Paper to be presented at the

35th DRUID Celebration Conference 2013, Barcelona, Spain, June 17-19

Does Knowledge Accumulation Increase the Returns to Collaboration?

Evidence from the Collapse of the Soviet Union

Ajay Agrawal
University of Toronto/Rotman School of Management
Strategic Management
ajay.agrawal@rotman.utoronto.ca

Avi Goldfarb
University of Toronto/Rotman School of Management
Marketing
agoldfarb@rotman.utoronto.ca

Florenta Teodoridis
University of Toronto/Rotman School of Management
Strategic Management
f.teodoridis09@rotman.utoronto.ca

Abstract

We examine the role of knowledge accumulation in explaining the increase in research team size over time by exploiting the collapse of the USSR as an instrument that led to the sudden release of previously hidden research. We examine changes over time in the propensity of non-Soviet mathematicians to collaborate in fields in which Soviet research was strong to fields in which Soviet research was weak. We find that coauthorship increased disproportionately in Soviet-rich subfields after 1990. Furthermore, consistent with the hypothesized mechanism, scholars in Soviet-rich subfields disproportionately increased citations to Soviet prior art. These scholars also became increasingly specialized.

Jelcodes:O33,O40

Does Knowledge Accumulation Increase the Returns to Collaboration? Evidence from the Collapse of the Soviet Union

June 2013

Abstract

We examine the role of knowledge accumulation in explaining the increase in research team size over time by exploiting the collapse of the USSR as an instrument that led to the sudden release of previously hidden research. We examine changes over time in the propensity of non-Soviet mathematicians to collaborate in fields in which Soviet research was strong to fields in which Soviet research was weak. We find that coauthorship increased disproportionately in Soviet-rich subfields after 1990. Furthermore, consistent with the hypothesized mechanism, scholars in Soviet-rich subfields disproportionately increased citations to Soviet prior art. These scholars also became increasingly specialized.

JEL: O33, O40

1. Introduction

Research teams are growing in size. Several plausible explanations may explain the rise in collaboration, including the accumulation of knowledge, declining communication costs, increasing capital intensity, shifting authorship norms, and increasing returns to research portfolio diversification. These different explanations yield distinct policy implications regarding, for example, subsidies to higher education and the composition of research evaluation committees.

In this paper, we examine whether the accumulation of knowledge leads to increased collaboration. We provide evidence consistent with Jones' (2009) "burden of knowledge" hypothesis, suggesting an important role for knowledge accumulation in the increase in research team size. While we do not rule out the other explanations as partial drivers of the increasing rate of collaboration, we document that a particular shock to the knowledge frontier led to increased collaboration and specialization. Specifically, we examine whether the shock to non-Soviet knowledge of theoretical mathematics that came with the fall of the Soviet Union led to an increase in collaboration among non-Soviet scholars. Using a similar identification strategy to Borjas and Doran (2012a), we identify Soviet-rich and Soviet-poor fields of theoretical mathematics before the collapse of the Soviet Union. We demonstrate that collaboration rose in Soviet-rich fields relative to Soviet-poor fields and that researchers grew more specialized in Soviet-rich fields relative to Soviet-poor fields. Thus, we test a particular part of the burden of knowledge hypothesis: the impact of a sudden outward shift in the knowledge frontier on collaboration and specialization.

Several prior studies present evidence that the size of research teams has increased steadily over time (Adams et al, 2005; Wuchty et al, 2007; Jones, 2009). For example, Wuchty et al (2007) show that over the latter half of the twentieth century, team size increased in 170 out of 171 fields in science and engineering, 54 out of 54 fields in the social sciences, and 24 of 27 fields in the arts and humanities. Furthermore, this increase even occurred in fields traditionally associated with individual-oriented research: “Surprisingly, even mathematics, long thought the domain of the loner scientist and least dependent of the hard sciences on lab scale and capital-intensive equipment, showed a marked increase in the fraction of work done in teams, from 19% to 57%, with mean team size rising from 1.22 to 1.84.” Moreover, they present citation-based evidence that the relative impact of team versus individual output is increasing over time, even after controlling for self-citations.

Scholars have advanced a number of hypotheses to explain this trend. Hesse et al (1993) and others emphasize the role of reduced communication costs due to advances in communication technology (Agrawal and Goldfarb, 2008; Kim et al, 2009) or reductions in the cost of travel. Stephan (2012) discusses several more alternatives. For example, increasing capital intensity in many fields, such as the role of particle accelerators in physics, may increase the returns to collaboration due to the indivisibilities of research equipment. Changing norms may mean that contributors who in the past may have been listed in the acknowledgements are increasingly likely to be included as coauthors, especially in lab-based sciences. Academics also may find increasing returns to mitigating publication risk by diversifying their research portfolios as publication requirements for promotion and tenure rise.

Jones (2009) emphasizes the “knowledge burden” hypothesis in which successive generations of innovators face an increasing education burden due to the advancing knowledge frontier. This advancing frontier, he posits, requires innovators to specialize more and thus necessitates working more collaboratively, which alters the organization of innovative activity towards teamwork. Jones provides descriptive statistics consistent with this theory. For example, he shows that over time: 1) the number of co-authors on academic publications increases, 2) Nobel laureates are older when they perform their great achievement, 3) the number of co-inventors per patent increases, 4) the age at first innovation increases, and 5) the probability of switching fields decreases. However, these statistics are also consistent with some of the other explanations.

While the various explanations are not mutually exclusive, it is instructive to know whether the outward shifting knowledge frontier does influence the propensity to collaborate, because this would raise a set of specific policy implications. For example, Jones (2011) presents a model in which this increased knowledge burden leads to a poverty trap. As the knowledge frontier shifts outwards, individuals compensate by specializing, and thus the returns to collaborating increase. However, in economies where the market for complementary skills is thin, individuals are less likely to invest in the human capital necessary to reach the frontier. This results in an increasingly thin market for specialized skills (i.e., a trap). Therefore, one policy prescription is to subsidize skills development in a concentrated area (e.g., infectious diseases) in order to address the complementary skills shortage for a finite period of time until the private returns to acquiring specialized skills are sufficient for the labour market to sustain the cycle without further intervention. This policy initiative is not appropriate if knowledge accumulation does not increase the returns to collaboration and the observed rise in team size is actually due to other factors in the economy, such as rising capital costs and/or falling communication costs.

In a separate paper, Jones (2010) proposes policies involving changes to the way ideas are evaluated. If research teams, rather than individuals, are needed to work on scientific problems due to an outward shifted knowledge frontier, then perhaps evaluation teams rather than individuals are needed to evaluate grant applications. Again, this policy prescription is not relevant if the observed increase in team size is not due to knowledge accumulation but rather other factors. For example, if team size is increasing due to rising capital costs, this does not imply increasing returns to team-based evaluation since the equipment is not required for evaluating the grant proposal. Jones also proposes increased subsidies for individuals who enter into science careers since, under the knowledge accumulation hypothesis, researchers bear increasing private costs to reach the frontier. Again, this policy prescription is not appropriate if the knowledge accumulation hypothesis is incorrect and the observed rise in collaboration is due to other factors.

Therefore, these policy implications suggest that identifying a causal relationship between an outward shift in the knowledge frontier and an increase in the propensity to collaborate, separately from other explanations for increasing collaboration, is important. However, identification is difficult because many unobservables may be (and likely are) correlated with both collaborative behavior as well as the march of time. In order to provide more compelling evidence that an outward shift in the knowledge frontier leads to a growing propensity to collaborate, we need an instrument that is correlated with a shift in the knowledge frontier but not with collaboration except indirectly through its effect on the frontier.

The collapse of the Soviet Union in 1989 provides such an instrument.[1] Although the USSR was a world leader in various subfields of mathematics, Communist government officials forced their researchers to work in isolation from the rest of the world. For example, with few exceptions, scholars were prohibited from traveling, publishing outside of the Soviet Union, and from accessing foreign publications without case-by-case government approval. Thus, when the Iron Curtain fell and Soviet science became widely available, the knowledge frontier in mathematics outside the USSR experienced a shock.

Furthermore, the degree of the knowledge shock across subfields of mathematics varied because Soviet researchers had made significant advances relative to the rest of the world in some subfields but not others. We therefore focus on theoretical mathematics. Borjas and Doran (2012a)

[1] Of course, this is not the first paper to use political shocks as an instrument to understand changes in knowledge production, knowledge dissemination, and growth. Many others also have used this empirical strategy, including Waldinger (2010, 2012), Fons-Rosen (2012), Stuen, Mobarak, and Maskus (2012), Jones and Olken (2005), and Acemoglu, Hassan, and Robinson (2011). Our specific identification strategy exploits the same political shock as Borjas and Doran (2012a, b, c). Their research examines the impact of the collapse of the Soviet Union on the rate of output of American and Soviet mathematicians and on the type of research done by American mathematicians, comparing Soviet-rich and Soviet-poor fields of mathematics. We exploit the same variation across fields to study a different question, emphasizing the impact on knowledge flows rather than labor market flows.

show that the Soviet mathematics community was very advanced relative to the West in some subfields of theoretical mathematics, such as “partial differential equations” and “operator theory,” and much less so in others, such as “abstract harmonic analysis” and “sequences, series, summability.”

We exploit this variation in the degree of knowledge shock across subfields using a difference-in-differences type of analysis. Specifically, we compare the propensity of mathematicians working outside the USSR to collaborate in “Soviet-rich” versus “Soviet-poor” subfields before and after the shock. We do this using 41 years of publication data in theoretical mathematics covering the period 1970-2010, 20 years both before and after the collapse of the Soviet Union.

We categorize papers using the internationally recognized Mathematics Subject Classification codes developed and assigned by the Mathematical Reviews division of the American Mathematical Society. We follow the Soviet-rich versus Soviet–poor subfield classification developed by Borjas and Doran (2012a), which they base on the fraction of publications produced by Soviet researchers during the period 1984-1989. We then focus our attention on mathematicians working outside the USSR and drop observations that involve collaboration with Soviet researchers.

We find that team size - the number of coauthors on a paper - increased after the fall of the Iron Curtain, in both Soviet-rich and -poor subfields. However, consistent with the theory, team size grew disproportionately more in Soviet-rich subfields after the shock. Specifically, we calculate the mean team size before and after the collapse of the Soviet Union. For the “treated” subfields (Soviet-rich), the mean team size for the 20-year period before 1990 was 1.34 compared to 1.78 for the 20-year period after. By comparison, for the “control” subfields (Soviet-poor), the mean team size was 1.26 before compared to 1.55 after. These differences in means suggest a disproportionate increase in team size for Soviet-rich subfields after the collapse of the Soviet Union (Figure 1). The mean team size for Soviet-rich subfields was just 6% higher than for Soviet-poor before 1990, but 15% higher after. This finding is consistent with the knowledge frontier effect. However, there may be systematic differences between

Soviet-rich and -poor subfields that are not accounted for when comparing these simple means. Therefore, we turn to our difference-in-differences estimation to study the relationship further. We find evidence of an up to 8% disproportionate increase in collaboration for Soviet-rich subfields after the collapse of the Soviet Union. This result is robust to various definitions of Soviet-rich versus -poor subfields. Pre-existing time trends do not drive these results: We show that the disproportionate increase in team size in Soviet-rich fields did not begin until shortly after 1990. Moreover, we find that authors in Soviet-rich fields disproportionately increased their propensity to draw upon Soviet knowledge after 1990, providing further evidence consistent with the knowledge accumulation explanation.

Next, we turn our attention to understanding the mechanism of the observed increase in team size and provide evidence that the increase in collaboration is consistent with the knowledge burden hypothesis. In particular, we find evidence of an increase in researchers' specialization in Soviet-rich subfields relative to Soviet-poor subfields after the fall of the Soviet Union. We employ an author-level measure of specialization based on of the number of fields that authors publish in. We observe an increased tendency of authors publishing in Soviet-rich subfields to specialize (relative to authors publishing in Soviet-poor subfields) after the collapse of the Iron Curtain.

An alternative explanation for the increased collaboration in mathematics after the fall of the Soviet Union is that the influx of Soviet mathematicians to American and European universities (documented in Borjas and Doran 2012a, 2013a, 2013b) increased competition for jobs and journal slots. We believe our results are more likely driven by an outward shift in the knowledge frontier for four reasons. First, we drop all papers with Soviet authors from our main specifications. Second, and more importantly, papers in Soviet-rich fields disproportionately cited Soviet papers after the fall of the Soviet Union, suggesting that these fields were disproportionately influenced by Soviet knowledge rather than Soviet scholars (especially given that these papers were written by non-Soviet scholars).

Third, the increased specialization in Soviet-rich fields is consistent with the direct mechanism described in Jones (2009). Last and perhaps most important, we show the same patterns of evidence consistent with the knowledge burden hypothesis when restricting our attention to journals local to Japan, a country that was not a destination choice for Soviet scholars.

We structure the remainder of the paper as follows. In Section 2, we provide historical context for our instrument, explaining how knowledge was developed in the Soviet Union and yet kept secret from Western mathematicians, creating the conditions for the 1990 shock to the frontier. In Section 3, we describe our differences-in-differences empirical strategy by comparing the propensity to collaborate in Soviet-rich versus –poor subfields before and after the knowledge shock. In Section 4, we describe the mathematics publication data we use to construct our sample as well as the method we employ for classifying subfields as Soviet-rich or –poor. We present our results in Section 5 and then our conclusions in Section 6.

2. Historical Context

Our empirical strategy relies on the assertion that the collapse of the Soviet Union around 1990 caused an outward shift in the knowledge frontier in mathematics and that it did so more for some subfields than others. We rely on three observations to substantiate this assertion: 1) the Soviet Union's effect on the knowledge frontier in mathematics was significant, 2) the Soviet Union's effect on the knowledge frontier was greater in some subfields than others, and 3) the knowledge produced in the Soviet Union was kept secret from the outside world such that its effect on the frontier came reasonably suddenly in the years following 1990. We offer historical context for each of these three points below.

The first observation is that the Soviet Union's contribution to knowledge in the field of mathematics was meaningful and significant. The Soviet Union was and Russia continues to be a worldrenowned center of scientific research, with mathematics holding a prominent position. Lauren Graham, a historian of Soviet science and technology states (Graham, 2008): “Of all fields of knowledge, it was mathematics to which Russia and the Soviet Union made the greatest contributions. The Soviet Union became a world power in mathematics. Indeed, Moscow is probably today the city of the greatest concentration of mathematical talent anywhere. The main competitor is no doubt Paris, since mathematicians in the United States, another leader in mathematics in the last generation, are more widely distributed geographically than in France or the Soviet Union.” Graham attributes the nation’s strength in scholarly research in mathematics to the fact that it attracted great minds; it was uniquely detached from politics, conferred status and prestige, and offered financial rewards superior to many other occupations.

The second observation is that the Soviet Union’s contribution to knowledge was significantly greater in some subfields of mathematics than others. Borjas and Doran (2012a) show this empirically by comparing across subfields the fraction of Soviet to American papers published during the period 1984-1989. We provide further evidence below by comparing the fraction of Soviet to non-Soviet worldwide papers published during the period 1970-1989.

Graham (1993) notes that although Soviet mathematics was strong across the entire spectrum of theoretical and applied mathematics, they seemed to have made the greatest advancements, relative to the rest of the world, in pure theory. One explanation for this is politics. Soviet policies were strict about secrecy and focused on maintaining control over technological development. It was easier for Soviet mathematicians to build on their progress in pure theory than in areas where technology implementation was more immediate. Many advances in applied mathematics were stalled for political reasons, with exceptions linked to government interests such as the space program (Graham, 1993). Differences in subfields were further amplified due to path dependency: subfields that attracted bright minds early on were more likely to subsequently attract more bright minds due to mentorship opportunities (Borjas and Doran, 2012a). The importance of mentorship is well known in science (Merton, 1973) and was likely particularly salient in this setting due to restrictions on travel and access to foreign journals. For example, the success of Moscow mathematics can be traced back to Ergorov and his student N. N. Luzin (Tikhomirov, 2007). Luzin, whose famous work was mainly focused on the theory of functions, a subfield of theoretical mathematics, mentored subsequent generations of eminent Soviet mathematicians. On the other hand, little outstanding mentorship was available to practitioners of some other subfields of theoretical mathematics, like algebraic geometry (Borjas and Doran, 2012a).

The third observation is that the knowledge produced in the Soviet Union was kept secret from the outside world such that its effect on the frontier came reasonably suddenly in the years following 1990. Soviet researchers were prevented from publishing their findings, traveling to conferences, communicating or collaborating with non-Soviets, and even accessing non-Soviet references. The Communist government kept strict control on international travel. Academics who wished to attend foreign conferences had to go through a stringent and lengthy approval process, with many researchers blacklisted because of “tainted” backgrounds. The few approvals granted were typically for travel in Eastern Europe (Ganguli, 2011).

Furthermore, Soviet advancements in mathematics remained relatively[2] unknown in the United States until the collapse of the Soviet Union mainly because the USSR government kept much of Soviet science secret (Graham and Dezhina, 2008). In addition, what escaped the secrecy filter was subject to the natural barrier imposed by the Russian language. Graham and Dezhina (2008) note that "the Russian language was known by few researchers outside the Soviet Union, and consequently the achievements of Soviet researchers were more frequently overlooked than those presented in more accessible languages."

[2]Borjas and Doran (2012a) provide extensive evidence that Soviet knowledge in mathematics was not known in the West, although translations of some Soviet scientific journals were available before the collapse of the Soviet Union.

This limited diffusion of Soviet mathematics into the West is evident in the aftermath of the collapse of the Soviet Union. Starting in 1990, Soviet discoveries began to spread through the West and were considered new and important. Communication and travel restrictions were lifted, publications were translated and indexed, and ideas and knowledge began to flow out from the Soviet Union into the broader research community. The following quote, from an article published on May 8, 1990 in the *New York Times*, provides an indication of the sudden outward shift of the knowledge frontier.

> *Persi Diaconis, a mathematician at Harvard, said: ''It's been fantastic. You just have a totally fresh set of insights and results.'' Dr. Diaconis said he recently asked Dr. Reshetikhin for help with a problem that had stumped him for 20 years. ''I had asked everyone in America who had any chance of knowing'' how to solve a problem of determining how organized sets become disorganized, Dr. Diaconis said. No one could help. But Dr. Reshetikhin told Dr. Diaconis that Soviet scientists had done a lot of work on such problems. ''It was a whole new world I had access to,'' Dr. Diaconis said.*

In sum, we argue that the fall of the Iron Curtain provides a plausible natural experiment differentially affecting the knowledge frontier across subfields of theoretical mathematics. This historical event was exogenous to the mathematics research community and set free a large pool of accumulated knowledge. Furthermore, Borjas and Doran (2012a) present comprehensive evidence indicating that the timing of the collapse took the global mathematics community by surprise; even in the late 1980s, both the Western mathematical community and Soviet scholars were quite certain that Soviet mathematics would remain secluded for the foreseeable future.

3. Estimation Strategy

We employ a difference-in-differences estimation strategy in which we compare collaboration rates in subfields where the knowledge frontier was most affected by Soviet knowledge ("treated") with subfields least affected ("control"), both before and after the fall of the Iron Curtain. In other words, we can see this as examining the difference between treated and control subfields in two periods, before and after the treatment. This helps us attempt to distinguish between the rise in team size directly attributable to the shift in the knowledge frontier, underlying differences between treated and control subfields, and underlying changes in collaboration patterns in theoretical mathematics over time.

The objective of our empirical analysis is to estimate the effect of the knowledge shock on collaboration, which we measure as a count of the number of unique authors on a publication. Thus, we estimate the following linear regression model using the academic paper as our unit of analysis:

$$TeamSize_{it} = \beta(SovietRich_i \times AfterIronCurtain_t) + Subfield_i + \gamma_t + \varepsilon_{it} \qquad (1)$$

$TeamSize_{it}$ is the count of authors for each academic paper *i* published in year t. $SovietRich_i$ is an indicator variable equal to 1 if academic paper *i* belongs to the treated group and 0 otherwise. $AfterIronCurtain_t$ is an indicator variable equal to 1 if academic paper *i* is published after 1990 and 0 otherwise. This applies to academic papers in both treated and control subfields. We include subfield and time fixed effects, hence the main effects $SovietRich_i$ and $AfterIronCurtain_t$ drop out of the estimating equation.

We are primarily interested in the estimated coefficient on the interaction between $SovietRich_i$ and $AfterIronCurtain_t$, which equals 1 for publications in treated subfields that were published after the knowledge shock and equals 0 for all others. We interpret a positive estimated value of this coefficient as implying that the average team size of Soviet-rich subfields increased disproportionately, relative to Soviet-poor subfields, after the knowledge shock, consistent with the knowledge frontier theory. After establishing this relationship, we provide evidence consistent with a mechanism driven by an outward shift in the knowledge frontier.

4. Data

We next describe our three main steps in the collection and preparation of our data set. First, we extract publication data, then we rank subfields in mathematics with respect to the relative contribution by Soviets, and finally we process the data for analysis.

4.1 Data Collection

We collect data on every publication in theoretical mathematics published during the 41-year period 1970 – 2010. This represents 20 years of data before and after the collapse of the Soviet Union in 1990. We follow Borjas and Doran's (2012a) interpretation of historical events that isolates 1990 as the year when academic seclusion was significantly lessened. We recognize that the political and social turmoil preceding and following the fall of the Iron Curtain spanned a period of roughly three years, between 1989 and 1991. Our results are robust to choosing 1989 or 1991 as the cutoff rather than 1990.

We collect these data from the American Mathematical Society (AMS). The Mathematical Reviews (MR) division of AMS maintains a comprehensive bibliographic database of worldwide academic publications in mathematics. The MR database includes all mathematics-related journal publications covering the three main categories of mathematics: mathematical foundations (including history and biography), pure or theoretical mathematics, and applied mathematics. Our focus is on theoretical mathematics, which includes analysis, algebra, and geometry (Figure 2).

4.2 Classification

Our empirical strategy relies on exploiting variation in the degree to which the knowledge frontier was shifted outwards as a result of the collapse of the Soviet Union. Specifically, we distinguish between subfields of theoretical mathematics where the Soviets were particularly strong in the years prior to the collapse versus subfields where they were less strong. We credit Borjas and Doran (2012a) for their insight on how to assemble these data to estimate this variation.

We rely on the careful and exhaustive work of the Mathematical Reviews division, which classifies each paper in mathematics using Mathematics Subject Classification (MSC) codes. The MSC schema is internationally recognized and facilitates targeted searches on research subjects across all subfields of mathematics. The MR team assigns precisely one primary MSC code to each academic publication uploaded to the MR database. A total of 40 active primary MSC codes (14 algebra, 19 analysis, 7 geometry) comprises the theoretical mathematics group.

We drop the six subfields that do not exist throughout the 40-year duration of our study period as well as one subfield for which we are not able to obtain the full data, leaving us with 33 subfields within theoretical mathematics. Next, we adopt Borjas and Doran's (2012a) ranking of the remaining 33 subfields, which is based on the degree to which Soviets contributed to a particular subfield. They construct their rank by calculating the ratio of Soviet to American publications in the subfield over the period 1984-1989 and define a publication as Soviet if at least one author has a Soviet institutional affiliation. They define similarly American publications. We list the 33 subfields and their rank in Table 1.

We use the Borjas and Doran (2012a) ranking throughout the paper but also show that the main results are robust to an alternate measure. While broadly similar to Borjas and Doran's measure, this measure differs on three dimensions. First, this alternative measure defines a publication as Soviet based on author name data rather than author affiliation data.[3] Second, this measure compares Soviet publication output relative to the rest of the world rather than relative to US publication output. Third, this measure uses ratios based on data from 1970 to 1989 rather than from 1984 to 1989. In the end,

[3] We identify Soviet last names based on conversations with experts and documented rules regarding Soviet surname endings. We then test and calibrate our algorithm by manually looking up and verifying if academics identified as having Soviet last names were indeed Soviets.

the rankings are reasonably similar, with a spearman rank correlation coefficient of 0.84. Furthermore, we show in the appendix that our main result remains robust to using this alternative name-based ranking.

4.3 Data Processing

In our main specifications, we drop all Soviet publications from the sample. We define Soviet publications as those with at least one Soviet author. We do this to avoid potential confounding effects. After 1990, not only was Soviet knowledge set free to contribute to global advancements in mathematics, but collaboration restrictions also were lifted for Soviet mathematicians. By excluding publications with at least one Soviet author, we account for the possibility of increased co-authorship rates due to removing the constraint previously preventing collaboration with Soviets.[4]

After dropping Soviet publications, our sample includes 563,462 publications spanning the 41-year period. We label a comparison between the three top (Soviet-rich) and bottom (Soviet-poor) ranked subfields, which represents 133,497 publications, as our main specification; however, we show the results are robust to alternative definitions of Soviet-rich: 1) top three ranking subfields relative to all other, 2) top five ranking subfields relative to all other, 3) top ten ranking subfields relative to all other and 4) a continuous measure which relies on variation within the 33 ranked subfields of theoretical mathematics. We provide descriptive statistics in Table 2.

[4] Our results remain robust when adding Soviet authors back to the sample (Appendix Table 2).

5. Results

5.1 Main Result: Disproportionate Increase in Team Size in Soviet-Rich Subfields After 1990

We report the estimated coefficients of Equation 1 in Table 3. We present our main specification in Column 1. The key result is the estimated coefficient on the interaction term *AfterIronCurtain*×*SovietRich*, which is positive and statistically significant. This implies that the difference in average team size between papers in Soviet-rich versus -poor subfields is greater after the shock than before.

We do not present estimates of the main effects of *AfterIronCurtain* or *SovietRich* because we drop these terms from the estimating equation due to the year and subfield fixed effects. Also, we cluster our standard errors by subfield. We cluster to address the possibility that shocks experienced in each of the 33 subfields may be correlated, both within subfield and over time (Bertrand, Duflo, and Mullainathan 2004; Donald and Lang 2007).

This main result is robust to various definitions of Soviet-rich and when using the full dataset in the subsequent four columns. In the first three columns we define Soviet-rich as the top three, five, and ten subfields and Soviet-poor as all other subfields. The point estimates are smaller (not surprisingly given that the difference between the definitions of Soviet-rich and Soviet-poor is less stark) but remain positive and significant. In the last column we employ a continuous rank measure of Soviet-rich/Soviet-poor, assigning the most Soviet-rich field a rank of 33 and the least a rank of 1. This expands our sample to the full dataset, increasing our sample size by 322% relative to the original, from 133,497 to 563,462 publications. The coefficient remains positive, though significance is lost in the continuous specification.

Next, we examine the timing of this effect, to demonstrate that there was no underlying trend toward increased collaboration in Soviet-rich fields relative to Soviet-poor fields. For example, perhaps the network of scholars in Soviet-rich fields were better positioned to leverage the diffusion of electronic communication technology that led to increased scientific collaboration starting in the 1980s (Agrawal and Goldfarb 2008). In this case, one might worry that the effect of lowered collaboration costs, although spread out over many years and during a slightly earlier period than the 1989-1991 events in the Soviet Union, could explain the result.

To check for such a possibility, we examine the timing of the relationship between the collapse of the Soviet Union and changes in the relative team size in Soviet-rich subfields. Specifically, we run a similar regression to the one shown in Table 3 Column 1; however, we replace the single interaction *AfterIronCurtain × SovietRich* with a sequence of dummy variables representing each year interacted with *SovietRich*.

We present the results in Figure 3. Each point represents the coefficient value on the covariate *Year×SovietRich* and thus describes the relative difference in collaboration rates between Soviet-rich and -poor fields in that year. The bars surrounding each point represent the 95% confidence interval. All values are relative to the base year of 1970. We also present these results in table form in the appendix. The most notable insight from Figure 3 is that the difference between team sizes in Soviet-rich and -poor fields was stable between 1971 and 1990. Then, starting in 1990, the difference in average team size began to increase, as evidenced by the higher coefficients. Interestingly, the difference in team size became statistically significant after about eight years and then continued to increase for the twelve remaining years in the sample.

5.2 Evidence that the Collapse of the Soviet Union Generated a Knowledge Shock

Next, we provide evidence that is consistent with our result being driven by a change in the knowledge stock, rather than some other factor, such as a change in the level of competition for jobs and journal slots due to the influx of Soviet mathematicians to the United States. To document that the collapse of the Soviet Union did in fact generate a knowledge shock, we turn to citation data. The intuition is that if the lifting of publication restrictions did indeed shift the knowledge frontier outwards and more so in Soviet-rich fields, then this should be observable through (non-Soviet) researchers in Soviet-rich subfields disproportionately increasing their propensity to cite Soviet prior art after 1990.

To accomplish this, we collect data on references for a subsample of our data. Specifically, we collect backward citation data for papers from the top three and bottom three subfields that were published in one of the top 30 journals of mathematics (as measured by Thomson Reuters measures of impact factor). We further restrict the data to a window of four years before and after the collapse of the Soviet Union (1998-1993) for tractability (this data collection process is manual). We extract 1,217 publications that meet these criteria and are authored by non-Soviet scholars.

Next, we search for these publications in the Web of Knowledge reference database maintained by Thompson Reuters. We find full text information on 1,012 papers for which we extract the list of references. We count references to Soviet prior art and calculate the percentage of Soviet references relative to the total number of references. We define a citation (prior art) as Soviet if at least one of the authors had a Soviet last name as identified by our name algorithm. We check the robustness of our finding by using an alternative definition, where we define a citation as Soviet if it was published in a Soviet journal.

We use these data to estimate a difference-in-differences linear regression, similar to the one estimated in Section 5.1 above, but this time employing a measure of citations to Soviet prior art as the dependent variable:

$$SovietArt_{it} = \beta(SovietRich_i \times \ AfterIronCurtain_t) + Subfield_i + \gamma_t + \varepsilon_{it}$$

We report our estimated coefficients in Table 4. In column 1, we define $SovietArt_{it}$ as a count of the number of references to Soviet citations (defined by journal affiliation) by academic paper *i* published in year *t*. The estimated coefficient on the interaction *SovietRich×AfterIronCurtain* is positive and significant, implying that researchers publishing in Soviet-rich fields disproportionately increased their propensity to cite Soviet prior art after 1990, relative to those publishing in Soviet-poor fields.

Next, we show that this result is robust to multiple definitions of "Soviet prior art." In Column 2, we define the dependent variable as the percentage of papers published in Soviet journals relative to the total number of references. We define in Column 3 the dependent variable as a count of references to papers that have at least one Soviet author identified using our last name algorithm and in Column 4 as the percentage of papers that have at least one Soviet author. The main result persists, though we lose statistical significance in column 4.

Thus, the Soviet rich subfields appear to have experienced a knowledge shock after the fall of the Soviet Union. Citations to Soviet papers increased substantially, even by non-Soviet authors.

5.3 Evidence of Specialization

We next provide evidence that the increase in collaboration in Soviet-rich subfields is consistent with the specific mechanism inherent in Jones' knowledge burden hypothesis. In particular, we document a decrease in researcher diversification (i.e. an increase in specialization) in Soviet-rich subfields, relative to Soviet-poor subfields, after the fall of the Iron Curtain.

For this subsection, we switch the unit of analysis to the author-year and examine the degree of diversification for authors who published in a given year. We measure diversification using an author-level count of the number of sub-classification areas (as defined by the AMS in their MSC schema) which were used in the author's publications over the previous five years. Each of the 33 subfields in our data has a large number of sub-classifications.

If we observe increasing specialization, then we expect the number of sub-classifications to fall in Soviet-rich fields after 1990. First we examine all authors and observe authors multiple times if they publish more than once. Then, we examine "junior" authors only by looking at the degree of specialization for each author exactly five years after their first publication. Thus junior authors each appear just once in the data. We analyze juniors separately because they represent a somewhat cleaner test. Specifically, by comparing the early research of scholars who began publishing after the collapse of the Soviet Union with the early research of scholars who entered the field earlier, we examine the degree of specialization in the years of more rapid knowledge accumulation. For author *a* in year *t*, we estimate:

$$DegreeOfDiversification_{at} = \alpha_1(SovietRich_a \times AfterIronCurtain_t) + Subfield_a + \gamma_t + \varepsilon_{at}$$

Here, we define Soviet-rich as equal to 1 for authors who publish in the top half ranking subfields (using the Borjas and Doran ranking). Degree of diversification is the number of sub-classifications that the author published in over the previous five years.

Table 5 shows a disproportionate decrease in diversification for authors who published in Soviet-rich fields after the fall of the Soviet Union. Or, stated differently, we find evidence of a disproportionate increase in specialization for authors who published their work in Soviet-rich subfields. The second columns shows that average number of primary classification codes and sub-codes in which Soviet-rich authors published shows 7% decrease relative to Soviet-poor authors after the collapse of the Soviet Union. Even after adding author fixed effects, and thereby looking at changes in specialization within individuals over time, the effect is a still-significant 1% decrease. Furthermore, the results hold if we focus on junior authors only, though author fixed effects cannot be estimated here because (by construction) we observe junior authors once. When comparing the degree of specialization of pre- and post-1990 junior scholars, we find that post-1990 junior scholars from Soviet-rich subfields were disproportionately more specialized than juniors from Soviet-poor subfields. The average number of primary classification codes and sub-codes in which Soviet-rich juniors published shows a 6% decrease relative to Soviet-poor junior after the collapse of the Soviet Union.

5.4 Knowledge Burden vs. Competition in Labor Markets

Borjas and Doran (2012a, 2013a, 2013b) emphasize the labor market impact of increased competition from Soviet scholars. This alternative explanation for the identified increase in collaboration in mathematics after the fall of the Soviet Union rests on the fact that the influx of Soviet mathematicians to American and European universities resulted in increased competition for jobs and journal slots. To disentangle these alternative explanations we test the knowledge burden hypothesis on a subset of our data. Specifically, we focus on Japan, a country with no documented evidence of Soviet immigration in mathematics (Dubois et al, 2011) and which ranks in the top ten in research in mathematics (Dubois et al, 2011). We show a disproportionate increase in team size for Japanese journal publications from Soviet-rich subfields of mathematics after the collapse of the Soviet Union. This finding is consistent with the knowledge burden hypothesis, identified separately from the alternative explanation of labor market impact due to an influx of Soviet scholars.

We start by identifying all Japanese journals in our data. We do so based on journals' documented affiliation information. Next, we separate Japanese journals included in Thomson Reuters' measures of impact factor from those not included in such ranking. The fact that Japan ranks high in research in mathematics raises concerns that some Japanese journals might be of international interest. Specifically, some of these journals might have been of interest to Soviet scholars located elsewhere. We identify Japanese journals of potential international interest as journals ranked by Thomson Reuters' measures of impact factor.

We estimate using our main difference-in-differences specification (1), restricted on the subset of publications from Japanese journals.[5] We provide separate estimates for all Japanese journal publications, ranked Japanese journal publications, and not ranked Japanese journal publications. Tables

[5] We draw this subset from the set of publications in mathematics, which already excludes all publications involving Soviet scholars.

7 (a, b, c) provide strong support for a disproportionate increase in team size for scholars publishing in Japanese journals, ranked or not.

6. Discussion and Conclusion

We find evidence that an outward shift in the knowledge frontier was associated with a subsequent increase in research team size and in researcher specialization. Importantly, this evidence is consistent with the knowledge frontier explanation but not the other explanations for the widely documented increase in research team size. In other words, although this evidence is not intended to (and does not) rule out other explanations, it does demonstrate the role of the knowledge frontier explanation in one setting, therefore suggesting that it as a plausible explanation for at least some of the overall increase in team size.

In our setting, a back-of-the-envelope calculation indicates that the knowledge frontier effect accounts for 24% of the increase in team size in Soviet-rich fields in theoretical mathematics. We calculate this as follows: team size in Soviet-rich fields increased by 33%, from 1.34 to 1.78, in the before versus after period. We estimate that the Soviet-rich fields experienced an 8% disproportionate increase (relative to Soviet-poor) during this period (Table 3, Column 1). This represents 24% of the overall percentage increase. While this rough calculation can be seen as a lower bound because it assumes none of the increase in Soviet-poor subfields was due to an outward shift in the knowledge frontier, we resist this interpretation because of the numerous other assumptions underlying the 24% value.

More broadly, it is important to clarify the limitations of our test of the knowledge burden hypothesis. First, we test a particular implication of the knowledge burden hypothesis: the impact of a sudden outward shift in the knowledge frontier on collaboration and specialization. An underlying assumption of our interpretation of our estimates is that the team size response to a shock is similar to that for a gradual outward shift in the knowledge frontier. However, that may not be the case. Researchers may be able to absorb gradual increases in the knowledge frontier in a manner that does not generate as high returns to collaboration as those resulting from a sudden shock that may be more costly for researchers to internalize. Thus, our empirical results may not measure the impact of a gradual shift in the knowledge frontier.

Second, there may have been other impacts of the collapse of the Soviet Union on the field of mathematics. Borjas and Doran (2012a, 2013a, 2013b) emphasize the labor market impact of increased competition from Soviet scholars. This increased competition also may have also driven the increase in collaboration if, for example, journals did not start accepting more papers or jobs searches became increasingly focused on quantity of papers. While we view our results on Japanese publications, citations to Soviet prior art, and specialization as more consistent with the knowledge burden hypothesis, we cannot definitively reject the possibility that changing labor markets played some role.

Third, we focus on one particular field: mathematics. Adams et al (2005) show that mathematics is somewhat of an outlier in team size relative to other disciplines. Mathematics has relatively small teams. In the first year of their study, 1981, mathematics publications had the fewest number of authors (of 12 fields). Furthermore, mathematics had the lowest annual growth rate in team size from 1981 to 1990 and the second lowest from 1990 to 1999. In contrast, physics and astronomy had the highest growth rates, which may have been partly driven by the increasing role of capital-intensive equipment (e.g., particle accelerators) in those fields. Therefore, even if 24% is a reasonable lower-bound estimate of the fraction of the percentage increase in team size in mathematics, it is likely an overestimate in fields where capital equipment plays a more central role.

Overall, we have documented that the collapse of the Soviet Union led to an increase in collaboration among non-Soviet researchers in those fields in which Soviet mathematicians were strongest. Our evidence on citations to Soviet work and increased specialization are consistent with the burden of knowledge hypothesis: a knowledge shock leading to increased specialization and collaboration. In a series of papers (2009, 2010, 2011), Jones presents a variety of interventions that are potentially welfare-enhancing in the presence of a knowledge frontier effect. These include subsidies and rewards to incentivize entry into research careers, team-based evaluation of grant applications, and national or regional subsidies and specialization to prevent poverty traps due to underinvestment in human capital from coordination failures arising from thin markets for complementary skills. The evidence presented here suggests the possibility that the knowledge frontier effect is indeed non-trivial and worthy of further research.

References

Acemoglu, Daron, Hassan, Tarek A., Robinson, James A. 2011. Social Structure and Development: A Legacy of the Holocaust in Russia. *Quarterly Journal of Economics*, 126(2), 895-946.

Adams J.D., Black, G.C., Clemmons, J. R., Stephan P. E. 2005. Scientific Teams and Institutional Collaborations: Evidence from U.S. Universities, 1981-1999. *Research Policy*, 34 (3), 259-285.

Agrawal, A., Goldfarb, A. 2008. Restructuring Research: Communication Costs and the Democratization of University Innovation. *American Economic Review*, 98(4), 1578–1590.

Borjas, G. J., Doran, K. B. 2012a. The Collapse of the Soviet Union and the Productivity of American Mathematicians. *The Quarterly Journal of Economics*, 127(3), 1143-1203.

Borjas, G. J., Doran, K. B. 2013a. Cognitive Mobility: Native Responses to Supply Shocks in the Space of Ideas. NBER working paper #18614. .

Borjas, G. J., Doran, K. B. 2013b. Which Peers Matter? The Relative Impacts of Collaborators, Collegues and Competitors.. Working paper, University of Notre Dame.

Dubois, P., Rochet, JC., Schlenker, M. 2013. Productivity and Mobility in Academic Research: Evidence from Mathematicians. Working paper.

Fons-Rosen, Christian. 2012. Knowledge Flows through FDI: The Case of Privatisations in Central and Eastern Europe. Working paper, Universitat Pompeu Fabra.

Ganguli, I. 2012. Saving Soviet Science: The Impact of Grants When Government R&D Funding Disappears. Working paper.

Graham, L. R. 1993. Science in Russia and the Soviet Union: A Short History. Cambridge University Press.

Graham, L. R. , Dezhina, I. 2008. Science in the New Russia: Crisis, Aid, Reform. Indiana University Press.

Grossman, J. W. 2002. The Evolution of the Mathematical Research Collaboration Graph. *Congressus Numerantium*, 158, 201-212.

Hesse, Bradford W., Sproull, Lee S., Kiesler, Sara B., Walsh, John P. 1993. Returns to Science: Computer Networks in Oceanography. *Communications of the ACM*, 36(8), 90-101.

Jones, B. 2009. The Burden of Knowledge and the Death of the Renaissance Man: Is Innovation Getting Harder? *Review of Economic Studies*, 76(1), 253-281.

Jones, B. 2010. As Science Evolves, How Can Science Policy? *NBER Innovation Policy and the Economy*, 11,103-131.

Jones, B. 2011. The Knowledge Trap: Human Capital and Development, Reconsidered. NBER Working paper #14138.

Jones, B., Olken, B.A. 2005. Do Leaders Matter? National Leadership and Growth Since World War II. *Quarterly Journal of Economics*,120(3), 835-864.

Kim, E.H., Morse, A., Zingales, L. 2009. Are Elite Universities Losing Their Competitive Edge? *Journal of Financial Economics*, 93(3), 353-381.

Merton, R. K. 1973. The Sociology of Science: Theoretical and Empirical Investigations. University of Chicago Press, Chicago.

Mowery, D., Nelson, R., Sampat, B., Ziedonis, A. 2004. Ivory Tower and Industrial Innovation. Stanford University Press.

Newman, M. E. J. 2004. Coauthorship Networks and Patterns of Scientific Collaboration. *Center for the Study of Complex Systems and Department of Physics*, University of Michigan, Ann Arbor.

Oettl, Alex. 2012. Reconceptualizing Stars: Scientist Helpfulness and Peer Performance. *Management Science* 58(6), 1122–1140.

Polyak, B.T. 2002. History of Mathematical Programming in the USSR: Analyzing the Phenomenon. *Mathematical Programming*, 91, 410-416.

Rosen, S. 1981. The economics of superstars. *American Economic Review* 71(5), 845–858.

Tikhomirov, V. M. 2007. On Moscow Mathematics - Then and Now. Golden Years of Moscow Mathematics, Second edition, co-publication of the AMS and the London Mathematical Society.

Singh, J., Fleming, L. 2010. Lone Inventors as Sources of Break-Through: Myth or Reality? *Management Science* 56(1), 41–56.

Sonnenwald, D. H. 2007. Scientific Collaboration. *Annual Review of Information Science and Technology* 41(1), 643-681.

Stephan, P. 2012. How Economics Shapes Science. Harvard University Press.

Stuen, E.T., Mobarak, A.M., Maskus, K.E. 2012. Skilled Immigration and Innovation: Evidence from Enrollment Fluctuations in US Doctoral Programmes. *Economic Journal* 112(565), 1143-1176.

Waldinger, F. 2010. Quality Matters: The Expulsion of Professors and the Consequences for PhD Student Outcomes in Nazi Germany. *Journal of Political Economy*, 118(4), 787-831.

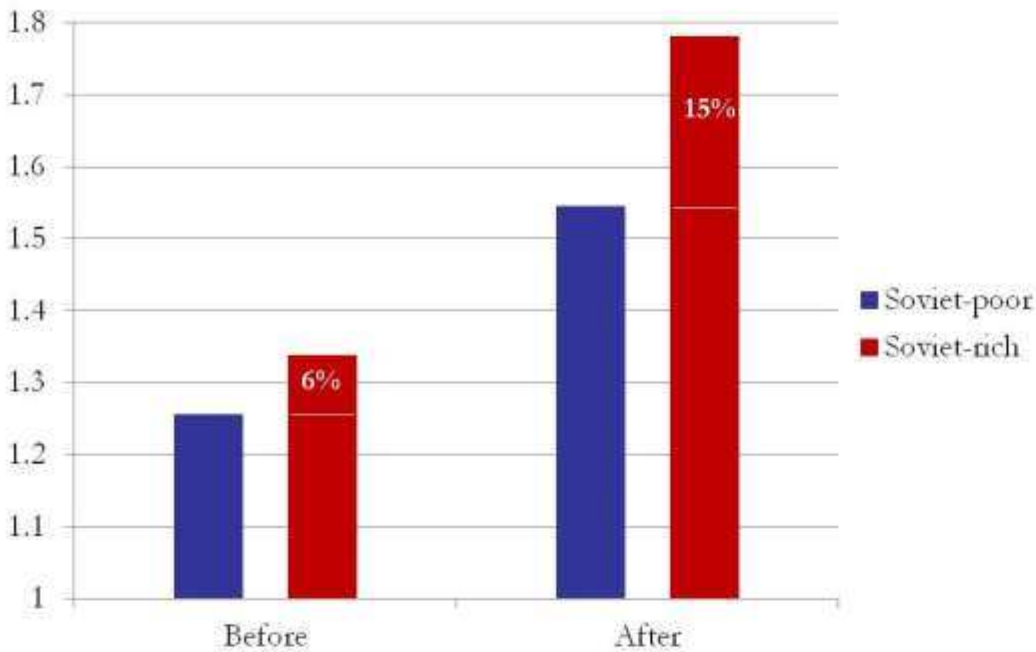
Waldinger, F. 2012. Peer Effects in Science—Evidence from the Dismissal of Scientists in Nazi Germany. *Review of Economic Studies* 79(2), 838-861.

Walsh, J. P., Bayma, T. 1996. Computer Networks and Scientific Work. *Social Studies of Science,* 26(3), 661-703.

Wuchy, S., Jones, B., Uzzi, B. 2007. The Increasing Dominance of Teams in Production of Knowledge. *Science* 316, p. 1036.

Zucker, L. G., M. R. Darby, M. B. Brewer. 1998. Intellectual human capital and the birth of U.S. biotechnology enterprises. *American Economic Review* 88(1) 290–306.

Figure 1: Disproportionate increase in mean team size in Soviet-rich subfields



Notes: We base this figure on 40 years of publication data for the three top and three bottom ranked subfields of theoretical mathematics. We plot the average team size for Soviet-rich and Soviet-poor subfields, before and after 1990.

Figure 2: Mathematics Taxonomy

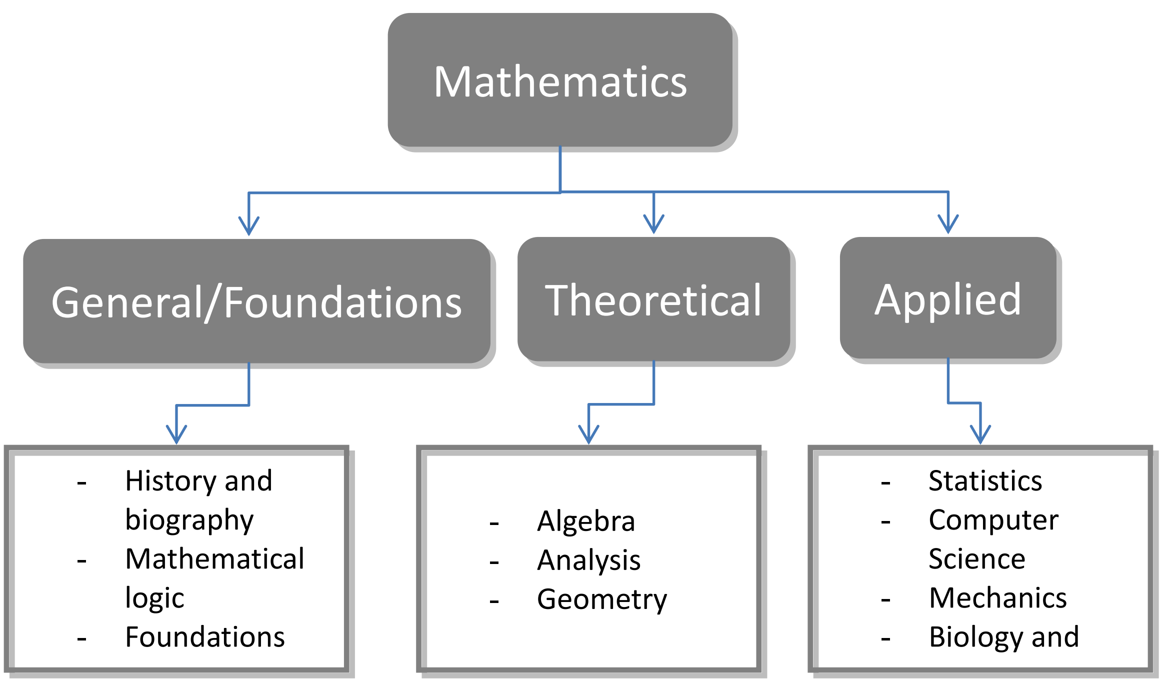
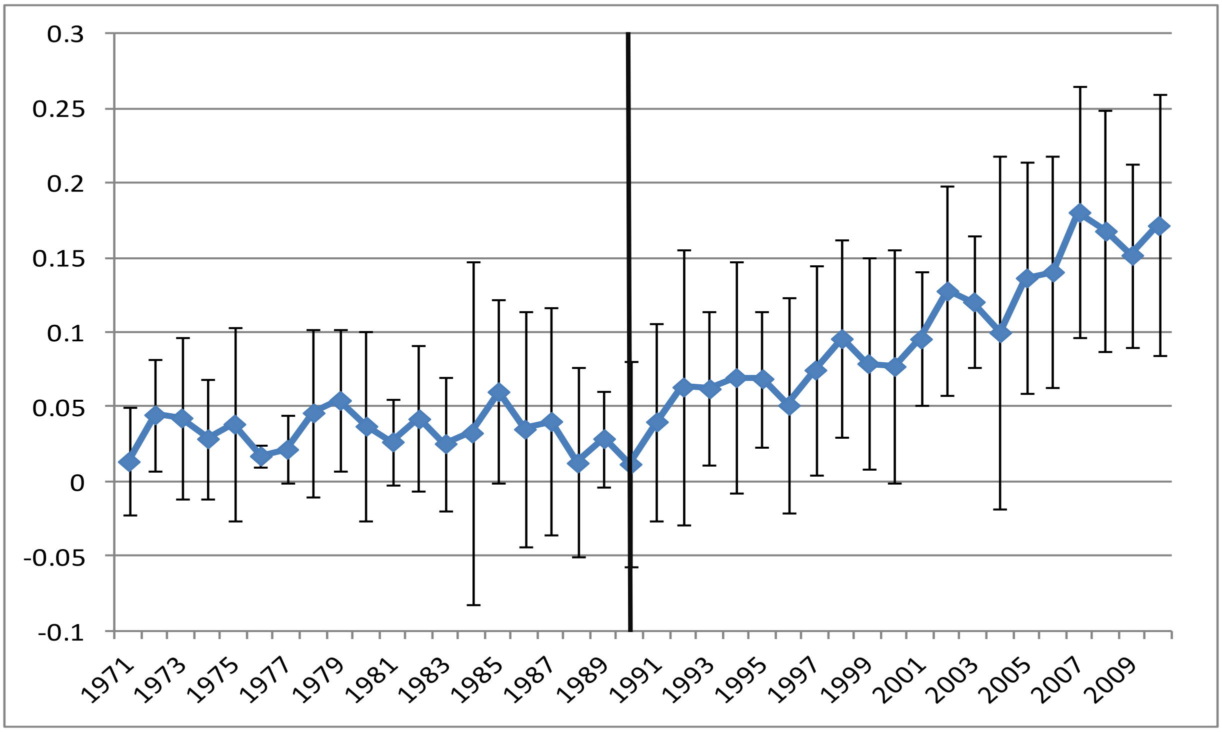


Figure 3: Plot of estimated coefficients on interaction between Soviet-rich and year (DV = Team Size)



Notes: We base this figure on 40 years of publication data for the three top and three bottom ranked subfields of theoretical mathematics. Each point on the graph represents the coefficient value on the covariate Year×SovietRich and thus describes the relative difference in collaboration rates between Soviet-rich and -poor fields in that year. The bars surrounding each point represent the 95% confidence interval. All values are relative to the base year of 1970. We also present these results in table form in Appendix Table 2.

Table 1: Subfield rank based on proportion of Soviet publications (1984-1989)

Subfield Rank as per Borjas and Doran (2012a)	MSC	Theoretical mathematics category	Description
1	45	Analysis	Integral equations
2	42	Analysis	Fourier analysis
3	35	Analysis	Partial differential equations
4	40	Analysis	Sequences, series, summability
5	31	Analysis	Potential theory
6	49	Analysis	Calculus of variations and optimal control; optimization
7	44	Analysis	Integral transforms, operational calculus
8	30	Analysis	Functions of a complex variable
9	8	Algebra	General algebraic systems
10	39	Analysis	Difference equations and functional equations
11	47	Analysis	Operator theory
12	17	Algebra	Non-associative rings and non-associative algebras
13	41	Analysis	Approximations and expansions
14	58	Geometry	Global analysis, analysis on manifolds
15	32	Analysis	Several complex variables and analytic spaces
16	33	Analysis	Special functions
17	22	Algebra	Topological groups, lie groups, and analysis upon them
18	54	Geometry	General topology
19	20	Algebra	Group theory and generalizations
20	28	Algebra	Measure and integration
21	18	Algebra	Category theory; homological algebra
22	55	Analysis	Algebraic topology
23	26	Algebra	Real functions, including derivatives and integrals
24	52	Geometry	Convex geometry and discrete geometry
25	14	Algebra	Algebraic geometry
26	43	Analysis	Abstract harmonic analysis
27	15	Algebra	Linear and multilinear algebra; matrix theory
28	6	Algebra	Order theory
29	12	Algebra	Field theory and polynomials
30	5	Algebra	Combinatorics
31	51	Geometry	Geometry
32	57	Geometry	Manifolds
33	13	Algebra	Commutative rings and algebras

Notes: We adapt this ranking from Borjas and Doran (2012a) and base it on the ratio of the number of Soviet versus American papers published in the particular subfield between 1984 and 1989. We define papers as Soviet if at least one author has a Soviet institutional affiliation. We similarly define American papers.

Table 2: Descriptive Statistics

	Mean	Standard Deviation	Minimum	Maximum	Number of Observations
All observations					
Log of author count	0.342	0.425	0	2.89	563,462
After Iron Curtain	0.625	0.484	0	1	563,462
Soviet Rich (top 3)	0.169	0.374	0	1	563,462
After Iron Curtain x Soviet Rich (top 3)	0.121	0.326	0	1	563,462
Soviet Rich (top 5)	0.183	0.386	0	1	563,462
After Iron Curtain x Soviet Rich (top 5)	0.128	0.334	0	1	563,462
Soviet Rich (top 10)	0.287	0.452	0	1	563,462
After Iron Curtain x Soviet Rich (top10)	0.194	0.395	0	1	563,462
Top and bottom three fields only					
Log of author count	0.362	0.428	0	2.19	133,467
After Iron Curtain	0.678	0.467	0	1	133,467
Soviet Rich	0.711	0.453	0	1	133,467
After Iron Curtain x Soviet Rich	0.511	0.500	0	1	133,467
Count of Soviet references by name	0.811	1.528	0	12	1,012
Percent of Soviet references by name	0.046	0.084	0	0.6	1,012
Count of Soviet references by journal	0.295	0.881	0	12	1,012
Percent of Soviet references by journal	0.015	0.047	0	0.5	1,012
Count of subfields (all authors)	2.039	1.705	1	47	315,161
Log of count of subfields (all authors)	0.490	0.613	0	3.850	315,161
Count of subfields (junior authors)	1.931	1.471	1	26	41,282
Log of count of subfields (junior authors)	0.463	0.580	0	3.258	41,282

Table 3: Teams in Soviet-rich subfields exhibit disproportionate increase in team size after 1990

	Dependent variable: log of author count				
	Top and bottom 3 subfields	**Soviet-rich defined as top 3 of subfields**	**Soviet-rich defined as top 5 of subfields**	**Soviet-rich defined as top 10 of subfields**	**Continuous**
AfterIronCurtain× SovietRich	0.0780***	0.0489***	0.0394***	0.0389**	0.0011
	(0.0117)	(0.0106)	(0.0138)	(0.0152)	(0.0011)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Subfield fixed effects	Yes	Yes	Yes	Yes	Yes
R-squared	0.113	0.106	0.106	0.106	0.106
Observations	133,497	563,462	563,462	563,462	563,462

The unit of analysis is the publication. All models are OLS with robust standard errors, clustered by subfield. *significant at 10%, **significant at 5%, ***significant at 1%

Table 4: Teams in Soviet-rich subfields exhibit disproportionate increase in propensity to cite Soviet prior art after 1990

	Dependent variable: References to Soviet art			
	Count of Soviet references (Defined by Soviet journal)	**Percentage of Soviet references (Defined by Soviet journal)**	**Count of Soviet references (Defined by name)**	**Percentage of Soviet references (Defined by name)**
SovietRich × AfterIronCurtain	0.4020*** (0.0423)	0.0172*** (0.0036)	0.4496** (0.1345)	0.0135 (0.0086)
Year fixed effects	Yes	Yes	Yes	Yes
Subfield fixed effects	Yes	Yes	Yes	Yes
R-squared	0.117	0.080	0.131	0.094
Observations	1,012	1,012	1,012	1,012

The unit of analysis is the publication. The sample includes the top/bottom three subfields drawn from the top 30 journals four years before and after the collapse of the Soviet Union. All models are OLS with robust standard errors, clustered by subfield.
*significant at 10%, **significant at 5%, ***significant at 1%

Table 5: Author specialization defined by count of codes published over last 5 years

	All authors; Top and bottom three subfields only				Junior authors only (less than 5 years since first publication); Top and bottom three subfields only	
	Dep. Var is Count of subfields	**Dep. Var is Logged count of subfields**	**Dep. Var is Count of subfields**	**Dep. Var is Logged count of subfields**	**Dep. Var is Count of subfields**	**Dep. Var is Logged count of subfields**
AfterIronCurtain	-0.2135***	-0.0709***	-0.0311**	-0.0112*	-0.1306***	-0.0609***
× SovietRich	(0.0334)	(0.0111)	(0.0145)	(0.0065)	(0.0339)	(0.0127)
SovietRich	-0.4174***	-0.1608***	N/A	N/A	-0.2305***	-0.0927***
	(0.0325)	(0.0108)			(0.0269)	(0.0097)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Individual FEs	No	No	Yes	Yes	N/A	N/A
R-squared	0.028	0.030	0.010	0.010	0.085	0.082
Observations	315,161	315,161	280,427	280,427	41,282	41,282

All models are OLS with robust standard errors, clustered by author. *significant at 10%, **significant at 5%, ***significant at 1%

Table 7a: Teams in Soviet-rich subfields exhibit disproportionate increase in team size after 1990 (Japanese journals)

	Dependent variable: log of author count				
	Top and bottom 3 subfields	**Soviet-rich defined as top 3 of subfields**	**Soviet-rich defined as top 5 of subfields**	**Soviet-rich defined as top 10 of subfields**	**Continuous**
AfterIronCurtain× SovietRich	0.0692*** (0.0173)	0.0581*** (0.0154)	0.0634*** (0.0162)	0.0699*** (0.0150)	0.0025*** (0.0006)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Subfield fixed effects	Yes	Yes	Yes	Yes	Yes
R-squared	0.076	0.068	0.068	0.068	0.068
Observations	5,096	17,209	17,209	17,209	17,209

The unit of analysis is the publication. All models are OLS with robust standard errors, clustered by subfield. *significant at 10%, **significant at 5%, ***significant at 1%

Table 7b: Teams in Soviet-rich subfields exhibit disproportionate increase in team size after 1990 (ranked Japanese journals)

	Dependent variable: log of author count				
	Top and bottom 3 subfields	**Soviet-rich defined as top 3 of subfields**	**Soviet-rich defined as top 5 of subfields**	**Soviet-rich defined as top 10 of subfields**	**Continuous**
AfterIronCurtain× SovietRich	0.0678*** (0.0203)	0.0653*** (0.0175)	0.0738*** (0.0189)	0.0751*** (0.0143)	0.0026*** (0.0007)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Subfield fixed effects	Yes	Yes	Yes	Yes	Yes
R-squared	0.093	0.070	0.070	0.070	0.070
Observations	3,859	13,003	13,003	13,003	13,003

The unit of analysis is the publication. All models are OLS with robust standard errors, clustered by subfield. *significant at 10%, **significant at 5%, ***significant at 1%

Table 7c: Teams in Soviet-rich subfields exhibit disproportionate increase in team size after 1990 (not ranked Japanese journals)

	Dependent variable: log of author count				
	Top and bottom 3 subfields	**Soviet-rich defined as top 3 of subfields**	**Soviet-rich defined as top 5 of subfields**	**Soviet-rich defined as top 10 of subfields**	**Continuous**
AfterIronCurtain× SovietRich	0.0956*** (0.0206)	0.0638* (0.0329)	0.0521 (0.0378)	0.0738** (0.0321)	0.0033*** (0.0011)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Subfield fixed effects	Yes	Yes	Yes	Yes	Yes
R-squared	0.101	0.109	0.109	0.110	0.110
Observations	1,237	4,206	4,206	4,206	4,206

The unit of analysis is the publication. All models are OLS with robust standard errors, clustered by subfield. *significant at 10%, **significant at 5%, ***significant at 1%

Appendix Table 1 – Robustness to alternative ranking measure

	Dependent variable: log of author count				
	Top and bottom 3 subfields	**Soviet-rich defined as top 3 of subfields**	**Soviet-rich defined as top 5 of subfields**	**Soviet-rich defined as top 10 of subfields**	**Continuous**
AfterIronCurtain× SovietRich	0.0800***	0.0475***	0.0404***	0.0364**	0.0012
	(0.0126)	(0.0107)	(0.0150)	(0.0157)	(0.0010)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Subfield fixed effects	Yes	Yes	Yes	Yes	Yes
R-squared	0.112	0.107	0.107	0.106	0.106
Observations	133,497	563,462	563,462	563,462	563,462

In this table, we use our own ranking measure rather than Borjas and Doran (2012a); our measure uses worldwide publications from 1970-1989 rather than US publications from 1984-1989 and relies on identifying Soviet publications by ethnicity of names rather than by affiliation data. All models are OLS with robust standard errors, clustered by subfield. *significant at 10%, **significant at 5%, ***significant at 1%.

Appendix Table 2 – Coefficient estimates used to plot Figure 3

Dependent variable: Log of author count per publication per year; Top and bottom three subfields only			
SovietRich×1971	0.0137	***SovietRich×1991***	0.0403
	(0.0139)		(0.0257)
SovietRich×1972	0.0452*	***SovietRich×1992***	0.0635
	(0.0147)		(0.0360)
SovietRich×1973	0.0428*	***SovietRich×1993***	0.0624**
	(0.0212)		(0.0200)
SovietRich×1974	0.0290	***SovietRich×1994***	0.0700*
	(0.0156)		(0.0303)
SovietRich×1975	0.0389	***SovietRich×1995***	0.0691**
	(0.0250)		(0.0178)
SovietRich×1976	0.0174***	***SovietRich×1996***	0.0513
	(0.0030)		(0.0280)
SovietRich×1977	0.0218*	***SovietRich×1997***	0.0750**
	(0.0089)		(0.0273)
SovietRich×1978	0.0465*	***SovietRich×1998***	0.0960**
	(0.0218)		(0.0259)
SovietRich×1979	0.0550**	***SovietRich×1999***	0.0792**
	(0.0187)		(0.0274)
SovietRich×1980	0.0373	***SovietRich×2000***	0.0773*
	(0.0249)		(0.0303)
SovietRich×1981	0.0269*	***SovietRich×2001***	0.0958***
	(0.0111)		(0.0175)
SovietRich×1982	0.0422*	***SovietRich×2002***	0.1279***
	(0.0190)		(0.0274)
SovietRich×1983	0.0256	***SovietRich×2003***	0.1206***
	(0.0175)		(0.0173)
SovietRich×1984	0.0327	***SovietRich×2004***	0.1000*
	(0.0449)		(0.0461)
SovietRich×1985	0.0604*	***SovietRich×2005***	0.1376***
	(0.0239)		(0.0303)
SovietRich×1986	0.0353	***SovietRich×2006***	0.1406***
	(0.0306)		(0.0302)
SovietRich×1987	0.0406	***SovietRich×2007***	0.1806***
	(0.0294)		(0.0329)
SovietRich×1988	0.0127	***SovietRich×2008***	0.1680***
	(0.0247)		(0.0312)
SovietRich×1989	0.0289*	***SovietRich×2009***	0.1518***
	(0.0125)		(0.0239)
SovietRich×1990	0.0119	***SovietRich×2010***	0.1717***
	(0.0270)		(0.0341)
Year fixed effects	Yes	**Subfield fixed effects**	Yes
R-squared	0.114	**Observations**	133,497

Estimated with OLS with robust standard errors, clustered by subfield. *significant at 10%, **significant at 5%, ***significant at 1%

Appendix Table 3 – Robustness to including Soviet papers

	Dependent variable: log of author count				
	Top and bottom 3 subfields	Soviet-rich defined as top 3 of subfields	Soviet-rich defined as top 5 of subfields	Soviet-rich defined as top 10 of subfields	Continuous
AfterIronCurtain× SovietRich	0.0696***	0.0424***	0.0346**	0.0283*	0.0010
	(0.0110)	(0.0108)	(0.0136)	(0.0154)	(0.0011)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Subfield fixed effects	Yes	Yes	Yes	Yes	Yes
R-squared	0.107	0.103	0.102	0.102	0.102
Observations	169,305	689,793	689,793	689,793	689,793

In this table we present estimates of the main effect when including Soviet authors back into the sample. The unit of analysis is the publication. All models are OLS with robust standard errors, clustered by subfield. *significant at 10%, **significant at 5%, ***significant at 1%