Scientific workforce

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<u>Outline</u>

1) Preliminaries: Stephan (2012)

2) Roy model (loosely defined!): Borjas and Doran (2012)

3) Compensating differentials: Stern (2004); Aghion, Dewatripont and Stein (2008)

1 Preliminaries: Stephan (2012)

If you are interested in a general background on the economics of science, I would highly recommend Paula Stephan's 2012 book *How Economics Shapes Science*. She is a real expert in this area, and the book does an excellent job of summarizing her work as well as others' research in this area.

Chapter 7 of her book covers the market for scientists and engineers. She notes that this market differs in many respects from other markets: the gestation (training) period is extremely long, the job prospects at the time of graduation are difficult to predict in advance, and aspirants often lack reliable information regarding the job outcomes of recent graduates. She argues that career decisions in this market may largely be made in the dark due to scientists' "love" of the subject. Below, we will discuss two empirical papers – Borjas and Doran (2012) and Stern (2004) – which explore some of these issues.

2 Roy model (loosely defined!): Borjas and Doran (2012)

Borjas and Doran (2012) investigate how a large, post-1992 influx of Soviet mathematicians affected the (publication) productivity of US mathematicians. The key idea is that prior to the collapse of the Soviet Union, there was little collaboration and only infrequent exchanges between Soviet and Western mathematicians; after the collapse of the Soviet Union, over 1,000 Soviet mathematicians migrated to other countries, with a large fraction settling in the US, and many mathematicians who stayed in the Soviet Union became part of the globalized publication market for mathematics.

2.1 Historical context

Following the establishment of the Soviet Union in 1922, Soviet mathematicians entered into a long period of development independent from mathematicians in Western countries. To varying degrees between 1922 and 1992, the Soviet government instituted strict controls on which scientists could communicate with Western peers, on the parameters of scientific travel, on the acceptable outlets for publication, and on access to Western research materials.

Figure 1. Figure 1 illustrates the striking differences in specializations between Soviet and American mathematics in 1984-1989, as measured by the number of papers published by Soviet mathematicians by field relative to the number of papers published by American mathematicians in each field. Borjas and Doran exploit this field variation - interacted with the fall of the Soviet Union, in their empirical strategy.

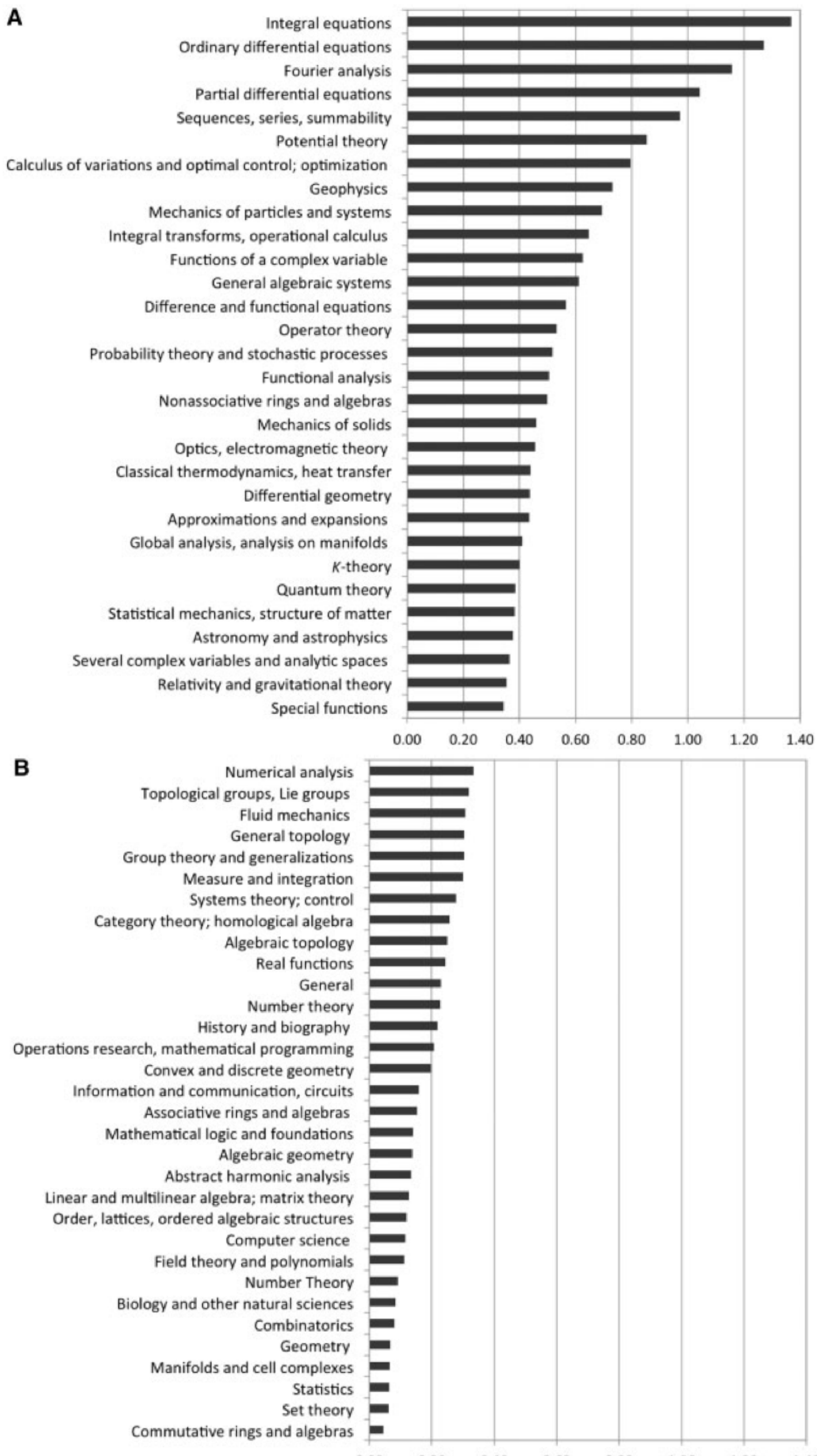


Figure 2. Figure 2 illustrates the negligible rate of pre-1990 coauthorship between mathematicians reporting Soviet research addresses and mathematicians reporting US addresses.

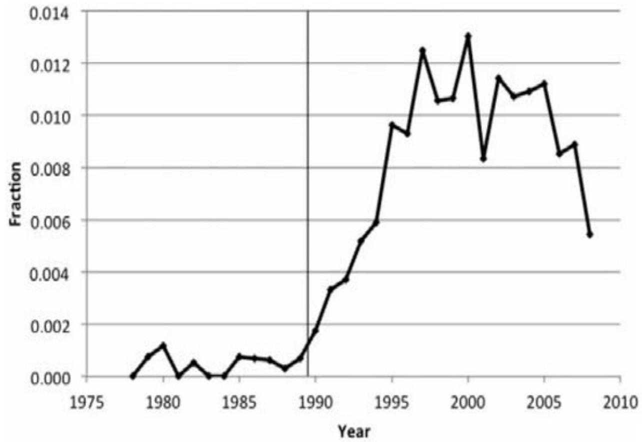


FIGURE II

Trend in Coauthorship Rate between Soviet and American Mathematicians

The denominator of this fraction is the number of papers published each year where at least one author reports an American affiliation. The numerator is the number of such papers in which one other author also reports a Soviet affiliation.

Figure 3. Figure 3 documents the employment trends of newly minted doctorates from North American institutions, which show clear evidence of a dramatic increase in the unemployment rate at the same time the Soviet influx occurred.

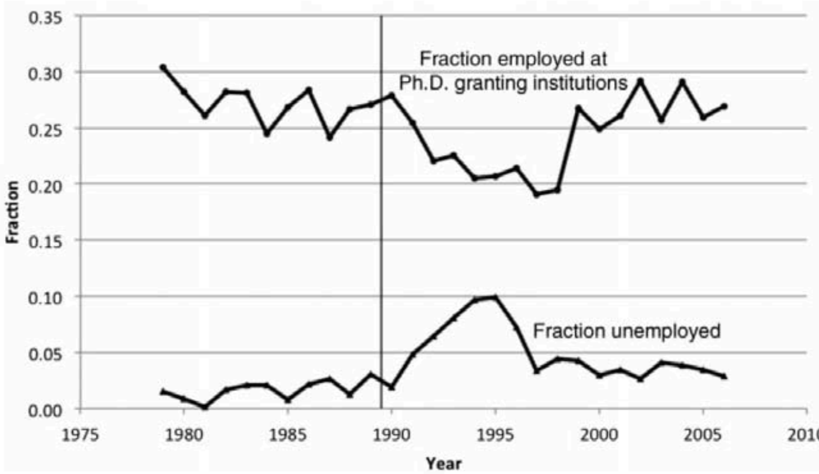


FIGURE III

Employment Trends for New Mathematics Doctorates Granted by North American Institutions

Source: Data compiled by the authors from American Mathematical Society (various issues).

2.2 Data

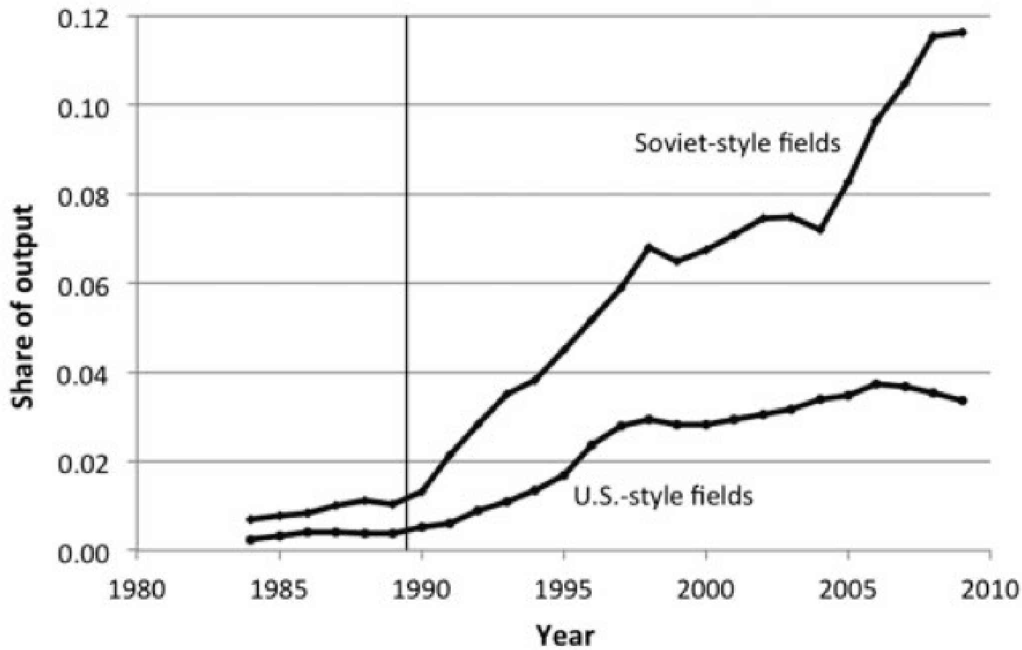
The authors construct a data set that contains information on the authorship of every paper published in mathematics over the past 70 years based on a database from the American Mathematical Society (AMS), supplemented by archives from the Thomson Reuters Institute for Scientific Information Web of Science (ISI) and the Mathematics Genealogy Project. Using these data, the authors are able to document the location, affiliation, and complete publication and citation records of mathematicians who were active predominantly in America and in the Soviet Union for the past few decades.

Table 1. Table 1 reports a very large degree of positive selection in the group of Soviet mathematicians who immigrated to America. Prior to their migration, these future Soviet émigrés were significantly more productive in terms of their number of publications and citations.

Summary Statistics for Samples of American and Soviet Mathematicians

	Group of mathematicians			
Variable	Americans	Soviet émigrés to U.S.	Soviet émigrés elsewhere	All other Soviets
Number of mathematicians	29,392	336	715	11,173
Papers published, 1978–1991				
Mean papers per mathematician	6.7	17.8	14.6	8.1
Median papers	3.0	13.0	10.0	5.0
Maximum number of papers	232.0	104.0	152.0	180.0
Papers published, 1992–2008				
Mean papers per mathematician	6.8	27.2	28.8	7.6
Median papers	1.0	21.0	22.0	1.0
Maximum number of papers	768.0	128.0	317.0	311.0
Citations, AMS, 1978–1991				
Mean citations per mathematician	29.1	74.6	32.8	8.6
Median citations	1.0	10.0	6.0	0.0
Maximum number of citations	5550.0	1276.0	1441.0	2928.0
Citations, AMS, 1992–2008				
Mean citations per mathematician	33.6	177.4	110.3	13.4
Median citations	0.0	62.0	37.0	0.0
Maximum number of citations	3404.0	1709.0	1988.0	1287.0
Citations, ISI, 1978–1991				
Mean citations per mathematician	110.2	185.1	79.8	25.3
Median citations	20.0	25.5	11.0	3.0
Maximum number of citations	20,274.0	7232.0	3040.0	3054.0
Citations, ISI, 1992–2008				
Mean citations per mathematician	52.1	209.0	156.2	27.3
Median citations	0.0	88.5	60.0	0.0
Maximum number of citations	11,688.0	3371.0	4442.0	1258.0
Median number of fields	2.0	5.5	5.0	2.0
Percent first published after 1980	45.2	40.5	46.7	48.8

Figure 6. Figure 6 documents a basic event study of the supply shock, as defined by the fraction of total papers published by Soviet émigrés. Note that the shock was much larger for the Soviet-style fields than for American-style fields.



2.3 Results

Their empirical strategy is a basic differences-in-differences strategy, as motivated above, based on the idea that US mathematicians specializing in different fields experienced different level of exposure to Soviet mathematicians. To quantify the degree of exposure, the authors calculate three indices reflecting the degree of field-overlap between the pre-1990 publication record of each American mathematician and that in the Soviet Union. For each American mathematician i in year t, the authors estimate regressions of the following form:

$$y_i(t) = \phi_i + \phi_t + X_i(t)\gamma + \theta(T \times Index_i) + \epsilon_i(t), \tag{1}$$

where $y_i(t)$ is the number of publications/citations of the American mathematician i in year t; ϕ_i are individual fixed effects; ϕ_t are year fixed effects; X is the years of work experience of the mathematician included as a quartic polynomial; T is a dummy variable for year 1992 or later; and $Index$ is one of the three overlap indices.

Table 3. Table 3 documents the θ estimates, which reveal a negative relationship between overlapping fields and the (publication) productivity of mathematicians who are predominantly in America. To be more concrete, for an American mathematician switching from a non-Soviet style field to a Soviet style field in and after 1992, there is a reduction of 0.13 papers per year as estimated in Panel A. Over the entire period of 1992-2008, the regression predicts a reduction of 2.2 papers, which is a third of the average publications by American mathematicians as shown in Table 1.

TABLE III

Impact of Soviet Supply Shock on American Mathematicians

	Mathematicians predominantly in U.S.		Mathematicians always in U.S.	
Specification/regressor	Number of papers	Number of citations	Number of papers	Number of citations
A. Author-year regressions				
Correlation coefficient	−0.133	−19.577	−0.116	−16.298
	(0.036)	(1.576)	(0.034)	(1.540)
Index of intensity	−0.047	−14.845	−0.042	−12.293
	(0.028)	(1.293)	(0.027)	(1.261)
Index of similarity	−1.523	−69.155	−1.419	−58.494
	(0.113)	(4.645)	(0.108)	(4.655)
B. Author-year regressions, short run				
Correlation coefficient	−0.102	−14.214	−0.085	−11.404
	(0.032)	(1.783)	(0.030)	(1.410)
Index of intensity	−0.045	−10.944	−0.039	−8.830
	(0.023)	(1.221)	(0.022)	(1.181)
Index of similarity	−1.056	−48.547	−0.985	−39.054
	(0.111)	(4.232)	(0.108)	(4.117)
C. Author-year regressions, long run				
Correlation coefficient	−0.122	−25.219	−0.108	−21.095
	(0.049)	(2.037)	(0.046)	(2.019)
Index of intensity	−0.019	−19.179	−0.015	−15.889
	(0.039)	(1.687)	(0.037)	(1.666)
Index of similarity	−1.930	−91.211	−1.802	−77.930
	(0.150)	(5.961)	(0.145)	(6.055)
D. Author-field-year regressions				
Correlation coefficient	−0.0021	−0.3048	−0.0020	−0.2578
	(0.0006)	(0.0249)	(0.0005)	(0.0244)
Index of intensity	−0.0007	−0.2378	−0.0007	−0.2005
	(0.0004)	(0.0206)	(0.0004)	(0.0202)
Index of similarity	−0.0238	−1.0248	−0.0240	−0.8696
	(0.0017)	(0.0732)	(0.0016)	(0.0732)

Figure 7. Figure 7 documents these main estimates graphically, conditional (Panel B) and not conditional (Panel A) on individual fixed effects.

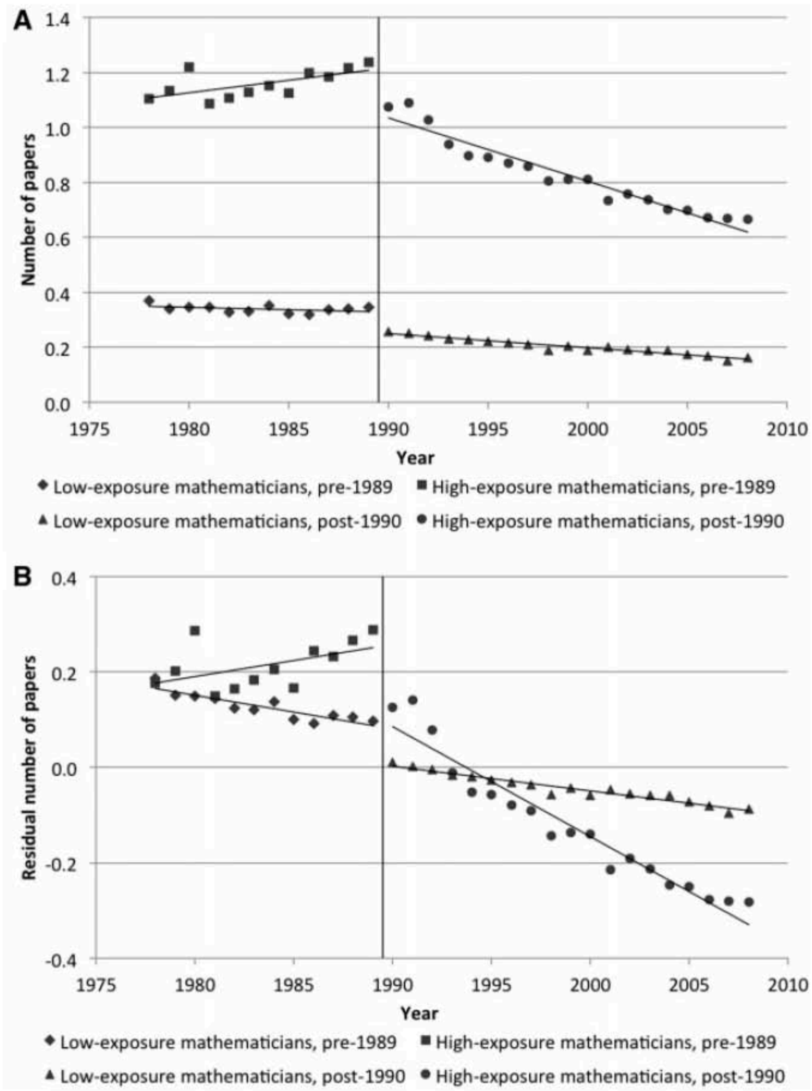


FIGURE VII

Impact of Index of Similarity on Output of American Mathematicians

(A) Annual number of papers per mathematician, (B) Annual number of papers per mathematician, removing individual fixed effects

The low-exposure group consists of mathematicians in the bottom quartile of the distribution of the index of similarity, and the high-exposure group consists of mathematicians in the top quartile. The residual papers in Panel B are calculated from a regression that contains individual fixed effects (demeaning the data for each individual).

The authors also present a number of additional analyses, including an estimate of the aggregate effects of this change on US mathematicians.

3 Compensating differentials: Stern (2004); Aghion et al. (2008)

3.1 Stern (2004)

The Stern (2004) paper is motivated by wanting to understand incentives that shape knowledge production (under the broad umbrella of understanding knowledge production as an input into innovation and economic growth). He draws on a characterization of "science" as an incentive system in which researchers are offered substantial discretion in choosing research projects, with rewards based on establishing intellectual priority (*i.e.* being the first to make a discovery) through journal publication. Stern highlights two possible reasons why a science-oriented approach could be pursued:

1. Scientists may have a "taste" for science. Researchers may have preferences for interacting with discipline-specific communities and for receiving recognition for their discoveries (Dasgupta and David (1994), Merton (1973)). Stern refers to this as the "preference effect."

2. Science may have productivity benefits, especially for private firms. Firms who adopt a science-oriented approach may have higher research productivity. Stern refers to this as the "productivity effect."

Stern notes that there is no inherent conflict between these two perspectives: scientists may have a taste for participating in science (the preference effect), and some firms may find it worthwhile to participate in science (the productivity effect). However, the two effects offer competing economic implications for the scientific labor market. The preference effect implies a negative association (compensating differential) between science and wages, whereas the productivity effect implies a positive association between science and wages (as long as there is "rent-sharing" between firms and researchers). In observational data, we might also expect a selection effect to bias the observed relationship between science and wages, if researchers with higher unobserved productivity both have a higher preference for science (potentially due to having higher expected benefits to science) and have higher wages.

3.1.1 Empirical framework

Stern's model has two stages. In the first stage, firm j chooses whether to adopt a scientific orientation for its research department ($SCI = 1$ or $SCI = 0$). In the second stage, firms hire a single researcher with ability γ_i (observable to market participants but unobserved by the econometrician). For firm j, the quality of worker i (the most attractive scientist who applies for a job at firm j) is drawn from a firm-specific distribution $g_j(\gamma)$, bounded below at zero with mean $\bar{\gamma}_j$.

Scientists' utility depends on the offered wage and the preference for a science-oriented job:

$$U_i = \lambda_0 + \alpha_s \gamma_i SCI_j + w_j \tag{2}$$

Following the logic outlined above, assume that scientists of higher ability place higher value on a science-oriented research environment. Firms earn profits as a function of the ability of hired scientists, the wages paid (w_j), and their science-orientation:

$$\pi_{i,j} = \gamma_i(\beta_0 + \beta_s SCI_j) - w_{i,j} - \delta SCI_j \tag{3}$$

This functional form for profits assumes that firms pay a fixed fee to adopt a scientific orientation (δ), but that the benefits that the firm receives from adopting a scientific orientation depend on the quality of the scientist. Firms who adopt science earn a quasi-rent that is increasing in γ_i (earnings in excess of post-investment opportunity cost). If firms face a search cost for new scientists and scientists can credibly threaten to receive outside job offers, then scientists may extract some of this quasi-rent in wage bargaining. Stern formalizes this idea with a "rent-sharing" parameter $\phi \in (0, 1)$ which determines the allocation of the quasi-rent between the scientist and the firm.[1] Wages are thus given by:

$$w^*_{i,j} = \gamma_i\beta_0 + \gamma_i(\phi\beta_s - \alpha_s)SCI_j \tag{4}$$

If the compensating differential α_s is larger than the part of the quasi-rent extracted by the scientist, then wages will be decreasing in the firm's scientific orientation.

Importantly, nothing in the paper rules out that the preference effect arises not from an intrinsic utility parameter but rather from career concerns on the part of researchers who want to build up a publication portfolio in order to have a publicly observable signal of their quality that could be useful in later job searches.

3.1.2 Data and estimation

In observational data, we might expect higher ability researchers to "consume" higher levels of scientific orientation, and for firms to be more likely to adopt a scientific orientation if they employ higher ability researchers (in which case, the private returns to adopting a scientific orientation will be higher for the firm). Stern's key estimation insight which he uses to try to overcome these challenges is that in job markets for "novice" professionals, many candidates receive multiple job offers prior to accepting a single job offer. For candidates who receive more than one job offer, he can construct different points on the wage-amenity curve for a given worker at a given point in time.

Stern collected the data for this paper by running a survey to collect "final-round" job offers to biology PhDs who were completing their first postdoctoral fellowship at a top-tier medical center or university, and who were participating in a job market for long-term employment. The data is a small sample, including 164 job offers from 66 individuals who received multiple job offers; Stern also examines data on individuals receiving a single offer.

[1] We will talk more about rent-sharing in a later lecture.

This empirical approach requires that firms' scientific orientation is uncorrelated with unobserved sources of variation in research productivity. Stern designed his survey to ask detailed questions that could provide controls for alternative hypotheses as best possible.

The key variables are SALARY (baseline salary) and a series of variables measuring scientific orientation of the employers:

1. PERMIT_PUB: are researchers allowed to publish discoveries?
2. INCENT_PUB: how strong are incentives for publication?
3. CONTINUE RESEARCH: are researchers allowed to continue postdoctoral research projects?
4. SCIENCE INDEX: principal factor of the three variables listed above

Table 1. Defines variables and presents summary statistics.

Table 1 Definitions and Descriptive Statistics

Variable	Definition	*N*	Mean	Std. dev.
Job market experience				
# OFFERS RECVD	Number of offers received	164	2.88	1.00
ACCEPTED JOB	Accepted this job = 1, No = 0	164	0.30	0.49
Job offer cardinal record information				
JOB TYPE	1 = Established firm, 2 = Startup firm, 3 = Government, 4 = Medical school/center, 5 = University, 6 = Postdoc	164	See appendix	
Monetary compensation and career incentive measures				
SALARY	Annual starting salary (in US dollars)	121	62,263.95	31,553.04
STOCK_DUMMY	Job offer includes stock options = 1, No = 0	72	0.36	0.48
PROMOTION	Likert scale rating (1–5) of opportunities for internal promotion	111	3.49	1.29
Scientific orientation indicators				
PERMIT_PUB	Permission to publish in external journals = 1, No = 0	114	0.92	0.27
INCENT_PUB	Likert scale rating (1–5) of incentives to publish in refereed outside journals	104	3.89	1.12
CONTINUE RESEARCH	Job allows continuation of current research project = 1, No = 0	111	0.46	0.50
SCIENCE INDEX	First principal factor of PERMIT_PUB, INCENT_PUB and CONTINUE RESEARCH; see Hamilton (1992)	99	0.00	0.57
EQUIPMENT	Likert scale rating (1–5) of access to "cutting-edge" equipment	112	4.07	0.86
Job offer ordinal record data (1 = highest)				
MONETARY	Ranking of offer in terms of monetary compensation	134	1.96	0.99
RESEARCH QUALITY	Ranking of offer in terms of internal research environment	124	1.90	0.99
FLEXIBILITY	Ranking of offer in terms of flexibility to choose research projects	116	1.90	0.98
FUNDING	Ranking of offer in terms of availability of research funding	117	1.93	1.00
CAREER	Ranking of offer in terms of impact on career advancement	130	1.95	0.99
JOBFIT	Ranking of offer in terms of how well it "fits" with prior research experience	116	1.91	1.01

3.1.3 Results

The main take-away from Stern's results is that there does appear to be a trade-off between offered wages and the scientific orientation of firms: offers that contain science-oriented provisions are associated with lower monetary compensation and starting wages. This pattern is robust to controls for job types and to restricting the sample to non-academic jobs. The data suggest that accepted and rejected job offers are comparable (consistent with equilibrium theories of wage determination), and job candidates receiving multiple offers look similar to candidates receiving only one offer. When Stern omits individual fixed effects, cross-sectional estimates are biased upwards - underestimating the size of the compensating differential for science.

Table 2. Comparison of variation in salary offers by the scientific orientation of different jobs. For each measure of scientific orientation, does a t-test of differences in means focusing exclusively on individuals who experienced variation in that characteristic across their offers. For each individual and characteristic value, calculates an "average deviation" measuring how salary offers associated with a given value of a characteristic differ from the average salary offer received by that individual. Can reject equality of deviations in salary offers in the full sample, and (somewhat less strongly) in the sample of nonacademic offers.

Table 2 Nonparametric Comparison of Deviations of Salary Means by Science Attributes

	PERMIT_PUB (0 vs. 1)	CONTINUE RESEARCH (0 vs. 1)	INCENT_PUB ({1, 2, 3} vs. {4, 5})
Overall sample			
Average difference	14,200	16,809	6,694
	(7,241)	(5,189)	(2,678)
t-stat for means equality	1.961	3.239	2.500
Degrees of freedom	8	26	30
p-value	0.086	0.003	0.018
Nonacademic offers only			
Average difference	7,200	8,143	8,430
	(2,352)	(5,954)	(3,223)
t-stat for means equality	3.061	1.368	2.615
Degrees of freedom	8	12	18
p-value	0.016	0.197	0.18

Notes. Each "average difference" cell contains the difference in the average deviation in salary for a science characteristic, using the following procedure. For each science characteristic, we identified those individuals whose offers differed in terms of that characteristic. For these individuals, we then computed (a) the average salary offer for that individual by that specific characteristic and (b) the (weighted) average salary offer for each individual, where the weight associated with each value of the characteristic is equal to 0.5. Finally, to abstract away from differences in the level of salary across individuals, we subtracted (b) from (a). We then performed a t-test for the equality of the means based on these average salary deviations by scientific characteristic.

Though INCENT_PUB is a five-point Likert scale measure, we implemented the above procedure by grouping the INCENT_PUB responses into two groups ({1, 2, 3} versus {4, 5}).

Table 3. Regresses log offered salary on measures of scientific orientation. Without individual fixed effects (column 1) the correlation is small, "wrong signed" (positive), and statistically insignificant; once individual fixed effects are added (column 2) the parameter estimate switches sign (negative) and is statistically significant. The magnitude of the compensating differential is similar when other controls are added. The point estimate in column 3 (-0.19) suggests there is a 20% discount on the wage rate for science-oriented firms. Columns 4-6 add additional scientific orientation measures.

Table 3 Hedonic Wage Regression: Overall Sample Dependent Variable = LN(SALARY), # of Observations = 121

	Permission to publish			Combination model	Science index model	
	(3–1)	(3–2)	(3–3)	(3–4)	(3–5)	(3–6)
	Baseline (NO FE)	Baseline (w/FE)	Full model (w/FE)	Full model (w/FE)	Full Model (w/FE)	Full Model (w/FE)
PERMIT_PUB	0.027 (0.186)	**−0.266** **(0.114)**	**−0.191** **(0.105)**	−0.089 (0.103)		
CONTINUE RESEARCH				**−0.134** **(0.060)**		
INCENT_PUB				−0.036 (0.028)		
SCIENCE INDEX					**−0.114** **(0.053)**	−0.078 (0.057)
EQUIPMENT				**0.063** **(0.033)**	**0.057** **(0.030)**	**0.053** **(0.031)**
CONTROLS						
PROMOTION			**0.041** **(0.025)**	**0.046** **(0.021)**	**0.042** **(0.021)**	0.031 (0.023)
STOCK_DUMMY			**0.196** **(0.085)**	**0.234** **(0.074)**	**0.260** **(0.067)**	**0.190** **(0.077)**
ACCEPTED JOB			−0.013 (0.040)	0.002 (0.043)	−0.0001 (0.043)	−0.002 (0.044)
JOBTYPE CONTROLS	no	no	yes (5; Sig.)	no	no	yes (5)
Individual fixed effects	no	yes (52; Sig.)	yes (52; Sig.)	yes (52; Sig.)	yes (52; Sig.)	yes (52; Sig.)
R-squared	0.001	0.915	0.955	0.958	0.954	0.958

Notes. Only persons with multiple job offers are included.
Standard errors are shown in parenthesis; significant coefficients (10%) are shown in bold.
Sig. stands for joint significance of fixed effects or job type controls (at 10% level).

Table 4. Similar to Table 3, but limits the sample to nonacademic offers (for individuals who received multiple nonacademic offers). Qualitatively similar to the results in Table 3 - suggesting differences in Table 3 are not just driven by variation across academic and non-academic jobs.

Table 4 Hedonic Wage Regression: Nonacademic Offers Dependent Variable = LN(SALARY), # of Observations = 71

	Permission to publish	Factor model
	(4–1)	(4–2)
PERMIT_PUB	**−0.150**	
	(0.077)	
SCIENCE INDEX		**−0.109**
		(0.047)
EQUIPMENT		−0.015
		(0.038)
CONTROLS		
PROMOTION	**0.056**	**0.054**
	(0.029)	**(0.029)**
STOCK_DUMMY	0.092	0.105
	(0.066)	(0.065)
JOB ACCEPTED	−0.049	−0.021
	(0.047)	(0.048)
Individual Fixed Effects	yes (30; Sig.)	yes (30; Sig.)
R-squared	0.967	0.970

Notes. Only persons with multiple job offers are included.

Regressions exclude postdoctoral positions and job offers from universities.

Standard errors are shown in parenthesis; significant coefficients (10%) are shown in bold.

Sig. stands for joint significance of fixed effects (at 10% level).

Table 5. Uses monetary rank of job as dependent variable, and job characteristics as well as individual fixed effects as right-hand-side variables. Results support salience of preference effect: research environments that allow workers access to high-quality research colleagues and an ability to choose their own projects offer less compensation.

Table 5 Regression: Job Offer Comparison Rankings Dependent Variable: Monetary

	(5–1)	(5–2)	(5–3)	(5–4)
Sample	All job types	Exclude academic job offers	All job types	Exclude academic job offers
RESEARCH QUALITY	**−0.34**	**−0.32**		
	(0.12)	**(0.16)**		
FLEXIBILITY			**−0.39**	−0.27
			(0.13)	(0.19)
JOBFIT	0.20	**0.29**	**0.32**	**0.35**
	(0.12)	**(0.16)**	**(0.12)**	**(0.17)**
CAREER	0.23	−0.04	**0.30**	0.04
	(0.12)	(0.16)	**(0.13)**	(0.18)
FUNDING	**0.34**	0.26	0.17	0.18
	(0.13)	(0.17)	(0.12)	(0.17)
Individual fixed effects	(51)	(28)	(51)	(28)
R-squared	0.48	0.41	0.48	0.38
# of observations	134	74	134	74

Notes. Only persons with multiple job offers are included.

Regressions (5–2) and (5–4) exclude postdoctoral positions and job offers from universities.

Standard errors are shown in parenthesis; significant coefficients (10%) are shown in bold.

Table 6. Investigates two assumptions underlying the previous analysis. The first assumption is that individuals who receive multiple offers are similar to those who receive only one offer (needed if we want to estimate the population-level compensating differential); Table 6a suggests job characteristics look similar. The second assumption is that all offers are equally "serious" (otherwise, differences in hiring strategies could explain results). In most regressions, ACCEPTED JOB indicator controls for this concern; the estimated coefficient on that variable is generally small and statistically insignificant. Table 6B takes a more direct approach, comparing characteristics of accepted and rejected offers. Suggestive evidence against a negative correlation between seriousness of offer and scientific orientation.

Table 6A Comparison of Single and Multiple Job Offers

	Single offers	Multiple offers
SALARY	58,074.01	61,958.85
	(26,859.57)	(31,394.96)
PERMIT_PUB	0.96	0.91
	(0.19)	(0.28)
CONTINUE RESEARCH	0.28	0.46
	(0.46)	(0.50)
INCENT_PUB	3.67	3.88
	(1.24)	(1.13)
EQUIPMENT	3.71	4.06
	(1.38)	(0.86)

Notes. Number of observations is different for every cell, depending on number of missing values.

Standard errors are shown in parenthesis.

Table 6B Comparison of Accepted and Rejected Offer Characteristics

	Rejected offers	Accepted offers
SALARY	60,925.06	64,782.93
	(32,647.24)	(29,602.07)
PERMIT_PUB	0.91	0.95
	(0.29)	(0.22)
CONTINUE RESEARCH	0.48	0.46
	(0.50)	(0.50)
INCENT_PUB	3.93	3.93
	(1.08)	(1.19)
EQUIPMENT	3.82	4.43
	(0.91)	(0.66)

Notes. Number of observations is different for every cell, depending on number of missing values.

Standard errors are shown in parenthesis.

3.2 Linking back to theory: Aghion, Dewatripont and Stein (2008)

Aghion, Dewatripont and Stein (2008) take Stern's compensating wage differential estimates as a "fact" that motivates a model clarifying the respective advantages and disadvantages of academic and private-sector research.

The traditional case for government funding of academic research is knowledge spillovers: the economic value of certain types of ideas cannot be fully appropriated by developers, leading to underinvestment by the private sector in "basic" research. Stepping away from this viewpoint, Aghion et al. (2008) write down a different line of reasoning that generates a role for academia. The key distinction they emphasize between academia and the private sector is a tradeoff between creative control and focus. They take the defining characteristic of academic research to be that scientists retain decision rights over what specific projects to take on, and what methods to use in tackling these projects. They take the defining characteristic of private-sector research to be that decision rights reside with the owner/manager of the firm, who can (and will) largely dictate project choice and methods to the individual scientists who work for the firm. They assume that scientists value creative control, and will have to be paid a wage premium in order to give it up (citing Stern's paper as evidence for this assumption).

This structure implies that one advantage of academia is that scientists can be hired more cheaply than in the private sector. However, a disadvantage of academia is that scientists may end up working on projects they find interesting (or prestige-enhancing) but that have little immediate economic value. In contrast, by virtue of their control rights firms can direct scientists to work on those projects that have the highest economic payoff.

In their model, the resolution of this tradeoff depends on how far from commercialization a particular line of research is. They consider a concrete example of a line of biotech research which consists of 10 distinct stages, and which will yield a drug worth $10 billion if and only if all ten stages are successfully completed:

- At the final stage, wages of individual scientists are relatively insignificant, and the most important consideration is pushing the project ahead. The directedness of the private sector make it optimal for the project to the privately owned at the last stage.

- At the first stage, the expected value of succeeding in the first stage is much smaller because the project would still need to make it through later stages in order to be ultimately successful. In this case, it becomes more important to cede creative control in order to economize on scientists' wages.

These basic ideas clarify why it may be socially optimal to have early-stage, basic research occur in academia.

3.2.1 Basic set-up of the model

Let I_0 denote the initial idea for the development of an economically valuable product (e.g., a new drug.) This idea can be built on by subsequent scientists in stages. If stage 1 is successful, then there is a refined idea I_1 based on idea I_0 and so forth. There are a total of k stages after the initial idea. If and only if all k stages are successful, there is a final idea I_k which generates a marketable product with value V.

The probability of succeeding at stage j and moving on to stage $j+1$ depends on:

1. The number of scientists who are active at stage j, which we denote as n_j. If the scientists choose to work on the current idea, then there is a probability $\phi_j(n_j)$ that I_j moves on to I_{j+1}. There are two specifications of the function $\phi_j(n_j)$: (i) $\phi_j(n_j) = p$ for all $n_j \geq 1$; and (ii) $\phi_j(n_j) = (1-(1-p)^{n_j})$. The first specification corresponds to the assumption that all scientists have a perfectly correlated draw from the same success/failure distribution. The second specification corresponds to the assumption that scientists have independent draws from the same success/failure distribution, with each individual having a success probability of p, so that the group's success probability is given by $(1-(1-p)^{n_j})$.

2. The research strategies that the scientists pursue. In this model, there are two options. First, the scientists can follow a "practical" strategy, which maximizes the probability of moving on to the next stage. Second, the scientists can follow an "alternative" strategy, which allows the scientists to not advance the current line of research but rather to work on other puzzle-solving activities – that is, a zero individual probability of success on the current research. Suppose in academia, scientists work on their preferred strategy, while in the private sector, scientists are forced to work on the "practical" strategy. Let α be the probability that all n_j scientists work on the practical strategy.

If stage j takes place in academia, the probability of advancing to stage $j+1$ is $\alpha\phi_j(n_j)$ because the scientists might choose the alternative strategy and not work on the current research. If stage j takes place in the private sector, the probability of advancing to stage $j+1$ is $\phi_j(n_j)$ because the practical strategy is required.

Let the wage in academia w_a be set at the floor of the scientist's wage R. To compensate the disutility z of being forced to take the practical strategy, the wage in the private sector w_p should be set at $R+(1-\alpha)z$.

Consider a single research line with $n=1$ for all k stages and $\phi(n)=p$. To find the optimal allocation of each stage, i.e. whether each stage should be conducted in academia or in the private sector, the social planner optimizes the expected payoff of each stage backward. That is, imagine that the first $(k-1)$ stages have been successful; if we successfully reach the final stage k, we can generate a payoff of V. Then compare

$$E(\pi_k^p) = pV - w_p \tag{5}$$
$$E(\pi_k^a) = \alpha pV - w_a \tag{6}$$

where $E(\pi_k^p)$ is the expected payoff if the last round of research is conducted in the private sector with one scientist hired, and analogously for $E(\pi_k^a)$ in academia.

There is a simple tradeoff: one the one hand, wages are lower in academia, without the wage premium z. On the other hand, scientists might not work on the current idea with probability α in academia. The social planner chooses whichever has the greater payoff for this final stage. The sufficient condition for $E(\pi_k^p) > E(\pi_k^a)$ is $pV > z$. The intuition is that the private sector is more attractive when the expected payoff is greater than the wage premium.

To maximize the payoff of stage $(k-1)$, denote $\Pi_k = \max(E(\pi_k^p), E(\pi_k^a))$. Folding back to stage $(k-1)$, the social planner compares $E(\pi_{k-1}^p) = p\Pi_k - w_p$ and $E(\pi_{k-1}^a) = \alpha p\Pi_k - w_a$. The sufficient condition for $E(\pi_{k-1}^p) > E(\pi_{k-1}^a)$ is $p\Pi_k > z$. This recursive logic can be extended backwards, so that at an earlier stage i, the social planner compares

$$E(\pi_i^p) = p\Pi_{i+1} - w_p \tag{7}$$
$$E(\pi_i^a) = \alpha p\Pi_{i+1} - w_a \tag{8}$$

where $\Pi_{i+1} = \max(E(\pi_{i+1}^p), E(\pi_{i+1}^a))$.

The sufficient condition for $E(\pi_i^p) > E(\pi_i^a)$ is again $p\Pi_{i+1} > z$. Moreover, observe that Π_{i+1} falls as the stage becomes earlier because by construction $\Pi_{i+1} \leq \Pi_{i+2} \leq \cdots \leq \Pi_k$. That is, as we move backward to earlier and earlier stages, it becomes progressively harder for the private sector to outperform academia. This observation immediately implies that it cannot be value maximizing to have academia operate at later stages than the private sector. To put it another way, once it is value maximizing to operate the research line in the private sector, all later stages will be conducted in the private sector.

However, this observation does not mean the private sector is always preferable to academia. Academia may become indispensable at the earlier stages if the total length k of the research line is sufficiently large. Specifically, they prove that a research line with a sufficiently large number of stages k will not be viable if located exclusivity in the private sector.

3.2.2 Branching out: the potential for new lines

If at any stage of the original research line, a scientist works on the alternative strategy, there is a probability p_r of a revolutionary new idea which will form the basis for γ entirely new "offspring" research lines, with $\gamma \geq 1$. That is, "offspring research" can only be born into academia. Academia thus now has the added benefit of "letting many more flowers bloom," which makes it optimal to wait longer before moving a project to the private sector, all else equal.

From an empirical perspective, what is interesting about the branching model is that it implies that once an idea becomes the property of a private firm, it will be developed along relative narrow lines. That is, the private sector's ownership of a given idea *will not yield as diverse an array of useful next-generation ideas as would be generated in academia.*

3.2.3 Take-aways

This model provides a framework for evaluating the pros and cons of academic as opposed to private-section research. Even in a world where ideas can be sold to the private sector at all stages of the research process, academia – by virtue of its commitment to leaving creative control in the hands of scientists – can play a valuable role in fostering research projects that would not be viable if located entirely in the private sectors. Moreover, it is possible for ideas to be privatized sooner than is socially optimal, with negative consequences for the overall rate of innovation by lowering the success probability and limiting the number of offspring research lines.

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