The pace of change and creative performance: Specialist and generalist mathematicians at the fall of the Soviet Union*

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Abstract

Past research is divided on whether specialists or generalists have superior creative performance. While many have highlighted generalists' advantage due to access to a wider set of knowledge components, others have underlined the benefits that specialists can derive from their deep expertise. We argue that this disagreement might be partly driven by the fact that the pace of change in a knowledge domain shapes the relative return from being a specialist or a generalist. Using the impact of the Soviet Union's collapse on the performance of theoretical mathematicians as a natural experiment, we show that generalist scientists performed best when the pace of change was slow, but that specialists had an advantage when the pace of change increased. We discuss and test the roles of cognitive mechanisms and of competition for scarce resources. Overall, our results highlight important trade-offs associated with the choice of becoming a specialist or a generalist.

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Since Schumpeter (1942), a vast literature emphasized the crucial role of scientists and inventors as catalysts of economic change. Through their ingenuity, creative workers produce new knowledge and technologies that spur social and economic growth (Romer 1990), boost or destroy organizational capabilities (Henderson and Clark 1990), shake old industries (Barnett 1990), or birth new ones (Hargadon and Douglas 2001). The literature points to two types of creative workers: specialists and generalists.[1] The distinction is rooted into a strategic trade-off that all creative workers face: either invest their limited time entirely within a specific knowledge domain and become a specialist in that domain; or invest it across several domains—achieving a less comprehensive understanding of each—and become a generalist. Which strategy leads to superior creative performance? Past research seems deeply divided on the answer.

On one hand, a large stream of work argued that because creativity is about producing novel knowledge recombinations, creative workers should seek access to diverse knowledge bases. Individuals who adopt this strategy—generalists—gain access to a wider array of knowledge, technologies, and heuristics that can help them break away from traditional thought patterns (Hargadon and Sutton, 1997; Benner and Tushman, 2002; Burt, 2004; Uzzi and Spiro, 2005; Fleming, Mingo, and Chen 2007; Taylor and Greve, 2006; Cattani and Ferriani, 2008). Scholars showed that breakthrough inventions often involve uncommon recombinations of knowledge components from distant domains (Ahuja and Lampert 2001; Fleming 2001), and others found a link between access to atypical knowledge sources and the creative performance of artists (Cattani

[1] In this paper, we define specialists as individuals who have experience and expertise in a narrowly defined domain of knowledge. In contrast, a comparable generalist is an individual with the same amount of experience spread across multiple related or unrelated knowledge domains. The notion of specialist in our paper is very close to the notion of expert in some other studies. In principle, a specialist is an individual who has expertise in a domain. A generalist with the same amount of experience spread across multiple domains would, by definition, have less expertise in each domain. We provide examples of specialists and generalists in our setting in future sections.

and Ferriani 2008), managers (Burt 2004), inventors (Reagans and Zuckerman 2001), and scientists (Schilling and Green 2011).

On the other hand, several studies argued for the opposite strategy: specialization. Specialization enables individuals to achieve deeper expertise and a more detailed understanding of the knowledge gaps in their domain of specialty. Specialists also benefit from a more extensive repertoire of domain-specific problem-solving and memory skills (Dane 2010). Empirical evidence indicated that specialized scientists (Leahey 2007) and inventors (Conti, Gambardella, and Mariani 2013) are more productive and successful. Other research showed that deeper expertise and local recombinations, as opposed to distant and diverse recombination, are more likely to yield more cognitively novel innovations (Kaplan and Vakili 2015). Moreover, there is some evidence that individuals lacking specialization might spread themselves too thin and be perceived as less credible (Birnbaum 1981; Weisberg 1998; Leahey 2007; Jones 2009; Leahey, Beckman, and Stanko 2017).

We propose that the seeming inconsistency between these two streams of work stems, in part, from efforts to generalize from different settings with different underlying characteristics. The amount of evidence highlighting the superior performance of both strategies suggests that specialists and generalists have strengths and weaknesses that make them better suited to different circumstances. However, past studies typically abstracted away from the specificities of their research settings and argued for one view or the other. We depart from this literature by highlighting a specific contingency that can differentially moderate the creative performance of specialists and generalists: the pace of change in a knowledge domain.

There are trade-offs associated with being a specialist or a generalist. Generalists benefit from their access to knowledge components and heuristics across multiple domains. However, this advantage might come at the cost of a shallower understanding of each domain as well as difficulties in keeping track with the knowledge frontier in multiple domains. Specialists, on the other hand, benefit from their deeper expertise and larger repertoire of domain-specific problem-solving and memory skills. This advantage might, however, be associated with greater difficulties in understanding knowledge components and problem-solving heuristics stemming from other domains. The respective advantages and disadvantages of generalists and specialists suggest that creative people face a trade-off between strategies that are best suited to different types of circumstances. We propose that the pace at which knowledge components become available in a domain can alter the cost-benefit balance of the two strategies in different directions. Specifically, we argue that generalists experience superior creative performance in slow-paced knowledge domains whereas specialists generally benefit from faster-evolving ones. We further discuss how the competition between specialists and generalists for limited resources in a knowledge domain can further reinforce the creative advantage (or disadvantage) of each creative type.

Testing this hypothesis empirically is challenging. While the pace of change in a domain may affect the performance of creative workers, their performance also shapes the availability of new components and, with it, the pace of change in that domain (Carnabuci and Bruggeman 2009). There is an intricate coupling between the performance of creative workers and the pace of change. We address this challenge by exploiting a natural experiment—the unexpected acceleration of the pace of change in some fields of theoretical mathematics but not in others after the collapse of the Soviet Union (hereafter the Soviet collapse) in 1989. The event provides a rare opportunity to identify the impact of the sudden shift in the pace of change on the relative creative performance of specialist and generalist mathematicians. Using a difference-in-difference-in-differences methodology, we investigate how shifts in the pace of change affected the relative creative performance of specialist and generalist mathematicians after the Soviet collapse. In so doing, we aim to reconcile, at least partly, existing debates about the relationship between the strategic choice of becoming a specialist (or generalist) and creative performance.

THE GENERALIST VERSUS SPECIALIST TRADE-OFF

Generalists and Creativity

A large stream of literature highlighted reasons why generalists are more likely to experience superior levels of creative performance. Since creative work is a recombination process, individuals who have access to a more varied set of knowledge components might be able to experiment with a larger set of recombinations. Ideas and knowledge from one domain can sometimes be productively applied to others (Hargadon and Sutton 1997; Burt 2004; Jeppesen and Lakhani 2010). Access to various knowledge domains might therefore prevent a situation in which the same set of familiar components is constantly used and reused, leading to decreasing returns to creative work (Fleming 2001). Moreover, access to diverse knowledge domains is likely to make creative workers more flexible in their problem-solving approaches, allowing them to use a broader repertoire of perspectives and heuristics in their work (Dunbar 1995). Individuals exposed to more diverse knowledge components and heuristics will be less likely to become "trapped" in specific thought patterns. The lack of a deep expertise in a single domain might therefore free creative workers to try unorthodox approaches, a phenomenon that Merton and Zuckerman (1972, 519) referred to as "focused naiveté" or "focused ignorance."

Becoming a generalist and engaging in boundary-spanning knowledge creation is not costless. It is difficult to identify relevant recombinations in general but even more so when searching across knowledge domains. Scientific knowledge tends to be complex—often including tacit components (Polanyi 1958; Orlikowski 2002). In any field, the literature is voluminous, and the quality of each contribution is uncertain. Different knowledge communities often use distinct approaches to creating, validating, and describing knowledge (Dougherty 1992; Knorr-Cetina 1999). To identify opportunities for recombination across knowledge domains and for implementing them, researchers must therefore invest time, effort, and resources not only to familiarize themselves with those different approaches but also to build a social network spanning those distinct communities. The associated challenges are considerable (Chai 2017). In addition, attempts to bridge knowledge domains often lead to dead ends (Fleming 2001; Leahey, Beckman, and Stanko 2017). Within a specific knowledge domain, creative workers progressively learn which combinations work and which do not. As familiarity with each component increases, creative workers become better at selecting productive recombinations and avoiding failures. However, generalists, by definition, span multiple domains. When spanning new domains, generalists have less prior experience in selecting promising recombinations. As a result, they are likely to face high rates of failure.

Specialists and Creativity

Specialists lack the knowledge breadth of generalists, but their narrow focus allows them to develop greater knowledge depth. Specialists have a more sophisticated appreciation of the different attributes of each component in their knowledge domain as well as of the relationships between those components (Dane, 2010). They can also recall larger amounts of domain-specific knowledge more effectively. For example, Chase and Simon (1973) showed that chess masters can recall the exact position of every piece on a chessboard by observing the board very briefly. Because of their more accurate and detailed perspective of the knowledge landscape in their field, specialists are also better equipped to see and understand the various knowledge gaps in their domain and to recognize opportunities to address them. In addition, they are likely to be particularly well equipped with a broad set of domain-relevant problem-solving heuristics. Kuhn (1970) noted that problem-solving is fundamental to scientific training because most scientific problems are solved by grouping objects and situations into similar sets. Through exposure to a large number of examples, specialists increase their ability to solve puzzles that are specific to their knowledge domain more efficiently. In experiments, psychologists found that physics and mathematics specialists use distinctive problem-solving techniques (Larkin et al., 1980; Sweller, Mawer, and Ward, 1983). In line with Kuhn's argument, Chi, Glaser and Rees (1982) showed that expert physicists tend to categorize domain-specific physics problems according to physics principles whereas non-experts categorize according to features noted in the problem statement. In turn, categorization based on principles helps experts activate knowledge structures related to each principle, helping problem-solving activities.

These benefits notwithstanding, specialization also has important downsides. Psychologists found that knowledge specialization leads to the development and reinforcement of thought processes that become taken for granted, a phenomenon known as the "Einstellung" effect (or "problem-solving fixation") (Luchins, 1942; Frensch and Sternberg, 1989; Bilalic et al., 2008a: 653). The effect was famously documented in Abraham Luchins' (1942) water-jug experiment. In this short study, participants faced a set of six problems—"Einstellung Problems"—all of which could be solved in the same manner. Following this, they were given another set of problems that could be solved laboriously with this method, but for which a much simpler method also existed. Of the participants exposed to the full set of Einstellung Problems, none found the simpler solution. In contrast, over 60 percent of participants in the control group identified the simpler solution. In other words, prior experience led to routinized problem-solving which in turn blinded participants to the existence of a better solution. This striking demonstration of the negative impact of expertise on creativity has since been replicated and extended in a large number of studies (see, e.g., references in Bilalić, McLeod, and Gobet, 2008; Dane, 2010). Specialization in a domain can also lead to the formation of habitual behaviors rooted in one's knowledge structure (Aarts, Verplanken, and van Knippenberg 1998; Aarts and Dijksterhuis 2000; Murray and Häubl 2007; Audia and Goncalo 2007). While habits can increase efficiency in dealing with routine tasks required in a domain, they can nonetheless slow the pace of adaptation to new tasks and heuristics.

Historians of science and culture also described many cases in which outsiders appear to have benefited from their lack of specialization to produce breakthroughs in areas such as physics (Kuhn 1970), neuroendocrinology (Latour and Woolgar, 1979), astronomy (Edge, 1977), psychoanalysis (McLaughlin, 2001), jazz (Kirschbaum and Vasconcelos, 2006), and painting (Sgourev, 2013). It was the telegraphy amateur Alexander Bell, a speech therapy professional, and not Elisha Gray, his specialist competitor, who pursued the development of the "talking telegraph." Bell was not influenced by the domain-specialist understanding of the telegraph as a toy-like device (Hounshell, 1975). Similarly, John Harrison solved the longitude problem by using clockwork rather than by searching the more specialist solution space of astronomy for which the Longitude Board Principal Scientific Advisor Sir Isaac Newton himself advocated (Andrewes, 1996).

THE PACE OF CHANGE AS A MODERATOR OF CREATIVE PERFORMANCE

There have been some attempts to reconcile the seemingly inconsistent findings in the literature regarding the relative creative advantage of specialists and generalists. Most of these attempts, however, focused on the trade-off between quantity and quality of output. The general idea is that whereas generalists are more likely than specialists to produce breakthroughs, this advantage comes at the cost of producing fewer innovations (Leahey, Beckman, and Stanko, 2017). Their access to more diverse knowledge components enables generalists to produce more novel recombinations. However, while some of these novel recombinations may have great impact, many others will fail. On the other hand, specialists face fewer barriers to recombination, but they lack access to the same variety of components. One might therefore expect them to produce more incremental recombinations (Carnabuci and Bruggeman 2009).

In this paper, we take a different approach to reconcile the inconsistency in prior research. Our approach is informed by the observation that previous studies, for the most part, abstracted away from the underlying characteristics of the context within which creative workers operate. They either explored the average performance of a certain creative strategy in an aggregated sample of creative workers across many different domains (e.g., Fleming, Mingo and Chen, 2007) or investigated the performance of creative workers in a single domain of knowledge or technology (e.g., Audia and Goncalo 2007). Despite the usual cautionary notes about the generalizability of findings, both categories of research generally overlooked how the variance in characteristics of knowledge domains moderates the performance of different creative strategies. Our aim here is to take a step toward addressing this gap by focusing on a specific characteristic of a knowledge domain, namely the pace at which new knowledge components become available in the domain, and by showing how it differentially affects the creative performance of specialists and generalists.

We build our argument on three premises. First, we follow the established notion that innovation is most often a process of knowledge recombination (Fleming, 2001). New ideas are essentially combinations of previously unconnected knowledge components. Creativity is cumulative, and each new recombination is a new component that can be used for future discoveries or inventions (Weitzman 1998).

Second, the set of knowledge components in a domain is not fixed. As scientific and technological advancements occur in a domain, new knowledge components become available. The emergence of new knowledge components thus affects the set of opportunities available to creative workers for knowledge recombination. The more knowledge components emerge in a domain, the more opportunities emerge for recombinations between new knowledge components themselves as well as between new knowledge components and the previously established ones.

Third, the pace of change varies substantially across knowledge domains and over time. Periods of intense change often alternate with more stable periods (Kuhn 1970; Dosi 1982), in a process analogous to the punctuated equilibrium framework developed by evolutionary biologists (Gould and Eldredge 1977). Numerous episodes of sudden acceleration or deceleration have been described. Tushman and Anderson (1986) showed that the cement, airline, and minicomputer industries experienced periods of rapid technological change followed by years of relatively slow improvements. Lim (2009) documented how IBM's breakthrough development of copper interconnects to replace aluminum ones in 1999 moved the knowledge frontier in the semiconductor industry considerably and paved the way for the production of smaller chips with superior conductivity. The biotechnology industry in its early stages was reportedly shaped and shaken by various scientific discoveries in genetics (Russo, 2003). Levinthal (1998) described how the broadcasting industry emerged almost overnight after the abrupt realization that there was a demand for this type of technology. In science, Boring (1955) noted that the invention of the telescope in 1608 enabled a flurry of astronomical discoveries. Kuhn (1970) described how the realization by Joseph Black in 1756 that air was not the only gas—and his identification of fixed air (CO_2)—opened the door to the rapid discovery of numerous other gases by Cavendish, Priestly, and Scheele. More recently, the Human Genome Project is credited with the birth of the new field of genomics and a nearly exponential increase in the pace of disease gene discovery.[2]

These three premises suggest that creative workers face different levels of opportunity for creative recombination depending on the pace of change in their domains. While the pace at which new knowledge components become available in a domain influences all knowledge workers in that domain, we expect the pace to have differential effects on the creative performance of specialists and generalists.

Consider the case of a slow-paced knowledge domain where the set of knowledge components available for recombination is relatively stable. In such an environment, specialists who largely rely on the knowledge available within the domain gradually exhaust any novel and impactful recombinations (Fleming 2001; Schilling 2005), a situation that Fleming (2002) called "combinatoric exhaustion." Over time, new ideas drawn from the same set of components become simple extensions of previously established ones, leading to, at best, incremental innovations (Audia and Goncalo, 2007).[3] Specialists see the benefits of specialization erode while they struggle to adopt fresh perspectives by borrowing ideas from other domains. On the other hand, stable environments benefit generalists. Their access to several knowledge domains opens the door to a greater variety of potential recombinations, and the slow emergence of new knowledge components within the field gives them enough time to avoid falling behind their specialist colleagues.

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[2] https://www.genome.gov/10001772/all-about-the--human-genome-project-hgp/

[3] Research also suggests that there are significant barriers in resolving the entrenchment problem through assembling a diverse team of specialists and facilitating "coordinated exploration" among them (Knudsen and Srikanth 2014). Using a simulation model, Knudsen and Srikanth (2014) highlight how the incompatibility of mental models between specialists from different backgrounds can lead to conflicts, mutual confusion, joint myopia, and eventually convergence around objectives that are "minimally acceptable for all team members." Several empirical studies have documented the negative impact of intense communication between specialists on innovation outcomes within new product development teams (Tyre and Hauptman 1992; Hauptman and Hirji 1996; Song and Montoya-Weiss 1998; Song, Thieme, and Xie 1998).

Hypothesis 1 (H1): In slow-paced domains, generalists produce more creative output than specialists do.

The situation changes when the pace of change in a field accelerates. Specialists are generally better equipped than generalists to take advantage of a fast-evolving knowledge frontier. Their narrow focus means that they can invest their time effectively to absorb newly emerging knowledge components. They can take advantage of their deeper understanding of the field not only to identify knowledge gaps but also to gauge recombination opportunities between new components and those previously available. The drawbacks of specialization become also less important. The rapid emergence of new components within the field lowers the value of borrowing knowledge components from other areas. Given the closer similarity and relevance of newly emerged knowledge components to extant knowledge components within a domain, the recombinations of the two could be less prone to failure than recombinations of components across different knowledge domains.

Generalists in fast-paced environments, in contrast, are likely to struggle to maintain their ties to various fields while staying current with the advancements of the fast-paced domain. Their reliance on riskier boundary-spanning recombinations becomes a liability. Therefore, in fast-paced knowledge domains, we expect specialists to produce more creative output than generalists do.

Hypothesis 2 (H2): In fast-paced domains, specialists produce more creative output than specialists do.

While cognitive processes are central to knowledge creation and innovation, creative work usually involves competition for additional resources such as money, research materials, and complementary human capital (e.g., research staff and collaborators). Complementary resources are crucial to making creative ideas a reality. Moreover, creative work usually occurs in a political economy which further influences the allocation of scarce resources (Kaplan, Milde, and Cowan 2017). One's credibility or authority in a knowledge domain can further facilitate access to scarce resources, above and beyond what one could access purely due to advantages associated with ability (Leahey 2007; Leahey, Beckman, and Stanko 2017). Importantly, scarce resources tend to accrue to those having a preexisting competitive advantage.

Prior studies on this type of competitive dynamics primarily focused on the impact of social status (Merton 1968; Simcoe and Waguespack 2011; Azoulay, Stuart, and Wang 2013), but the notion of cumulative advantage also has crucial implications for the outcome of creative strategies. In short, the performance of a creative worker depends not only on their own strategy but also on the success of their competitors' strategy. More specifically, the creative advantage of one creative type (whether generalist or specialist) can also result in preferential access to complementary resources required for innovation. In the presence of limited resources, the preferential access of one type can further crowd out the access of the other. Take the context of scientific knowledge production in a fast-paced domain as an example. Specialists' superior advantage, due to specialists' deeper expertise, might help them attract resources such as funding and better collaborators. Their preferential access to these resources can further help them exploit more impactful opportunities faster, leaving generalists with fewer opportunities to explore. In addition, many creative settings have limited capacity to exhibit and consume creative output. In science, for example, the capacity of top journals has remained relatively stable over time. Similarly, artists face a limited set of venues for exhibiting their productions. Specialists' superior performance can further crowd out generalists' access to the scarce space available for exhibiting output.

These competitive forces have an important, and often overlooked, implication for the performance of specialists and generalists in domains with varying paces of change. In the absence of competition, one would expect generalists in a fast-paced domain to have greater creative performance than comparable generalists in a slow-paced domain. Those generalists presumably have access to more knowledge components to recombine than comparable generalists in more stable domains. However, in the presence of cumulative advantage, generalists in fast-paced domains are likely to be crowded out by specialists in those domains and hence to perform even worse than generalists in slow-paced domains who face much weaker competition from specialists. Similarly, we expect specialists in slow-paced domains to perform worse than comparable specialists in fast-paced domains, not only because of their more limited access to new knowledge components but also because they face much stronger competition from generalists who have preferential access to resources.

Hypothesis 3 (H3): In fast-paced domains, generalists produce less creative output than generalists do in slow-paced domains, while the reverse occurs for specialists.

METHODS

Empirical Setting

To test these predictions, we focused on the field of theoretical mathematics and the publication output of mathematics scientists. We follow a growing literature using scientific publications to measure scientists' creative output (Leahey 2007; Schilling and Green 2011; Jones and Weinberg 2011; Uzzi et al. 2013; Leahey, Beckman, and Stanko 2017; Teodoridis 2017). Moreover, we exploited a natural experiment—the Soviet collapse, in 1989—to address the endogeneity issues involved with testing our predictions. For several reasons, this event provides a unique opportunity to examine the relative performance of specialists versus generalists in knowledge domains with varying paces of change.

The unexpected, exogenous release of new knowledge in certain areas of theoretical mathematics due to the Soviet collapse enabled us to control for the endogenous link between the activity of creative workers and the pace of change of knowledge domains. Specifically, our empirical strategy relies on the assertion that the Soviet collapse caused a sudden and unexpected increase in the pace of change in theoretical mathematics and that it did so more for some subfields of mathematics than for others (Agrawal, Goldfarb, and Teodoridis 2016). We based this claim on three main observations. First, the Soviet Union was, and Russia continues to be, a world-renowned center of scientific research, with mathematics holding a prominent position. Scholarly research in theoretical mathematics attracted great minds, as it was uniquely detached from politics, conferred status and prestige, and offered financial rewards superior to those of many other occupations. Second, although Soviet mathematics was strong across the entire spectrum of mathematics, Soviet mathematicians made greater advancements in some subfields than in others (Graham, 1993). These differences reflect historical path dependency. Specifically, some subfields of theoretical mathematics built on strong mentorship from the early 1900s and continued to attract bright minds thereafter (Borjas and Doran, 2012). For example, the success of Moscow mathematics can be traced back to Ergorov and his student N. N. Luzin (Tikhomirov, 2007), whose famous work focused mainly on the theory of functions. Finally, Soviet knowledge in theoretical mathematics was kept secret from the outside world because of the Communist government's rules and regulations. The Soviet government strictly controlled international travel. Academics seeking to attend foreign conferences had to undergo a stringent and lengthy approval process, and many researchers were blacklisted because of their "tainted" backgrounds. The few approvals granted were typically for travel in Eastern Europe (Ganguli, 2014). Additionally, Soviet researchers were prevented from publishing their findings outside the Soviet Union, from communicating or collaborating with non-Soviets, and even from accessing non-Soviet references. Thus, Soviet advancements in mathematics remained relatively unknown to the outside world until the Soviet collapse (Graham and Dezhina, 2008), when they were suddenly made available.[4]

Using an extensive dataset of publication and citation data in the field of mathematics, we carefully tracked the creative output and performance of mathematicians over a long period (1980–2000). The data come from the Mathematical Reviews (MR) division of the American Mathematical Society (AMS). The MR Database includes all academic publications in mathematics worldwide.

We observed the specialization levels of mathematicians in our sample based on a manual detailed categorization of research output provided by the MR Database. Specifically, we relied on the careful and exhaustive work of the MR division, which classifies each paper in mathematics using Mathematics Subject Classification (MSC) codes. The MSC schema are internationally recognized and facilitate targeted searches on research subjects across all subfields of mathematics. The MR team assigns one primary MSC code to each academic publication uploaded to the MR Database. There are 33 codes covering theoretical mathematics (Table 1). Using the MSC codes assigned to each paper, we can measure the degree of specialization of each individual mathematician at a given time.

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[4] The following quote, from an article published on May 8, 1990, in the *New York Times*, indicates 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.*

– Insert table 1 about here –

The field of theoretical mathematics plays a fundamental role in knowledge and technological progress across a wide range of domains. The examples are numerous. Wavelet and Fourier transforms are widely used in electronics, computer graphics, and medical equipment such as MRI machines. Algebraic topology is used extensively in data mining and processing. Number theory, and particularly the theory of prime numbers, has immensely influenced computer and network security algorithms. Turing's theories of computability provided the foundation for the field of computing. Many advancements in space technology and exploration would have been impossible without foundational geometry theories. Theoretical math has substantially influenced many areas in the social sciences such as linguistics, economics, and political science. Put simply, theoretical mathematics provides the abstract foundation and structure for formulating and understanding our physical world. Corporations such as Microsoft, Google, and IBM employ theoretical mathematicians in various areas of security and computing. Hence, the field of theoretical mathematics provides valuable insights into one of the fundamental engines of economic, technological, and social progress.

Data

As noted, we collected our data from the MR Database, the most comprehensive database on academic publications in the field of mathematics. The database covers the three main branches 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. Our sample tracks academic publications of mathematicians over a 21-year period, 1980 to 2000 inclusive.

To construct our sample, we first collected data on every academic publication in theoretical mathematics published between 1980 and 2000, 10 years before and after the collapse of the Soviet Union, in 1989. The data on publications includes year of publication, MSC classification code, full set of authors per academic publication, and number of academic citations received from subsequent publications. Next, we re-arranged the data at the author-year level and counted the number of academic publications and citations per author, per year. We excluded all Soviet authors, since they were already at the frontier of knowledge, and focused on all other mathematicians, since they experienced the frontier advancement. We also excluded all publications with at least one Soviet author to ensure that our results are not driven by preferential direct access to Soviet knowledge. We further restricted our sample to authors with at least four publications before the Soviet collapse, namely between 1980 and 1989.[5] The choice of a minimum of four publications helped us carefully separate specialists from generalists in our sample and ensure that our results are not driven by unproductive individuals classified as specialists because of their low number of publications. For example, individuals with one publication would otherwise be automatically classified as specialists. However, their lack of diversification would be mechanically driven by their low productivity. We provide details on our measure of diversification in the next sections. Finally, using the diversification measure described below, we identified all individuals who could be cleanly categorized as either a specialist or a generalist and dropped the rest from the sample. In our robustness checks, we provide sensitivity analyses on our categorization of specialists and generalists. The final core dataset contains data on 6,358 mathematicians and their full record of publications between 1980 and 2000.

[5] The results are robust to choosing cut-off minimums of three, five, and six publications. At cut-offs smaller than three publications, we cannot properly distinguish between specialist and novice mathematicians.

Last, we matched specialists and generalists on their productivity in the period before the Soviet collapse. As we discuss below, there are some significant differences between specialists and generalists for productivity in the years before the collapse. This is not surprising, since our measure of diversification relies on breadth of publications across mathematics subfields. In other words, the higher the productivity, the higher the probability of diversification. Thus, to ensure that our results are not biased because of systematic differences in quality between specialists and generalists driven by our sample selection method, we further constructed a matched sample based on individuals' observables before the Soviet collapse. To construct the matched sample, we used a one-to-one Coarsened Exact Matching (CEM) method (Blackwell et al., 2009; Iacus et al., 2011) based on mathematicians' publication records in the pre-collapse period.[6] The matched sample contains data on 4,076 mathematicians, of whom 2,038 are specialists and 2,038 are generalists. We report our estimations for both the full and the matched samples.

Dependent Variables

To compare the creative output of specialists and generalists, we used three variables to capture both the quantity and the quality of their output. First, we used the count of publications per year to measure the quantity of their creative output. The issue with using the simple count of publications is that an increase in the number of publications may come at the expense of a decrease in their quality. To address this issue, we also used the quality-adjusted count of publications per year. More specifically, following previous studies (e.g., Furman and Stern, 2011; Azoulay, Stuart, and Wang, 2013; Vakili and McGahan, 2016), we used the number of citations each publication received in subsequent publications to construct a citation-weighted count of publications per mathematician per year. Each publication is counted as 1 plus the number of future

[6] To perform the one-to-one matching, we used the total citation-weighted number of publications, total number of publications, the first year of publication, and the publication trend during the 10 years prior to the Soviet collapse.

citations it received. For example, if a mathematician had two publications in 1985, one with 10 future citations and the other with 20 future citations, her quality-adjusted research output for 1985 is 32. We also measured the number of breakthrough publications per year for each scientist. The quality of creative output is highly skewed. Past research distinguished between processes that increase the mean distribution of creative output and those that increase the variance. While the former can raise the average quality of creative output, the latter can lead to an increase in the number of highly impactful output—that is, breakthroughs. Following past research (Ahuja and Lampert 2001; Phene, Fladmoe-Lindquist, and Marsh 2006; Bikard, Murray, and Gans 2015; Kaplan and Vakili 2015), we first coded the publications belonging to the top 5 percent of highly cited publications in any given year as breakthroughs. Next, we counted the number of breakthroughs for each individual mathematician in any given year to construct an individual measure of breakthrough output per year. As a robustness check, we also constructed a separate measure of breakthrough output per year based on publications in the top 10 percent of highly cited publications.

Independent Variables

We used three indicators (and their interactions) as main independent variables in all estimations. The first variable, $Specialized_{i,t}$, captures whether a mathematician in our sample is a specialist or generalist at the time of the Soviet collapse. To construct this variable, we first built an index of diversification at the individual level capturing the heterogeneity in breadth of knowledge based on each mathematician's publication portfolio during the period before the collapse (1980–1989). The index is calculated as 1 minus the Euclidian distance in the multidimensional space of 33 subfields (or MSC codes) of theoretical mathematics (Table 1) and is based on shares of publications in each of the 33 subfields, per mathematician. The Euclidian distance is equal to the square root of the Herfindahl index, and hence is a more conservative measure of diversification. Formally, we calculated:

$$DiversificationIndex_i = 1 - \sqrt{\sum_{s=1}^{33}(\frac{PubCount_{s,i}}{PubCount_i})^2}$$

By construction, the higher the value of $DiversificationIndex_i$, the greater the breadth of areas in which mathematician i published before the Soviet collapse. The diversification measure is greater than or equal to 0 and never reaches 1. The highest possible value of the diversification index is 0.83 and characterizes researchers who published an equal number of publications in all 33 subfields of theoretical mathematics. The lowest diversification index is 0 and characterizes mathematicians who published in one subfield of theoretical mathematics exclusively. For example, a mathematician who published a total of 10 papers, half in one subfield of theoretical mathematics and half in another, would have a diversification index of 0.29, and an equally productive colleague who published all her papers in one subfield of theoretical mathematics would have a diversification index of 0. In our sample, the highest diversification index is 0.531 and the lowest is 0. In our main specification, we define generalists as mathematicians having a diversification index in the top 10 percent of the distribution (above 0.290) and specialists as those having a diversification index of 0 (those who published in only one subfield). Our results remain robust to using a continuous measure of diversification (see Tables A1 to A3 in the appendix for robustness checks).

The second variable, $SovietImpact_i$, captures the degree to which each mathematician in our sample was affected by the Soviet collapse or, in other words, by the pace of advancement of the knowledge area. The variable separates mathematicians who experienced a substantial movement of the knowledge frontier in their areas, that is, those operating in a fast-paced knowledge domain, from mathematicians who experienced less of a movement, that is, those operating in a slow-paced domain. We followed the ranking in Agrawal, Goldfarb, and Teodoridis (2016) of the 33 primary MSC codes of theoretical mathematics indicating the degree to which Soviets contributed to each subfield before the Soviet collapse. Table 1 lists the 33 subfields and their ranks. Based on these rankings, we constructed an index of Soviet exposure for each scientist in our dataset who published between 1980 and 1989. The index is calculated as the sum of shares of publications in each of the 33 subfields of theoretical mathematics, weighted by the ranking of the 33 subfields, per individual, for the entire period before the Soviet collapse. The higher the percentage of one's publications in subfields where Soviets made greater contributions, the higher the Soviet impact index. Formally, we calculated:

$$SovietImpactIndex_i = \sum_{s=1}^{33} \frac{PubCount_{si}}{PubCount_i * SubfieldRankOrder_s}$$

where $PubCount_{si}$ is the total count of publications of scientist *i* in subfield *s*, $PubCount_i$ is the total count of publications of scientist *i*, and $SubfieldRankOrder_s$ is the rank order of the corresponding subfield *s* in theoretical mathematics. The calculation considers the full publication portfolio during the period before the collapse (1980–89). For example, a mathematician who published all his papers in "Integral Equations," the subfield of theoretical mathematics most affected, would have a Soviet impact index of 1. If he were to publish all his papers in "Fourier Analysis," the second most affected subfield of theoretical mathematics, his Soviet impact index would be 0.5. And if he were to publish half his work in "Integral Equations" and half in "Fourier Analysis," his Soviet index impact would be 0.75. In our sample, the minimum value of the Soviet impact index is 0.030, the maximum value is 1, the mean is 0.108, and the standard deviation is 0.112. We defined mathematicians most affected by the Soviet shock ($SovietImpact_i = 1$) as those having a Soviet impact index in the top 10 percent of the range. The indicator is equal to 0 for others. Our results remain robust to considering a continuous measure of soviet impact (see Tables A4 to A6 in the appendix for robustness checks).[7]

The third variable, $AfterSovietCollapse_i$, is an indicator equal to 1 for years after the collapse of the Soviet Union (1990 and after) and 0 otherwise.

Control Variables

In all estimations, we included individual and year fixed effects. Individual fixed effects controlled for all time-invariant, idiosyncratic characteristics of each mathematician, such as first year of publication, innate quality, gender, race, and year of graduation. The year fixed effects controlled for all macro time trends that could influence mathematicians in the sample.

We also controlled for the past productivity of mathematicians using cumulative number of publications (since 1980). The variable is logged to account for its skewed distribution. Last, we controlled for the nonlinear effect of age by including an age-squared term in all estimations.[8] Since we could not observe the actual age of individuals, we used the number of years since their first publication in our sample.

Estimation Strategy

We used a difference-in-difference-in-differences (DDD) estimation method to compare the research output of specialists and generalists affected by the forward movement of the knowledge frontier in theoretical mathematics due to the Soviet collapse. The DDD estimation strategy is meant to address the endogeneity of output behavior and forward movement of the frontier by

[7] We use a 0/1 indicator instead of a continuous variable for ease of exposition. Our estimations rely on a triple interaction between our independent variables; hence using 0/1 indicators facilitates interpretation of the magnitude of the estimation results.
[8] Note that the inclusion of both individual fixed effects and year fixed effects automatically controls for the linear effect of individual age.

controlling for the underlying difference in the performance of specialists and generalists in relation to the forward movement of the frontier. Formally, we estimated:

$$DV_{i,t} = f(\beta_1.Specialist_i.SovietImpact_i.AfterSovietCollapse_t + \beta_2.Specialist_i.AfterSovietCollapse_t + \beta_3.SovietImpact_i.AfterSovietCollapse_t + C_{i,t} + I_i + \gamma_t + \varepsilon_{i,t})$$

where $DV_{i,t}$ represents mathematician i's output of interest (citation-weighted publication count, breakthrough count, and collaboration rate) in year *t*. $Specialist_i$, $SovietImpact_i$, and $AfterSovietCollapse_t$ are the three main independent variables. $C_{i,t}$ represents the set of control variables (cumulative number of publications and age-squared). I_i and γ_t indicate individual and year fixed effects, respectively. Note that $Specialist_i$ and $SovietImpact_i$ are not included independently because they are absorbed by individual fixed effects since their values are fixed at the individual level. Similarly, $AfterSovietCollapse_t$ is not included independently since its effect is absorbed by the year fixed effects.

β_2 is the main coefficient of interest for testing H1 and captures the difference between post-Soviet outcome trends of specialists and generalists whose research was primarily in slow-paced areas—areas less affected by the Soviet collapse. β_1 is the main coefficient of interest for testing H2 and captures the differential performance of specialists relative to generalists in fast-paced areas of theoretical mathematics—areas most affected by the Soviet collapse—using the difference in areas less affected as the baseline. β_3 captures the change in the outcome trend of generalists who were active in fast-paced areas compared with generalists whose research was predominantly in slow-paced areas, and $\beta_1 + \beta_3$ captures the equivalent change between specialists in fast- and slow-paced areas. Together, β_3 and $\beta_1 + \beta_3$ are the coefficients of interest for testing H3.

Because all three dependent variables are count variables, we used a conditional fixed-effects panel Poisson model with robust standard errors clustered at the individual level and calculated using the Huber–White method in all estimations. The estimator is consistent in the presence of heteroskedasticity and overdispersion of the dependent variable (Silva and Tenreyro 2006).

RESULTS

Descriptive statistics and correlations for the full sample and the matched sample are shown in table 2. In the full sample, a typical mathematician in our sample has produced approximately 0.7 papers per year (or about two papers every three years) and has a citation-weighted publication count of approximately 5.7. She has also produced, on average, one publication in the top 5 percent and two publications in the top 10 percent during the whole sample period (1980–2000). Note that the figures are skewed. Hence, while many mathematicians in our sample have not produced any breakthroughs, others have produced multiple breakthroughs during the sample period. Furthermore, a typical mathematician has collaborated with at least one person every other year, and most of her collaborations are unique. The means for the matched sample are slightly smaller than those for the full sample due to a lack of proper matches for individuals with extremely high levels of productivity. Nevertheless, overall there is substantial overlap between the full sample and the matched sample.

– Insert table 2 about here –

Table 3 details the differences between specialists and generalists on the key dimensions of interest for the period before the Soviet collapse. Panel A shows the differences in the full sample, and Panel B reports them in the matched sample.

– Insert table 3 about here –

In the full sample (Panel A) there are almost twice as many specialists as generalists. This is not surprising given their graduate training and the importance of establishing a domain of specialty for career advancement in academia (e.g., Franzoni, Scellato, and Stephan, 2011; Stephan, 2012). The generalists in our sample produce on average approximately one more publication and 17 more citation-weighted publications in the period before the collapse. Furthermore, generalists generate approximately 0.2 more publications in the top 5 percent cited list, relative to specialists, in that period. In other words, a typical generalist is 1.6 times more likely to produce highly cited publications. The difference is similar when focusing on the number of publications in the top 10 percent cited. Interestingly, specialists seem to collaborate more frequently on their papers but have fewer unique collaborators. This is consistent with the idea that generalists are more likely to work with a more diverse set of individuals across a wider range of domains. Panel B presents the comparative descriptive statistics for the matched sample. The main takeaway is that the differences between specialists and generalists in the full sample disappear once we restrict our sample to the CEM one. Last, due to our strict one-to-one matching, the numbers of specialists and generalists are the same in the matched sample. The number of generalists in the matched sample is not considerably different from the number of generalists in the full sample.

Table 4 shows estimation results for the change in the creative output of specialists and generalists in slow and fast-paced domains. Model 1 of table 4 shows estimation results using count of publications as the dependent variable. The estimated β_2 suggests a statistically significant 8 percent relative decline in the number of publications by specialists in slow-paced areas of theoretical mathematics.[9] The decline is equivalent to approximately one fewer publication after the collapse. These results are consistent with H1, that generalists have a creative advantage over specialists when a knowledge domain remains stable over time. In contrast, there is a relative increase of approximately 37 percent in the number of publications by specialists over generalists in fast-paced areas of mathematics, using the change in the differential performance of specialists relative to generalists in less affected areas as a baseline. The 37 percent increase is equivalent to approximately three extra publications after the collapse. This creative advantage of specialists is consistent with H2, that specialists have a creative advantage over generalists in fast-paced knowledge domains. The negative and significant β_3 suggests a 23 percent decrease in creative output of generalists in fast-paced knowledge domains compared with generalists in slow-paced knowledge domains, consistent with H3. Also, although not statistically significant (p = 0.35), compared with specialists in the less affected areas of mathematics, specialists in the most affected areas increased their publication count by approximately 5 percent after the fall of the Soviet Union (based on the sum of β_1 and β_3).

– Insert table 4 about here —

Model 2 shows results for the citation-weighted number of publications. The interpretation of results is similar to those reported for model 1. However, the coefficients are larger, which suggests that the relative increase in creative performance of specialists in affected areas after the Soviet collapse is driven partly by an increase in the quantity of their creative output and partly by an increase in the average quality of their creative output (measured as the number of citations to their publications). The estimated β_2 suggests that, in slow-paced areas of mathematics, specialists

[9] To calculate percentage change in output trends, we compute the incidence rate ratio from the estimated coefficients.

produced approximately 22 percent fewer citation-weighted publications per year than generalists did in years after 1989. The decline is equivalent to producing approximately three fewer citation-weighted publications per year after the collapse. In contrast, when we use the change in the differential performance of specialists versus generalists in less affected areas as the baseline, the estimated β_1 suggests that in fast-paced areas of mathematics, specialists increased their citation-weighted publication output relative to generalists by approximately 83 percent in years after 1989. This is equivalent to producing approximately 4 more citation-weighted publications per year during the post-Soviet period. The negative and significant β_3 suggests a 37 percent decrease in creative output of generalists in fast-paced knowledge domains compared with generalists in slow-paced knowledge domains. The results also indicate that, compared with specialists in less affected areas, specialists in the most affected areas increased their performance by a statistically significant margin of approximately 16 percent after the Soviet collapse.

Models 3 and 4 report the analog estimation results for the matched sample. The estimated coefficients of β_1 and β_3 are slightly larger. They, are in line with those for the full sample, and depict trends aligned with those described above. Overall, the results in table 4 provide strong support for the effects hypothesized in H1, H2, and H3.

One potential concern with these interpretations is that the observed change in the differential performance of specialists and generalists in the fast- and slow-paced areas of mathematics might have begun before the Soviet collapse and that our estimations are driven by these pre-trends. To address this concern, we checked the timing of changes in specialists' performance by estimating their differential performance compared with generalists in years before and after the Soviet collapse in 1989. We used the 1987 to 1989 performance difference of specialists and generalists in the non-affected areas as the baseline (i.e., the time right before the

Soviet collapse) and examined the change in citation-weighted output of specialists and generalists over six periods: 1981–1983, 1984–1986, 1990–1992, 1993–1995, 1996–1998, and 1999–2000. The use of citation-weighted output helps us capture the changes in both quantity and quality over time. The estimations are based on the same DDD estimator as before, where we replace the $AfterSovietCollapse_t$ dummy with dummies for each of the three-year periods described. We used groups of three years because many mathematicians in our sample publish once every few years. Using three-year periods thus helps minimize the noise because many mathematicians do not publish every year. In testing for pre-trends, we used the unmatched sample (i.e., full sample) to ensure that the pre-trends are not masked due to our matching procedure. In the appendix, we show that the graphs are similar if we use the matched sample (figure A1). If changes in the differential performance of specialists and generalists indeed predate the Soviet collapse, we should observe these trends in the 1981–1983, 1984–1986, and 1996–1998 periods. In figure 1a we plot the estimated yearly β_2 coefficients, which represent the difference in citation-weighted outputs of specialists relative to generalists in slow-paced area. In line with H1, we observe a decrease in the estimated difference in output between specialists and generalists in slow-paced areas after the collapse of the Soviet Union.

– Insert figure 1 about here –

In figure 1b we plot the estimated yearly β_1 which represents the relative difference in citation-weighted outputs of specialists relative to generalists in fast-paced areas. The estimates suggest that the change in the differential performance of specialists and generalists in these fast-paced areas increases after the fall of the Soviet Union, in line with H2. In figure 1c we plot the estimated yearly β_3, which represents the difference in citation-weighted outputs between generalists in fast-paced areas and generalists in slow-paced areas. Figure 1d further shows the difference in citation-weighted output between specialists in fast-paced areas and specialists in slow-paced areas ($\beta_1 + \beta_3$). In line with H3, we observe a decrease in the performance of generalists in fast- versus slow-paced areas of theoretical mathematics after the Soviet collapse. In contrast, we observe an increase in the performance of specialists in fast-paced areas after the collapse. In all figures there are no indications of pre-Soviet collapse trends, confirming that the estimated changes in table 1 are attributed to years following the fall of the Soviet Union.

In table 5 we examine the differential propensity of generalists and specialists to produce breakthroughs in fast- and slow-paced knowledge domains. The estimates are in line with those reported in table 1 for overall creative output. The estimated β_2 in model 1 indicates a significant decline of about 25 percent in the number of breakthroughs—defined as publications in the top 5 percent of cited output—produced by specialists relative to that produced by generalists in slow-paced areas of theoretical mathematics. The effect is in line with H1, that generalists have more opportunities to generate breakthroughs in slow-paced knowledge domains because of their more diverse knowledge sources. In contrast, using the change in the differential performance of specialists and generalists in slow-paced knowledge areas as the baseline, the estimated β_1 suggests that specialists produced on average 75 percent more breakthroughs than generalists in fast-paced knowledge areas, those most affected by the Soviet collapse, post-1989. This finding is aligned with H2 and shows that specialists were almost twice as likely as generalists to generate a breakthrough after the Soviet collapse in areas where Soviet mathematicians had the greatest impact on the knowledge frontier. The negative, though not statistically significant, β_3 is in line with H3, showing a 20 percent decline in the number of breakthroughs by generalists in fast-paced knowledge domains compared with generalists in slow-paced domains. The estimates suggest the opposite effect for specialists: specialists in fast-paced area significantly increase their breakthrough output, by 39 percent, compared with specialists in slow-paced areas. The results hold when replacing our dependant variable with the alternative measure of breakthroughs based on the top 10 percent cited publications. The results also persist in the matched sample, with the estimates suggesting a slightly larger relative change in the breakthrough output of specialists and generalists in slow- and fast-paced areas of mathematics.

– Insert table 5 about here –

One might be concerned that the differential change in the breakthrough outputs of specialists and generalists in fast-paced versus slow-paced domains are directly driven by their differential rates of publication. In other words, mathematicians who produce more output are also more likely to produce more breakthrough output due to a statistical order effect (Conti et al., 2013), even though each of their outputs may be of lower quality compared with those who produce fewer outputs but potentially of higher quality. There is some evidence in past research suggesting a trade-off between quantity and quality of creative output. For example, Leahey, Beckman and Stanko (2017) showed that individuals who are involved in more interdisciplinary projects produce fewer publications but that each of their publications is more likely to be highly impactful. To test whether our results are driven by a mechanical relationship between quantity and breakthrough output, we examined the change in the number of publications produced by specialists and generalists in different citation brackets after the Soviet collapse. For each scientist, we assigned their papers into four categories based on their citation impact: papers in the top 5 percent of citation impact bracket (breakthroughs), those in the 25 to 5 percent bracket, those in the 50 to 25 percent bracket, and those in the bottom 50 percent bracket. If the increase (or decrease) in breakthrough counts is driven mechanically by the increase (or decrease) in the number of publications, we should expect to see a similar change in the number of publication in all brackets.

Tables 6 and 7 show changes in publication count for each citation bracket. The estimates in Table 6 suggest that specialists in fast-paced domains overall produce more publications in the top 5 percent and the top 25 to 5 percent citation brackets. The results in Table 7 suggest that the effects become insignificant in lower-impact brackets. In other words, most of the extra creative output of specialists in fast-paced domains is of higher impact. In slow-paced domains, generalists produce more publications in top citation brackets than specialists do, but again the results fade away in low-impact brackets. Overall, the results suggest that the results for breakthrough output are not driven by a statistical order effect.

– Insert tables 6 and 7 about here –

Theoretically, the findings imply that specialists not only absorb the newly emerged knowledge components faster than generalists but also use the new knowledge more quickly to address the more fundamental gaps in their domain of specialty. Their faster and more effective absorption and use of new knowledge can potentially crowd out generalists' efforts and push generalists to tackle less impactful opportunities. The opposite argument holds for generalists in slow-paced domains. The results suggest that the usual trade-off between quantity and quality does not necessarily hold in all contexts. In certain conditions, one creative type may show superior performance on both dimensions of quantity and quality. The findings also shed more light on the underlying mechanisms: it is not only about access to more knowledge components. Rather, the advantage that specialists enjoy in fast-paced domains stems from their faster absorption and use of new knowledge as well as their deeper understanding of the fundamental problems that can be addressed using newly emerged knowledge components.

We also tested the role of competition for complementary resources as a force driving the differential performance of specialists and generalists after the Soviet collapse. We examined this mechanism by investigating the change in the collaboration patterns of specialists and generalists. Access to complementary collaborators is an important and limited resource in academia, as in many other creative contexts. Past research suggested that scientists choose collaborators strategically (Leahey and Reikowsky 2008; Bikard, Murray, and Gans, 2015). Following our theoretical arguments, we expect specialists to be more sought-after in fast-paced domains but generalists to be more sought-after in slow-paced domains. We therefore expect an increase in collaboration levels of specialists (compared with generalists) in fast-paced domains of mathematics and a decline in their collaboration levels in slow-paced domains. Furthermore, we expect a decrease in collaboration of generalists in slow- versus fast-paced domains and a reverse effect for specialists.

To test these assertions, in table 8 we present results for the change in the collaboration rates of specialists and generalists after the fall of the Soviet Union. As before, we present results using our full sample in models 1 and 2, and results using our matched sample in models 3 and 4. As anticipated, the estimated β_2 suggests a relative decline of 7 percent and 10 percent in specialists' number of collaborators and specialists' number of unique collaborators, respectively, compared with generalists, in slow-paced domains. In fast-paced domains, however, specialists' total number of collaborators and the number of unique collaborators increased by up to 46 percent and 59 percent, respectively, compared with generalists, using their differential change in the slow-paced domains as the baseline. Similarly, we observe declines of 31 and 33 percent in generalists' numbers of collaborators and numbers of unique collaborators, respectively, in fast- versus slow-paced domains, while specialists in fast-paced domains experience increases of 18 percent and 7 percent, respectively, over their specialist counterparts in slow-paced domains. Figures A2 and A3 in the appendix shows the timing of change in specialists' and generalists' collaboration rates. As before, we do not observe any pre-trends in years before the Soviet collapse.

– Insert table 8 about here —

While these results show the change in collaboration rates of specialists and generalists after the Soviet collapse, they do not show changes in the compositions of collaborations—changes in the rates of specialist–specialist, specialist–generalist, and generalist–generalist collaborations. Unpacking the changes in collaboration composition is not empirically straightforward. Collaboration is a matching process which adds an additional layer of complexity to our estimations. For example, while one creative type (say, specialists) may decide to reduce its collaboration with the other (say, generalists) due to its lower benefits, the latter may put more effort in securing collaborations with the former due to its higher benefits. Hence, it is difficult to make an ex-ante theoretical prediction about changes in some collaboration types. Moreover, since mathematicians on average have few collaborators, breaking down the small number of collaborators into different categories can lead to less accurate estimations with larger standard errors. Nonetheless, we provide some evidence of change in collaboration compositions in tables 9 and 10. The estimates suggest a statistically significant decline in collaboration among specialists and an increase in collaborations between specialists and generalists in slow-paced domains (β_2). In comparison, the fast-paced environments do not experience such a change (β_1). In other words, specialists and generalists in fast-paced domains remain more likely to collaborate with specialists and less likely to collaborate with generalists than their counterparts in slow-paced domains who prefer collaborating with generalists over specialists. Moreover, generalists in fast-paced environments reduce collaboration with other generalists, when compared with generalists in slow-paced environments, while maintaining approximately the same levels of collaboration with specialists (β_3). At the same time, specialists in fast-paced domains increase collaboration with other specialists and decrease collaboration with generalists, when compared with specialists in slow-paced domains ($\beta_1 + \beta_3$), a statistically significant result. This finding is in line with our assertion that the observed creative advantages of specialists in fast-paced domains and of generalists in slow-paced domains are associated with a higher propensity of these individuals to be desired collaborators.

– Insert tables 9 and 10 about here —

We conducted several additional robustness checks to further corroborate our findings. One source of concern is that our results might be affected by an increase in labor market competition due to the rise in the migration of Soviet mathematicians to other countries. To address this concern, we tested whether our results hold in geographical areas with little to no Soviet impact. Specifically, we followed the empirical strategy in Agrawal, Goldfarb, and Teodoridis (2016) and focused on Japan, "a country with no documented evidence of Soviet immigration in mathematics" and "which consistently ranks in the top ten mathematics research." We find that all our results for generalists and specialists persist in the subset of Japanese-flagged authors, which indicates that our estimations are the result of the pace of the emergence of new knowledge components and not of labor market competition. The results are reported in Tables A7 to A9 in the appendix.

Moreover, we provide a battery of additional robustness checks for our estimations in the appendix. Tables A10 to A12 shows that our results hold if we use the 50 percent threshold on the diversification index to define specialists and generalists. In addition, we show the robustness of results to the use of a continuous measure of specialization (tables A1 to A3) and a continuous measure of impact of Soviet collapse on different domains of mathematics (tables A4 to A6).

Finally, tables A13 to A15 show the sensitivity of our estimates to the exclusion of individual fixed effects and year fixed effects. Overall, the estimates and their interpretation are robust to these additional tests.

DISCUSSION AND CONCLUSION

Creative workers face a trade-off between concentrating their research efforts in a single knowledge domain, and becoming a specialist, or spreading their efforts across several domains, and becoming a generalist. Both creative strategies present advantages, and the superiority of each is a matter of debate in prior literature. We propose that those disagreements might be driven in part by attempts to generalize from different domains exhibiting different paces of change. Just as the performance of firms' strategy is tightly linked to the dynamics of the field in which they compete, we argue, the creative performance of individuals with different strategies is tightly linked to the dynamics of the knowledge domain in which they work.

In particular, the pace of change in a domain is likely to affect the relative benefits of being a specialist or a generalist because it determines the availability of new knowledge components. Conceptualizing the creative process as an act of recombination (Gilfillan 1935; Schumpeter 1939), we theorize that generalists are likely to perform better in slow-changing domains because they have access to a diverse set of knowledge components from other domains. At the same time, specialists in those domains might struggle to find recombinations that are yet untried. As the pace of change increases, however, specialists can take advantage of their deep understanding of the domain and of their rich toolkit of domain-specific heuristics to identify and use emerging recombination opportunities efficiently. Generalists in fast-paced domains are thus likely to be less able to take advantage of emerging knowledge components because their understanding of the knowledge domain tends to be shallower than that of specialists. Moreover, those dynamics are likely to be amplified by within-domain competition for scarce resources. As Merton (1968) famously noted, the rich get richer. The performance of a specific creative strategy depends on the performance of the competitors' strategy. Even though generalists in fast-changing domains are likely to have access to more recombination opportunities than generalists in slow-changing domains, they are likely to suffer much more from the competition of specialists.

We hypothesized and found empirical support that generalists perform relatively better than specialists in slow-paced environments but perform relatively worse as the pace of change increases. The Soviet collapse led to an unexpected and substantial acceleration of change in some subfields of theoretical mathematics but not in others. In the fields most affected, the performance of specialists improved sharply relative to that of generalists. At the same time, generalists performed relatively better than their specialist colleagues in the less affected fields, where the pace of change remained relatively stable. Differences in performance are visible across a variety of measures including publication counts, citation-weighted publication counts, counts of breakthroughs, and even individual ability to attract collaborators. Furthermore, we find that the performance of generalists in affected fields decreases as the pace of change accelerates, presumably because of the steep increase in the ability of specialist competitors to secure scarce resources in those domains.

One should note that our theoretical arguments do not rely on the type of sudden change in the knowledge frontier that we observe in our empirical setting. The collapse of the Soviet Union and the sudden influx of new knowledge in some areas of theoretical mathematics versus others is an essential part of our empirical strategy but is not required theoretically. This natural experiment helps us empirically isolate the variance in the pace of change across domains independent of the ex-ante activities of the creative workers in those domains. Nevertheless, while the natural experiment of the unexpected Soviet collapse provides a rewarding test for our theoretical predictions, some limitations remain. First, despite the richness of our data and the comprehensive role of theoretical mathematics in creative work across a multitude of areas, we study one setting. Thus, we make no strong claims of generalizability and invite future research to investigate other knowledge creation areas.

Second, our study is limited by our somewhat static operationalization of the generalist and specialist creative strategies. The ability of individuals to become generalists or specialists varies. Moreover, the distinction between specialists is not always as clear as it appears in theoretical mathematics. The implications of our results for individuals specializing in tools or topics that have broad applications (e.g., general purpose technologies) remain unclear. Besides, individuals might shift strategy over the span of their career (Mannucci and Yong 2017). For example, junior researchers might exhibit greater specialization whereas senior individuals might exhibit greater diversification. In our empirical analysis, we controlled for a quadratic effect of age to account for this possibility. However, this approach does not consider that junior specialists might become increasingly diverse as they advance in their careers. At the same time, it is unclear whether generalists might narrow their focus as they encounter a prolific area of research. To address this concern, we calculated our index of diversification on a rolling basis to seek evidence of significant changes in diversification at the individual level throughout the course of our dataset. We did not find such evidence.

Our study makes several theoretical contributions. First, we attempt to reconcile current debates on the superiority of becoming a generalist or a specialist. Before this study, a large stream of work described the advantages of being a generalist, highlighting the benefits of brokering otherwise distant knowledge components (Hargadon and Sutton, 1997; Uzzi and Spiro, 2005;

Audia and Goncalo, 2007; Cattani and Ferriani, 2008; Jeppesen and Lakhani, 2010). Other studies instead emphasized benefits of specialization such as specialists' deeper understanding of their knowledge domain and their clearer identity (Birnbaum 1981; Leahey 2007; Jones 2009; Conti, Gambardella, and Mariani 2013). We extend this literature by investigating what appears to be a common assumption in many of those studies: the relative stability of knowledge domains. The set of knowledge components for use by generalists and specialists is not fixed but constantly evolving. Furthermore, this evolution appears to affect generalists and specialists differently.

Second, and related, we propose that change in creative domains evolves at different speeds in different domains and over time. The pace of change appears to play an important—and hitherto understudied—role as a driver of creative performance because it benefits some individuals more than others. That generalists appear to do better in slower-paced domains and specialists in faster-paced ones might explain in part the apparent conflicting evidence about the benefits of both strategies in prior research. While here we study a specific type of change, we hope that future research will explore whether different types of change might have different consequences. At times, some discoveries challenge the very foundations of entire knowledge domains, provoking what Kuhn (1970) referred to as scientific revolutions. For example, the introduction of Einsteinian dynamics in theoretical physics challenged many of the assumptions held by Newtonian physicists. Past research suggested that specialists in a domain that has experienced a scientific revolution are more likely to resist adapting to the foundational changes in their domain of expertise (Kuhn 1970, 151). In cases of scientific revolution in a domain, specialists' domain-specific heuristics and problem-solving skills may no longer give them any advantage over generalists, as they may all be challenged by the radical changes in the foundations of the field.

Third, our study highlights the crucial role of cumulative advantage in creative work. Prior research described such a dynamic in the case of individual social status in science. The typical argument is that high-status individuals can reap more rewards from the products of their work, which further increases their performance and their ability to reap even more rewards in the future (Merton 1968; Simcoe and Waguespack 2011; Azoulay, Stuart, and Wang 2013). Our study extends this stream of research by highlighting that the same dynamic of cumulative advantage shapes the performance of creative strategies. More specifically, we find that the same creative strategies can lead to different levels of performance depending on the success of the competitors' strategy. Studies of creative performance that overlook these competitive dynamics might therefore lead to erroneous conclusions.

Fourth, and related to the issue of cumulative advantage, our study contributes to the literature on collaboration in knowledge creation by contextualizing the common finding that collaboration is associated with high creative performance. Past research emphasized the key role of collaboration in fostering creativity by facilitating more diverse knowledge recombinations and more efficient selection of good ideas (Reagans, Zuckerman, and McEvily, 2004; Fleming, Mingo, and Chen, 2007; Singh and Fleming, 2010). However, these studies usually overlook that collaboration is often a choice. Our findings therefore contribute to a growing literature exploring the determinants of collaboration strategies in creative work (Leahey and Reikowsky 2008; Bikard, Murray, and Gans 2015) by highlighting how the relative cognitive advantage of individuals in a domain can shape their collaboration opportunities. We also highlight how preferential access to complementary collaborators can reinforce the creative advantage. More broadly, our results call for more research to understand the dynamics of competition for collaboration and the complex market for collaborators.

Fifth, our study contributes to the discussion on the emergence of breakthroughs. Creative breakthroughs are traditionally associated with distant search, whereas local search is believed to lead to more incremental improvements (e.g., Fleming, 2001). At its core, this view assumes that truly novel recombinations can only occur by drawing on elements not considered before—that is, those that stem from outside the knowledge domain in question. In contrast, we show that when new knowledge components emerge from inside a rapidly evolving knowledge domain, breakthroughs are likely to stem from local (deep) rather than distant search. The promise of local and distant search for breakthrough emergence therefore varies with the pace of knowledge-domain advancement.

Additionally, our study has implications for the organization of firms' R&D. At one level, it suggests that the composition of the R&D team, with respect to the balance of specialists and generalists, should depend on the pace of innovation in the industry. However, it also highlights the different roles that specialists and generalists might play on R&D teams seeking to absorb external knowledge (Cohen and Levinthal 1990). Specifically, although specialists might run the risk of always using the same heuristics, they may be better able to absorb external knowledge in their domains of expertise and, in so doing, more likely to help firms navigate fast-changing environments. Generalists, on the other hand, might be more advantageous in slower-paced industries because they bring in useful knowledge from other domains. This is important not only for increasing organizational performance but also, more fundamentally, for organizational survival. Prior work emphasized the importance of R&D not only as a product development channel but also as an avenue for firms to gain new knowledge and keep abreast of the competition (e.g., Cockburn and Henderson, 1998; Owen-Smith and Powell, 2004).

Our paper is a first step in highlighting how the pace of change shapes the performance of creative workers. Our study also suggests that specialists and generalists fulfill different and complementary creative roles. The importance of furthering this line of research should not be understated. Creativity and innovation play a growing role in individual and firm performance, and there is no sign that the pace of economic change might stop evolving differently across domains and over time. By highlighting the fact that creative workers rarely evolve in static knowledge domains, we hope, our study enhances our understanding of the drivers of creative performance and triggers future research on creative strategies in a changing world.

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Table 1. Subfield Rank of Soviet Contributions to Theoretical Mathematics

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

Notes: The ranking on the left indicates the level of impact of the fall of Soviet Union on the subfield. The higher the subfield's ranking, the more it was affected by the shock. The ranking is based on Agrawal, Goldfarb, and Teodoridis (2016).

Table 2. Summary Statistics for the Full Sample and the Matched Sample (1980–2000)

Panel A: Full Sample

Variable	N	Mean	Std. Dev.
Citation-weighted number of publications per year	123,139	5.724	35.193
Simple publication count per year	123,139	0.732	1.299
Number of breakthrough publications (in top 5% cited) per year	123,139	0.043	0.275
Number of breakthrough publications (in top 10% cited) per year	123,139	0.090	0.402
Number of collaborators between 1980 and 1988	123,139	0.541	1.519
Number of unique collaborators between 1980 and 1988	123,139	0.413	0.937

Panel B: Matched Sample

Variable	N	Mean	Std. Dev.
Citation-weighted number of publications per year	81,762	4.678	20.178
Simple publication count per year	81,762	0.690	1.151
Number of breakthrough publications (in top 5% cited) per year	81,762	0.037	0.229
Number of breakthrough publications (in top 10% cited) per year	81,762	0.081	0.346
Number of collaborators between 1980 and 1988	81,762	0.505	1.327
Number of unique collaborators between 1980 and 1988	81,762	0.412	0.920

Table 3. Specialists versus Generalists before the Collapse of the Soviet Union (1980–1989)

Panel A: Full Sample

Variable	**Specialists**	**Generalists**	**t-test difference**
Number of mathematicians	4,042	2,213	
Total citation-weighted number of publications between 1980 and 1988	44.777 (108.712)	61.568 (148.799)	-16.791*** (p=0.000)
Total number of publications between 1980 and 1988	8.047 (9.413)	8.856 (10.386)	-0.809** (p=0.002)
Total number of breakthrough publications (in top 5% cited) between 1980 and 1988	0.356 (1.116)	0.560 (1.579)	-0.204*** (p=0.000)
Total number of breakthrough publications (in top 10% cited) between 1980 and 1988	0.780 (1.710)	1.102 (2.244)	-0.322*** (p=0.000)
Average number of collaborators between 1980 and 1988	0.703 (1.386)	0.588 (0.729)	0.115*** (p=0.000)
Average number of unique Collaborators between 1980 and 1988	0.446 (0.572)	0.480 (0.517)	-0.034** (p=0.019)

Panel B: Matched Sample

Variable	**Specialists**	**Generalists**	**t-test difference**
Number of mathematicians	2,038	2,038	
Total citation-weighted number of publications between 1980 and 1988	39.915 (66.830)	41.728 (67.621)	-1.813 (p=0.389)
Total number of publications between 1980 and 1988	7.261 (5.395)	7.337 (5.323)	-0.075 (p=0.655)
Total number of breakthrough publications (in top 5% cited) between 1980 and 1988	0.340 (0.910)	0.376 (0.891)	-0.036 (p=0.204)
Total number of breakthrough publications (in top 10% cited) between 1980 and 1988	0.816 (1.537)	0.835 (1.490)	-0.019 (p=0.694)
Average number of collaborators between 1980 and 1988	0.528 (0.772)	0.533 (0.631)	0.018 (p=0.823)
Average number of unique Collaborators between 1980 and 1988	0.410 (0.520)	0.448 (0.478)	0.037** (p=0.017)

Table 4. Changes in the publication output of specialist and generalist mathematicians after the collapse of the Soviet Union

Dependent variable	Simple count of publications	Citation-weighted count of publications	Simple count of Publications	Citation-weighted count of publications
Sample	Full sample	Full sample	Matched sample	Matched sample
Estimation model	Panel Poisson	Panel Poisson	Panel Poisson	Panel Poisson
	(1)	(2)	(3)	(4)
Specialist × SovietImpact × AfterSovietCollapse (β_1)	0.315*** (0.113)	0.605*** (0.205)	0.390*** (0.129)	0.777*** (0.253)
Specialist × AfterSovietCollapse (β_2)	-0.078** (0.032)	-0.254** (0.103)	-0.056 (0.038)	-0.241*** (0.080)
SovietImpact × AfterSovietCollapse (β_3)	-0.264*** (0.099)	-0.454*** (0.176)	-0.382*** (0.114)	-0.610*** (0.208)
Controls for cumulative publications and non-linear age profile	Yes	Yes	Yes	Yes
Individual and year fixed effects	Yes	Yes	Yes	Yes
No. of observations	113,512	113,406	76,795	76,783
No. of mathematicians	6,140	6,132	4,024	4,024
Chi^2	1059.76***	203.81***	663.53***	104.60***
Log-likelihood	-104275.08	-786985.39	-68821.16	-451570.52

Notes: The data is a panel at the author level based on publication data between 1980 and 2000. The unit of analysis is author-year. All models are conditional fixed-effect Poisson with robust standard errors, clustered at the author level. The difference in the number of observations across models is a consequence of estimating all our models using the xtpoisson command in Stata; the command drops units without within-individual variance after factoring in all the independent and control variables.
* p < 0.10, ** p < 0.05, *** p < 0.01.

Table 5. Changes in the breakthrough output of specialist and generalist mathematicians after the collapse of the Soviet Union

Dependent variable	Count of breakthroughs (publications in top 5% cited)	Count of breakthrough (publications in top 10% cited)	Count of breakthroughs (publications in top 5% cited)	Count of breakthrough (publications in top 10% cited)
Sample	Full sample	Full sample	Matched sample	Matched sample
Estimation model	Panel Poisson	Panel Poisson	Panel Poisson	Panel Poisson
	(1)	(2)	(3)	(4)
Specialist × SovietImpact × AfterSovietCollapse (β_1)	0.587** (0.257)	0.461** (0.203)	0.685* (0.369)	0.736** (0.292)
Specialist × AfterSovietCollapse (β_2)	-0.285*** (0.094)	-0.315*** (0.068)	-0.265** (0.114)	-0.343*** (0.082)
SovietImpact × AfterSovietCollapse (β_3)	-0.227 (0.224)	-0.171 (0.178)	-0.413 (0.316)	-0.455* (0.252)
Controls for cumulative publications and non-linear age profile	Yes	Yes	Yes	Yes
Individual and year fixed effects	Yes	Yes	Yes	Yes
No. of observations	30,642	49,110	20,641	34,061
No. of mathematicians	1,634	2,617	1,075	1,771
Chi^2	192.90***	338.44***	97.87***	200.33***
Log-likelihood	-10427.39	-19880.25	-6399.02	-12668.48

Notes: The data is a panel at the author level based on publication data between 1980 and 2000. The unit of analysis is author-year. All models are conditional fixed-effect Poisson with robust standard errors, clustered at the author level. The difference in the number of observations across models is a consequence of estimating all our models using the xtpoisson command in Stata; the command drops units without within-individual variance after factoring in all the independent and control variables. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6. Changes in the publication output of specialist and generalist mathematicians across top citation brackets after the collapse of the Soviet Union

Dependent variable	Count of publications in top 5% citation bracket	Count of publications in 25% to 5% citation bracket	Count of publications in top 5% citation bracket	Count of publications in 25% to 5% citation bracket
Sample	Full sample	Full sample	Matched sample	Matched sample
Estimation model	Panel Poisson	Panel Poisson	Panel Poisson	Panel Poisson
	(1)	(2)	(3)	(4)
Specialist × SovietImpact × AfterSovietCollapse (β_1)	0.558** (0.257)	0.251* (0.155)	0.685* (0.369)	0.476*** (0.180)
Specialist × AfterSovietCollapse (β_2)	-0.285*** (0.094)	-0.186*** (0.048)	-0.265** (0.114)	-0.209*** (0.056)
SovietImpact × AfterSovietCollapse (β_3)	-0.228 (0.224)	-0.116 (0.134)	-0.413 (0.316)	-0.339** (0.147)
Controls for cumulative publications and non-linear age profile	Yes	Yes	Yes	Yes
Individual and year fixed effects	Yes	Yes	Yes	Yes
No. of observations	30,642	77,440	20,641	54,027
No. of mathematicians	1,634	4,139	1,075	2,817
Chi^2	192.90***	674.87***	97.87***	427.70***
Log-likelihood	-10427.39	-37763.58	-6399.02	-25032.97

Notes: The data is a panel at the author level based on publication data between 1980 and 2000. The unit of analysis is author-year. All models are conditional fixed-effect Poisson with robust standard errors, clustered at the author level. The difference in the number of observations across models is a consequence of estimating all our models using the xtpoisson command in Stata; the command drops units without within-individual variance after factoring in all the independent and control variables. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7. Changes in the publication output of specialist and generalist mathematicians across bottom citation brackets after the collapse of the Soviet Union

Dependent variable	Count of publications in 50% to 25% citation bracket	Count of publications in bottom 50% citation bracket	Count of publications in 50% to 25% citation bracket	Count of publications in bottom 50% citation bracket
Sample	Full sample	Full sample	Matched sample	Matched sample
Estimation model	Panel Poisson	Panel Poisson	Panel Poisson	Panel Poisson
	(1)	(2)	(3)	(4)
Specialist × SovietImpact × AfterSovietCollapse (β_1)	0.271 (0.205)	0.189 (0.146)	0.218 (0.238)	0.263 (0.170)
Specialist × AfterSovietCollapse (β_2)	-0.043 (0.044)	0.054 (0.047)	0.010 (0.052)	0.040 (0.055)
SovietImpact × AfterSovietCollapse (β_3)	-0.444** (0.188)	-0.416*** (0.129)	-0.528** (0.218)	-0.379*** (0.138)
Controls for cumulative publications and non-linear age profile	Yes	Yes	Yes	Yes
Individual and year fixed effects	Yes	Yes	Yes	Yes
No. of observations	105,804	92,133	72,557	63,218
No. of mathematicians	5,673	4,982	3,790	3,313
Chi^2	4556.66***	37.94***	3381.46***	821502.83***
Log-likelihood	-53043.48	-39338.67	-35113.98	-25066.18

Notes: The data is a panel at the author level based on publication data between 1980 and 2000. The unit of analysis is author-year. All models are conditional fixed-effect Poisson with robust standard errors, clustered at the author level. The difference in the number of observations across models is a consequence of estimating all our models using the xtpoisson command in Stata; the command drops units without within-individual variance after factoring in all the independent and control variables.
* p < 0.10, ** p < 0.05, *** p < 0.01.

Table 8. Changes in the collaboration rates of specialist and generalist mathematicians after the collapse of the Soviet Union

Dependent variable	Total number of collaborators	Total number of unique collaborators	Total number of collaborators	Total number of unique collaborators
Sample	Full sample	Full sample	Matched sample	Matched sample
Estimation model	Panel Poisson	Panel Poisson	Panel Poisson	Panel Poisson
	(1)	(2)	(3)	(4)
Specialist × SovietImpact × AfterSovietCollapse (β_1)	0.428*** (0.157)	0.340** (0.139)	0.457** (0.179)	0.380** (0.157)
Specialist × AfterSovietCollapse (β_2)	-0.110** (0.046)	-0.074** (0.037)	-0.100* (0.054)	-0.057 (0.044)
SovietImpact × AfterSovietCollapse (β_3)	-0.260** (0.132)	-0.270** (0.119)	-0.396** (0.155)	-0.371*** (0.135)
Controls for cumulative publications and non-linear age profile	Yes	Yes	Yes	Yes
Individual and year fixed effects	Yes	Yes	Yes	Yes
No. of observations	96,917	96,917	65,986	65,986
No. of mathematicians	5,243	5,243	3,459	3,459
Chi^2	122.91***	196.63***	63.56***	116.44***
Log-likelihood	88857.85	-71016.25	-57694.92	-48285.65

Notes: The data is a panel at the author level based on publication data between 1980 and 2000. The unit of analysis is author-year. All models are conditional fixed-effect Poisson with robust standard errors, clustered at the author level. The difference in the number of observations across models is a consequence of estimating all our models using the xtpoisson command in Stata; the command drops units without within-individual variance after factoring in all the independent and control variables.
* p < 0.10, ** p < 0.05, *** p < 0.01.

Table 9. Changes in collaboration with specialist mathematicians after the collapse of the Soviet Union

Dependent variable	Total number of collaborators	Total number of unique collaborators	Total number of collaborators	Total number of unique collaborators
Sample	Full sample	Full sample	Matched sample	Matched sample
Estimation model	Panel Poisson	Panel Poisson	Panel Poisson	Panel Poisson
	(1)	(2)	(3)	(4)
Specialist × SovietImpact × AfterSovietCollapse (β_1)	0.195 (0.412)	0.348 (0.356)	0.191 (0.484)	0.399 (0.397)
Specialist × AfterSovietCollapse (β_2)	-0.621*** (0.092)	-0.541*** (0.071)	-0.616*** (0.101)	-0.526*** (0.081)
SovietImpact × AfterSovietCollapse (β_3)	0.071 (0.397)	-0.213 (0.345)	-0.013 (0.466)	-0.299 (0.381)
Controls for cumulative publications and non-linear age profile	Yes	Yes	Yes	Yes
Individual and year fixed effects	Yes	Yes	Yes	Yes
No. of observations	53,812	53,812	34,459	34,459
No. of mathematicians	2,905	2,905	1,798	1,798
Chi^2	372.09***	540.51***	203.90***	266.56***
Log-likelihood	-28263.91	-21838.02	-16367.74	-13485.23

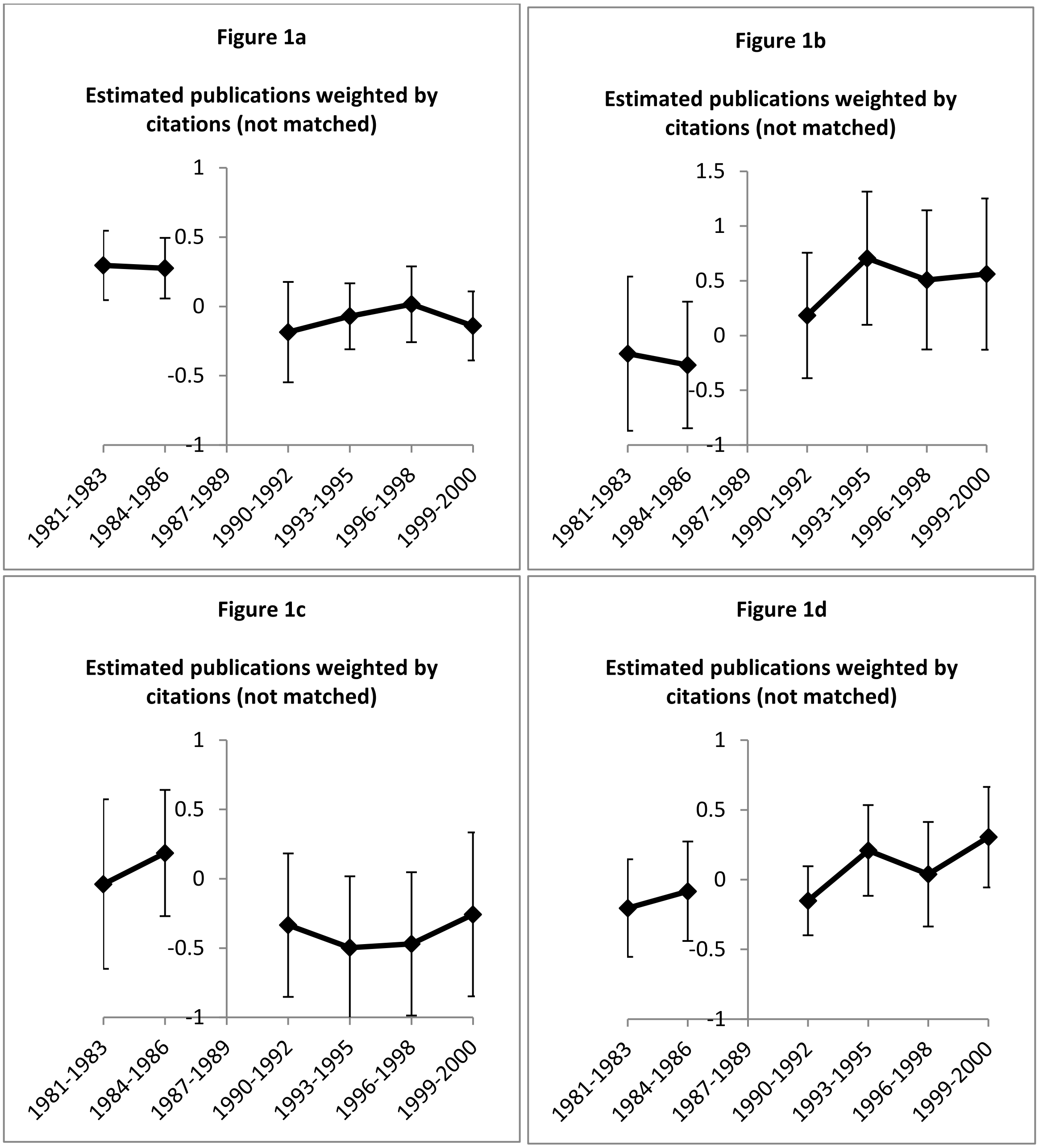
Notes: The data is a panel at the author level based on publication data between 1980 and 2000. The unit of analysis is author-year. All models are conditional fixed-effect Poisson with robust standard errors, clustered at the author level. The difference in the number of observations across models is a consequence of estimating all our models using the xtpoisson command in Stata; the command drops units without within-individual variance after factoring in all the independent and control variables. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 10. Changes in collaboration with generalist mathematicians after the collapse of the Soviet Union

Dependent variable	Total number of collaborators	Total number of unique collaborators	Total number of collaborators	Total number of unique collaborators
Sample	Full sample	Full sample	Matched sample	Matched sample
Estimation model	Panel Poisson	Panel Poisson	Panel Poisson	Panel Poisson
	(1)	(2)	(3)	(4)
Specialist × SovietImpact × AfterSovietCollapse (β_1)	0.177 (0.263)	0.117 (0.247)	0.758** (0.317)	0.521* (0.306)
Specialist × AfterSovietCollapse (β_2)	0.416*** (0.088)	0.402*** (0.075)	0.276** (0.115)	0.340*** (0.100)
SovietImpact × AfterSovietCollapse (β_3)	-0.530*** (0.185)	-0.444** (0.172)	-0.797*** (0.200)	-0.658*** (0.192)
Controls for cumulative publications and non-linear age profile	Yes	Yes	Yes	Yes
Individual and year fixed effects	Yes	Yes	Yes	Yes
No. of observations	44,207	44,207	33,611	33,611
No. of mathematicians	2,352	2,352	1,754	1,754
Chi^2	274.43***	332.42***	251.86***	287.85***
Log-likelihood	-19700.48	-15988.21	-14616.25	-12246.95

Notes: The data is a panel at the author level based on publication data between 1980 and 2000. The unit of analysis is author-year. All models are conditional fixed-effect Poisson with robust standard errors, clustered at the author level. The difference in the number of observations across models is a consequence of estimating all our models using the xtpoisson command in Stata; the command drops units without within-individual variance after factoring in all the independent and control variables. * p < 0.10, ** p < 0.05, *** p < 0.01.

Figure 1. Estimated relative difference in the quality-adjusted output of specialists versus generalists after the collapse of the Soviet Union



Notes: We base this figure on 10 years of publication data before the collapse of the Soviet Union and 10 years after the collapse. Each point on graph (a) represents the coefficient value on the covariate *Specialist* × *TimePeriod* and thus describes the relative difference in quality-adjusted publication rates between specialists and generalists in slow-paced areas. Each point on graph (b) represents the coefficient value on the covariate *Specialist* × *SovietImpact* × *TimePeriod* and thus describes the relative difference in quality-adjusted publication rates between specialists and generalists in fast-paced areas and the same difference in slow-paced areas. Each point on graph (c) represents the coefficient value on the covariate *SovietImpact* × *TimePeriod* and thus describes the relative difference in quality-adjusted publication rates between generalists in fast- versus slow-paced areas. Each point on graph (d) represents the sum of coefficients $\beta_1 + \beta_3$ and thus describes the relative difference in quality-adjusted publication rates between specialists in fast- versus slow-paced areas. The bars surrounding each point represent the 95% confidence interval. Note that the larger confidence intervals are due to reduced degrees of freedom, as we split the post-Soviet dummy into multiple period dummies. All values are relative to the base year-group of 1987–1989.