2006): "What Has Mattered to Economics since 1970," *The Journal of Economic Perspectives*, 20(4), 189–202.

——— (2009): "Are elite universities losing their competitive edge?," *Journal of Financial Economics*, 93(3), 353 – 381.

Laband, D. N., and M. J. Piette (1994): "The Relative Impacts of Economics Journals: 1970-1990," *Journal of Economic Literature*, 32(2), 640–666.

Oreopoulos, P., T. v. Wachter, and A. Heisz (2008): "The Short- and Long-Term Career Effects of Graduating in a Recession: Hysteresis and Heterogeneity in the Market for College Graduates," Mimeo.

Oyer, P. (2006): "Initial Labor Market Conditions and Long-Term Outcomes for Economists," *Journal of Economic Perspectives*, 20(3), 143-160.

——— (2008): "The Making of an Investment Banker: Stock Market Shocks, Career Choice, and Lifetime Income," *The Journal of Finance*, 63(6), 2601–2628.

Philippon, T., and A. Reshef (2009): "Wages and Human Capital in the U.S. Financial Industry: 1909-2006," (14644).

ROY, A. D. (1951): "SOME THOUGHTS ON THE DISTRIBUTION OF EARNINGS," *Oxford Economic Papers*, 3(2), 135–146.

Schmieder, J. F., T. von Wachter, and S. Bender (2009): "The Long-Term Impact of Job Displacement in Germany During the 1982 Recession on Earnings, Income, and Employment," Mimeo.

Stock, W. A., and J. J. Siegfried (2006): "Time-to-Degree for the Economics Ph.D. Class of 2001-2002," *The American Economic Review*, 96(2), 467–474.

Sullivan, D., and T. von Wachter (2009): "Job Displacement and Mortality: An Analysis Using Administrative Data," *The Quarterly Journal of Economics*, 124(3), 1265–1306.

von Wachter, T., J. Song, and J. Manchester (2008): "Long-Term Earnings Losses due to Job Separation During the 1982 Recession: An Analysis Using Longitudinal Administrative Data from 1974 to 2004," Mimeo.

Waldinger, F. (2009): "Peer Effects in Science - Evidence from the Dismissal of Scientists in Nazi Germany," Mimeo.

Appendices

A Automated Data Processing

In a first step we downloaded the PDF version of all issues of the American Economics Associations (AEA) yearly “List of Doctoral Dissertations in Economics”.

To convert the PDF version of the AEA doctoral list (available at JStor) to a computer readable format we used the OCR programs included in the Adobe Acrobat Professional Suite. We also tried several other programs, but the quality was best with the Adobe technology. This procedure worked very well in general and made the compilation of the dataset much faster but, as with every automated procedure, it also entailed several problems and was sometimes imperfect. The original PDFs were in some cases scans of old printed versions and therefore the character recognition was imperfect for some records, due to the quality of the source files. Particularly, there were problems with the letter "r", which was from time to time mistaken as "n" or "i". "O" was sometimes read as zero, "H" as "II", and "M" as "IVI". Also, dots were not readily recognized. We were able to correct faulty university names and graduation years, because the set of those is finite. For example we always replaced "IVIichigan"' with "Michigan". Because of limited resources we were not able to correct all errors in the name spellings. We decided to drop the observations with names that contain characters or sequences of characters that are highly unlikely to be correct and thus had no chance to return accurate results in a query for publications in Jstor.

In a next step we used regular expressions, a way to assign database fields for some string combinations, to convert the ASCII files in a database format. The data structure of the AEA doctoral list is quite regular so this procedure worked reasonably well. On some instances, the program was not able to determine the end of a data entry due to missing dots or other OCR errors. The program then searched for the next end of a data entry and therefore at least two data points were lost.

In a third step we used a Java program to match each record with its publication record in Jstor. To do this we used the newly available XML Application

Programming Interface of Jstor, called “Data for Research”. Specifically, we entered the names and given names of all researchers contained in our database and extracted all recorded publications with journal title, page count and the number and identity of coauthors in the 10 years after their graduation. To be as specific as possible, we restricted our search to articles classfied as “research articles” published in English language in the fields of economics, business and finance. A problem which occurred when we matched the graduates in our database with the JStor publication data, was that there are several economists who share the same name. If possible we then relied on a second name to identify the correct author and restricted our publication sample to 10 years after graduation. Unfortunately, using the second name did not always solve the problem: Paul Robin Krugman published his first papers as Paul R. Krugman because apparently there was another economist called Paul Krugman. Later Paul Robin Krugman dropped the “R”. With our methodology we would have two different records, one for Paul R. Krugman and one for Paul Krugman with the latter being attributed all later work of the Nobel prize winning economist. Sometimes conditioning on the decade following graduation helped to ameliorate this problem. If neither the second name nor the time period gave us an idea which author deserved a given the publication, we randomly assigned it.

We believe that all these errors are orthogonal to our effect of interest and that they thus just add noise to our data. An exception would be if the number of PhD students with a hard-to-read-in name varies with the business cycle. This seems rather unlikely to us (unless the fraction of foreigners with hard-to-read-in names is affected by the macroeconomy). Nethertheless we want to test how many read-in names are faulty: To do this, we first correct some years perfectly by hand and compare the resulting “complete” graduation numbers to data from the National Science Foundation (NSF). We find that the “complete” graduation numbers from the AEA list are about 90% of the NSF graduation numbers. Then, for every year, we compare the fraction of the “not corrected” number in our database to the number in the NSF data. This fraction fluctuates from 0.6 to 0.9, which suggests that in the worst case we lose about 40% of graduates due to the imperfect automated reading-in procedure. We do not know how many articles we wrongly assign to economists because they share the same given and second name. Here the error is also orthorgonal, if parents do not systematically start to name their children after famous economists in recessions. Despite the recent popularity of economics this seems unlikely to us.

B Robustness

In this part of the appendix, we analyze the robustness of our results. We first show in section B.1 that our aggregation procedure to university-year level is innocuous for our results, but simplifys the test theory. Next we consider the effect of academic superstars on our results (section B.2). For section B.1 and B.2 we abstain from grouping the data on the university-year level as we do in the main text. In the last part of the robustness section we consider different measures of academic success.

B.1 Regressions on the Individual Graduate Level

In the main text we group the observation according to university and year. The reason is, that the group means are approximately normally distributed (Angrist and Pischke (2008)) and therefore the test theory is much simpler. Once we consider each individual graduate separately, we have to decide how to adjust the standard errors in order to draw correct inference. Table 7 reports our regression of macroeconomic variation on graduates' publication success using clustered, non-adjusted, bootstrapped, and robust standard errors. The last column displays a regression on the probability to publish with standard errors clustered on the university-graduation year level. This table shows, that our results are robust to the different methods of estimating standard errors. The significance of the coefficients is virtually the same as for the respective grouped regressions in the main text.

	(1)	(2)	(3)	(4)	(5)	(6)
Unempl Ch. (Grad)	2.281***		2.281***	2.281***	2.281***	0.00227
	(3.19)		(3.26)	(3.22)	(3.06)	(0.59)
Unempl Ch. (Appl)	1.509**		1.509**	1.509**	1.509**	-0.0103***
	(2.25)		(2.24)	(2.25)	(2.05)	(-2.75)
GDP growth (Grad)		-0.711**				
		(-2.02)				
GDP growth (Appl)		-0.641**				
		(-2.14)				
Adj. R-Squared	0.0825	0.0821	0.0825	0.0825	0.0825	0.0596
N	13624	13624	13624	13624	13624	13624

Note: Regressions (1),(3),(4) and (5) correspond to column one in table 4 and (2) corresponds to column (3) in this table. In (1) and (2) standard errors are clustered on the university-graduation year level, in (3) they are not adjusted, in (4) they are bootstrapped using 50 iterations and in (5) they are robust. Column (6) corresponds to column (1) in table 4 with the probability to publish as the dependent variable. Standard errors are again clustered on the university-graduation year level. t statistics are in parentheses. *, ** , *** indicates significance at the 1%, 5% and 10 % level.

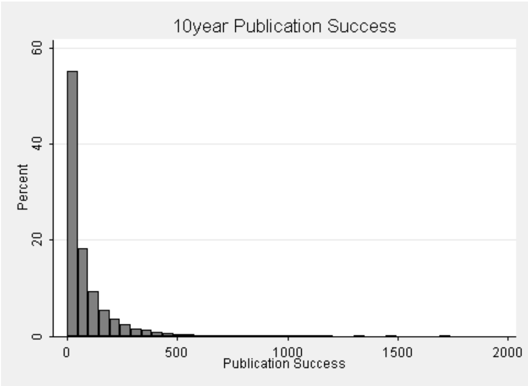
Table 7: Regressions on the individual (non-grouped) level

B.2 Academia: A Superstars Market

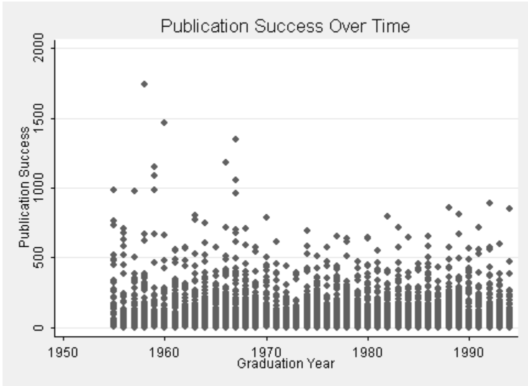
The publication success of academic economists is highly skewed with a few superstars producing a multiple of the quality-adjusted output of the “average” economist. Moreover, about 64 percent of Ph.D. graduates never publish according to our data. Figures 6(b) and 6(c) provide two plots of the distribution of publication success of academics in our data.

In table 8 we use regressions on increasingly restricted subsamples to shed light on the influence of such superstars on our results. We only analyze in the following only academics, to ensure consistency.

The first column reports the results from a regression of academics’ publication success on unemployment change at application and at graduation with standard errors clustered on the university-graduation year level. The following columns restricts the sample to academics who publish below 750, 500, 250, and 50 points, respectively. Hence it sequentially removes those individuals or observations that one might call “superstars” or “outliers” and checks how much of our results is driven by them.



(b)



(c)

Figure 6: 10year Productivity Distribution

The effect of our macroeconomic variables on average publication success decreases monotonically as expected. The significance of our effect also declines, but it remains significant at the 5% level. The significance remains, even if we restrict our sample to academics who publish below 50 points, which is between the average and the median of publication success (83 and 39, respectively) in the sample.

	(1)	(2)	(3)	(4)	(5)
Unempl Ch. (Grad)	3.890***	3.826***	3.668***	1.283*	0.411*
	(2.68)	(2.98)	(3.40)	(1.83)	(1.89)
Unempl Ch. (Appl)	5.121***	3.593**	3.112***	1.357*	0.531**
	(3.28)	(2.56)	(2.63)	(1.73)	(2.18)
Adj. R-Squared	0.136	0.135	0.126	0.0972	0.0640
N	5198	5176	5109	4752	2873

Note: All the columns report regressions of academics' publication success on unemployment change at application and at graduation with standard errors clustered on the university - graduation year level. Columns (2) to (5) restrict the sample to academics who publish below 750, 500, 250, and 50 points, respectively. t statistics are in parentheses. *, ** , *** indicates significance at the 1%, 5% and 10 % level.

Table 8: Regressions on increasingly restricted subsamples

Table 9 adds quantile regressions to this analysis. Clustering of standard errors is problematic in quantile regressions and is not implemented in our version of STATA. Further, if we control for full graduation decade and university effects as well as their interaction terms, the degrees of freedom are reduced significantly and the implementation in STATA breaks down.

Therefore we only control for university tier, graduation decade and their full interactions and we do not adjust the standard errors in these regressions. Column (1) of table 9 provides the baseline regression to the mean whereas the remaining columns provide regressions to the 25, 50, 75, and 95 percentile of the distribution of publication success, repectively. Again, we see that the effect of our macroeconomic variables is more pronounced for higher quantiles. The effect is significant on conventional levels for all quantiles.

	(1)	(2)	(3)	(4)	(5)
Unempl Ch. (Grad)	3.337**	0.691**	2.325***	4.498**	6.833
	(2.12)	(2.10)	(2.58)	(2.08)	(1.01)
Unempl Ch. (Appl)	5.782***	0.621*	1.630*	7.687***	17.36**
	(3.60)	(1.90)	(1.78)	(3.51)	(2.53)
Adj. R-Squared	0.121				
N	5198	5198	5198	5198	5198

Note: Column one provides the baseline regression to the mean with graduation decade, university tier and full interactions as controls. Standard errors are not clustered. Columns (2) to (5) report regressions to the 25, 50, 75, and 95 percentile of the distribution of publication success. t statistics are in parentheses. *, ** , *** indicates significance at the 1%, 5% and 10 % level.

Table 9: Quantile regressions

We conclude that, while some of our results are driven by exceptional individuals who started their Ph.D. during recessions, there is a clear and significant effect on all quantiles of the distribution of academics' publication success.

B.3 Alternative Outcome Measures

In this section we use different measures of researchers' productivity and likelihood to publish to check for the robustness of our results. Table 10 reports results of our standard regression from table 4 for different alternative measures of a researcher's productivity. In Columns (1) and (4) we use our preferred dynamic journal ranking for tier 1 to 3 universities and the tier 1 subsample, respectively. In columns (2) and (5) we use the h-index to weigh the impact of different publications. The h-index is a recently developed index which attempts to measure both the scientific productivity and the apparent scientific impact of a journal.[19] Columns (3) and (6) use the simple count of the number of publications in the (arguable) six top journals.[20]

The parameter estimates for the different measures cannot be compared directly because of the different scales of the productivity measures (most notably for the count of top journal articles). In terms of direction and significance our effect is persistent. Please note, that the two alternative measures have important problems. The h-index is not dynamic and ignores the changeing importance of journals over time. The top journal measure ignores all but the six top journals and it doesn't account for (changes in) the relative importance of these journals over time.

	(1)	(2)	(3)	(4)	(5)	(6)
Unempl Ch. (Grad)	2.281***	3.934***	0.0333***	4.307*	7.042**	0.0630***
	(3.15)	(3.79)	(4.06)	(1.97)	(2.28)	(2.60)
Unempl Ch. (Appl)	1.509**	1.127	0.0133*	5.316**	5.602*	0.0589**
	(2.16)	(1.13)	(1.68)	(2.53)	(1.90)	(2.54)
Adj. R-Squared	0.515	0.511	0.496	0.371	0.317	0.317
N	1068	1068	1068	234	234	234

Note: Columns (1) and (4) repeat the results using our preferred dynamic journal ranking for all the tier 1-3 universities and the tier 1 subsample, respectively. In columns (2) and (5) we use the h-index to weigh different publications' impact. Columns (3) and (6) use the simple count of the number of publications in the "The Quarterly Journal of Economics", "The Journal of Political Economy", "The American Economic Review", "The Review of Economic Studies", "Econometrica", and "The Journal of Finance". t statistics are in parentheses. *, ** , *** indicates significance at the 1%, 5% and 10 % level.

Table 10: Alternative productivity measures

Table 11 reproduces table 5 from the main text without the three year requirement in the "publish" measure. The unemployment rate at application has the same impact on the likelihood to publish if we count all publications or only the publications three years after graduation. In any case, the unemployment rate at graduation is again not significantly related to the "publish" variable. Overall, our results are robust to dropping the three year requirement.

[19] Refer to the IDEAS RePEc website: http://ideas.repec.org/top/top.journals.hindex.html

[20] The Quarterly Journal of Economics, The Journal of Political Economy, The American Economic Review, The Review of Economic Studies, Econometrica, and The Journal of Finance

	(1)	(2)	(3)	(4)	(5)	(6)
Unempl Ch. (Grad)	0.00437	0.00354		0.00418	0.00539	0.0184*
	(1.01)	(0.59)		(0.87)	(0.66)	(1.89)
Unempl Ch. (Appl)	-0.0101**	-0.0142**		-0.00833**	-0.0131*	-0.0129
	(-2.42)	(-2.49)		(-1.97)	(-1.66)	(-1.43)
GDP growth (Grad)			0.000357			
			(0.18)			
GDP growth (Appl)			0.00463**			
			(2.45)			
Adj. R-Squared	0.407	0.237	0.406	0.410	0.393	0.265
N	1068	1068	1068	1068	234	234

Note: Regression (1) and (3) is OLS with observations weighted by cohort size. In regression (2) observation are not weighted by cohort size. In column (4) a linear and quadratic time trend is added. Regression (5) and (6) restricts the sample to Tier 1 weighted and unweighted by cohort size respectively. t statistics are in parentheses. *, ** , *** indicates significance at the 1%, 5% and 10% level.

Table 11: Effect of macro conditions without 3 years requirement

C Interpretation of publication points

Throughout this paper, the outcome measure is denominated in publication points. To interpret these points, please refer to table 12 which shows the points awarded for an article in a certain journal from 1960 onwards. The best journal in each decade receives 100 points and all others are scaled accordingly. We use for every decade a different ranking because the importance of a journal changes over time. For example, an single-authored "Econometrica" Article in 1960 was worth 46.6 points in the 1960s and 96.8 points in 1990. The impact of the "American Economic Review" changed even more dramatically: In the 1960s and in the 1990s it was a leading journal with 93.3 and 100 respectively. In contrast, in the 1970s, 1980s and 2000s it is only a top tier journal with 30-40 publication points. Consequently it is not straightforward to interpret our results above e.g. in "article in American Economic Review" equivalents, but only in articles in "article in American Economic Review in the 1990s" equivalents.

Rank	Journal (ordered by 2000 rank)	1960	1970	1980	1990	2000
1	The Quarterly Journal of Economics	65.6	16.2	41.6	58.1	100
2	Econometrica	46.6	31.6	78.4	96.8	68.7
3	Journal of Economic Literature	-	100	100	18.8	63.5
4	The Review of Economic Studies	100	30.7	40.7	45.2	54.3
5	Brookings Papers on Economic Activity	-	96.9	15.9	0.7	51.5
6	The Journal of Political Economy	63.5	59.1	63	65.2	49.8
7	Economic Policy	-	-	-	-	45.7
8	Journal of Labor Economics	-	-	15.4	12.8	45.5
9	The American Economic Review	93.3	34.5	40.2	100	39.9
10	The Journal of Economic Perspectives	-	-	23.3	34.3	39.8
11	The Review of Financial Studies	-	-	-	-	39.2
12	Journal of the European Economic Association	-	-	-	-	38.6
13	The RAND Journal of Economics (Bell Journal of Economics)	-	39.5	40.2	11.4	38.2
14	The Journal of Finance	37.8	14.6	34.1	34.1	31.1
15	The Review of Economics and Statistics	59.8	12.4	6.5	28	21.7
16	Journal of Business & Economic Statistics	-	-	7.9	38.4	20.8
17	The Economic Journal	47.5	28	23.9	20.7	20.5
18	Journal of Applied Econometrics	-	-	-	16.6	19.1
19	Journal of Money, Credit and Banking		18.5	22.1	18.6	18.6
20	The World Bank Economic Review	-	-	-	5.7	18.5
21	International Economic Review	35.1	19	12.3	23	18.4
22	IMF Staff Papers	-	-	-	5.1	18.3
23	Journal of Law, Economics, & Organization	-	-	-	4.1	16.1
24	Journal of Law and Economics	51.8	43.3	33.1	3.9	14.1
25	The Journal of Human Resources	-	13.6	4.6	21.3	13.4
26	Journal of Population Economics	-	-	-	2.41	10.6
27	The Scandinavian Journal of Economics	2.5	7.1	2.1	10.7	9.2
28	The Journal of Business		18.5	37.4	8.7	8.7
29	The Journal of Industrial Economics	14.9	16.4	16	3.85	8.7
30	The World Bank Research Observer	-	-	-	0.9	8.5
31	The Journal of Financial and Quant. Analysis	-	10.8	20	2.1	7.9
32	Oxford Economic Papers	35.2	16.8	25	3.7	7.9
33	Economica	20.7	36.2	4.1	4.5	7.2
34	Economic Theory	-	-	-	22.4	6.8
35	Industrial and Labor Relations Review	17	18.8	23.4	-	6.1
36	Econometric Theory	-	-	3.3	45.8	5.9
37	The Canadian Journal of Economics	-	11.8	10.2	5.09	5.6
38	The Journal of Legal Studies	-	-	51.6	5.4	5.4
39	Financial Management	-	-	-	-	5.1
40	Journal of Accounting Research	-	-	-	-	4.2

Note: These are the first 40 out of 74 journals. The ranking of 1960, 1970, 1980 and 1990 are taken from Laband and Piette (1994). For the 2000s, we normalize current discounted recursive impact factors ranking from the IDEAS RePEc website to make it comparable to the other rankings.

Table 12: Ranking of journals in different decades.