‘Never Let a Good Crisis Go To Waste’: The impact of the 2014 ebola epidemic on West African science

Caroline Viola Fry
Massachusetts Institute of Technology
Sloan School of Management

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Abstract

Relationships with more prominent affiliates can be crucial to the success of a scientist’s career. In practice, relationships with those more elite are limited to high achieving or high potential scientists, making their value very hard to measure. The 2014 West African ebola epidemic afforded scientists working in endemic countries an unexpected opportunity to build relationships with more prominent affiliates from around the globe. Using a matched sample of scientists from non-endemic countries I estimate the effect of the ebola epidemic on international collaborations and publication rates of endemic country scientists. I find evidence of a persistent post-epidemic boost in international collaborations and increases in publication rates. However, these results are only found for those endemic country scientists who were already well connected with international scientists and working in similar disease areas prior to the epidemic. This rare causal evidence highlights the importance of opportunities to build relationships with more prominent affiliates, but at the same time raise concerns over the potential implications of global networks on inequality within groups of scientists outside the exclusive elite.

Keywords: sociology of science, economics of innovation, stratification, social networks, inequality, emerging economies, innovation

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1 Introduction

Global science is highly stratified and the predominant production of knowledge by a few elite scholars has been characteristic ever since the 17th Century, with finite number of positions available in the early academies of science in England and France. Merton’s seminal work in 1968 (Merton 1968) developed several possible mechanisms driving this stratification and highlighted concerns on the relative role of merit in the distribution of reward in science. Driven by these concerns, research on the mechanisms driving this unequal distribution of scientific production have been a central focus of the sociology of science over the past fifty years.

In Merton’s classic account, small differences in initial status between scientists amplify over time generating cumulative advantage. Evidence from a variety of settings supports Merton’s proposition that shifts in status increase perceptions of quality, or the attention given to an actor (Simcoe and Waguespack 2011; Azoulay et al 2014; Roberts et al 2011), and that those with higher status or initial endowments tend to receive more resources, resulting in actual improvements in quality (Arora et al 1998; Arora and Gambardella 2005; Sorenson and Waguespack 2006; Waguespack and Sorenson 2011). These channels together result in observed cumulative advantage, or the ‘rich get richer and the poor get poorer’.

While much of the focus of the existing literature has been on benefits accruing to those with higher status, it is possible that those more prominent can transfer these benefits to their less elite affiliates. Two main mechanisms could drive performance benefits from relationships with more prominent affiliates. First, it is well established that relationships can be a conduit through which knowledge and resources flow (Granovetter 1973; Marsden 1983). With superior access to knowledge and resources, those more prominent can share these with their less elite affiliates, resulting in performance improvements of the less elite affiliate. Second, within a system organized by hierarchy and particularly where there is uncertainty surrounding those less elite, those more prominent can implicitly transfer their status to their less elite affiliates (Blau 1964; Merton 1972; Goode 1978; Latour 1987; Burt 2010). These reputational advantages facilitate the mobilization of resources and could lead to performance improvements. Observational evidence supporting this view of the value of relationships with more prominent affiliates has been found for junior scientists and entrepreneurial firms (Long et al 1979; Stuart et al 1999; Burton et al 2002).

Despite the possibility that relationships with more prominent affiliates can overcome inequality between groups of different status, these relationships could concurrently increase inequality within low status groups. One setting in which this has been explored is that of the impact of globalization on low-income countries. A growing macro-level empirical evidence base finds that while globalization de-
creases inequality between countries, it also increases inequality within low-income countries (Kremer and Maskin 2006). Theoretical models supporting this finding hypothesize that while high-skilled workers from low-income countries collaborate with higher-income countries, lower-skilled workers from these countries cannot participate in the global economy and thus their wages decrease or remain constant (Kremer and Maskin 2006; Maskin 2015). The relevance of this theory and evidence in the scientific setting, which is increasingly based on cross-country team work (Wagner and Leydesdorff 2005; Wuchty et al 2007), seems particularly significant.

Finding causal evidence of this phenomenon is difficult. Individuals may have features that are unobservable to researchers that determine both their relationships and their outcomes. This suggests that an examination of an individual’s relationships with more elite actors and their outcomes may be biased (Manski 1993; Jackson and Wolinsky 1996; Goldsmith-Pinkham and Imbens 2013). The other challenge in using observational data is that measurement of the impact of relationships that are observable begs the question of the impact of relationships that do not survive to observation. It is possible that the sample on which current estimates are formed are different from the rest of the population. Furthermore, observation of existing relationships raises challenges in defining a reasonable control group who do not have such relationships, but are similar on every other dimension. To avoid these problems we would need an experiment that assigns ties to those more prominent for a randomly selected group of less elite, allowing for attrition of the relationship, and starting the observation period before the assignment of the tie.

The contribution of this paper is a research design that provides rare causal evidence of the impact of a tie, or an opportunity to build relationships, with more prominent affiliates on subsequent performance. I leverage a unique natural experiment that randomly provided some less elite individuals with an opportunity to build relationships with more prominent affiliates. The advantage of this approach is twofold. First, because the tie is randomly assigned, challenges associated with unobserved heterogeneity described above are mitigated. Second, because the measurement period begins prior to the assignment of the tie, it is possible to generate a control group of individuals by which to compare those assigned the tie. The measurement of outcomes of an individual before and after they are assigned an opportunity to build relationships makes it possible to net out the individual quality at the same time as accounting for general trends and baseline changes throughout an individual’s lifetime. Furthermore, because the analysis includes those who are assigned the tie irrespective of whether it survives or not, it is possible to understand the conditions under which ties are most beneficial to those less elite.

The 2014 ebola epidemic in West Africa provided an unexpected opportunity to scientists working in affected countries (endemic countries) to build ties with more prominent affiliates from around the world. Scientists from around the world turned their research agendas to focus on ebola during the outbreak.
With unique access to patient populations, local knowledge and a presence on the ground, endemic country scientists experienced an unprecedented opportunity to build relationships with more prominent scientists from around the globe during the epidemic. I compare changes in international collaborations and publication rates of endemic country scientists with those of observably similar scientists in non-endemic countries in a difference-in-differences framework.

In a test of the proposition that opportunities to build relationships with more prominent affiliates can affect the performance of those less elite, this paper find that these opportunities can help, but that an average effect of the opportunity hides striking heterogeneity. Specifically, I find that scientists in endemic countries with prior tropical disease focus (intellectual capital) and international connections (social capital) experience large and persistent increases in international collaborations and publication rates following the ebola epidemic, whereas those without such intellectual or social capital experience no, or negative effects. Consequently, inequality between endemic country scientists increases as a result of the epidemic.

The primary contribution of this paper is to provide causal evidence that ties with more prominent affiliates can help some less elite scientists to overcome disadvantages of stratification, while leaving others behind. To the extent that the benefits of ties with more prominent affiliates turn out to be varying in their effectiveness, and to the extent that this variation has not been recognized in prior research (Long et al 1979; Stuart et al 1999; Burton et al 2002), I propose that this could be due to the survivorship bias built into observational research studies that masks varying effectiveness of ties. This paper also contributes to the literature exploring the impact of globalization on low-income country inequality. Extant theory in this line of research suggests that the skill set of low-income country workers determines their positioning in the status distribution following globalization. This paper provides the first evidence to my knowledge that social capital also plays a significant role in determining the beneficiaries of globalization.

More broadly, the study focuses on a novel and important context: scientists in Africa. While growing and significant attention is given by policy makers and donors to the development of scientific capacity in low-income countries, little is know about the factors that contribute towards the success of such scientists. I show that connections with more prominent scientists in higher-income countries can help the careers of some scientists in countries with emerging ecosystems, but at the same time affect the system in unexpected ways.

The rest of the paper proceeds as follows. Section 2 discusses the theoretical framework. Section 3 describes the empirical approach and provides details of the setting. Section 4 describes the data, measures and statistical approach. Section 5 presents descriptive statistics and results and section 6
concludes and outlines implications of the findings.

2 Theoretical Framework

2.1 Stratification in Science

In the last fifty years, research on the observed stratification in science has been a central focus of the sociology of science. Studies have demonstrated stratification within scientific disciplines (Allison et al 1982; Zuckerman 1970; Cole and Cole 1973), divergence in outcomes throughout scientific careers (Allison et al 1982; Allison and Stewart 1974), unequal distribution of publications across institutions (McNamee and Willis 1994) and the under-representation of groups distinguished by gender and race (Lewin and Duchan 1971; Muhs et al 2012; Cole and Cole 1973). A small number of scientists serve as the predominant producers of knowledge in the world (Crane 1965; Crane 1972; Zuckerman 1988; Furman et al 2002). The members of this exclusive ‘invisible college’ tend to define the discipline (Crane 1972) and enjoy benefits such as increased recognition and resources.

For those outside of the college, it can be challenging to receive recognition and access to resources. Perceived uncertainty about the quality of those less elite, as well as limited attention to their work makes moving out of positions of disadvantage even more challenging. Difficulties faced by less elite scientists is summarized by Merton’s early work: ‘These social processes of social selection that deepen the concentration of top scientific talent create extreme difficulties for any efforts to counteract the institutional consequences of the Matthew principle’ (Merton 1968).

2.2 The Effect of Relationships with Prominent Affiliates

One way that those less elite can counteract the disadvantages of cumulative advantage is to affiliate with those more prominent. There are two possible mechanisms by which relationships with those more prominent can improve outcomes. First, the less elite affiliate could gain access to knowledge and resources that the prominent affiliate has access to (Granovetter 1973; Marsden 1983; Burt 1992). Second, the prominent affiliate could act as a ‘sponsor’ to the less elite (Blau 1964; Merton 1973; Goode 1978; Latour 1987; Burt 2010). This implicit transfer of status can serve to signal the less elite’s quality (Spence 1974), and subsequently affect their access to connections, knowledge, resources and attention given to their work. Together, these mechanisms suggest that having a more prominent affiliate can enhance access to connections, knowledge, resources and attention that may lead to subsequent actual
or perceived improvements in performance.

A growing literature building on these ideas provides evidence of the link between relationships with more prominent affiliates and performance. For example, in a study on job placements of graduate students, Long et al (1979) find that the prestige of a doctoral department and mentor is correlated with the success of the placement of the graduate student in their first job. Beyond the scientific setting, Stuart et al (1999) measure relative outcomes for entrepreneurial firms that are affiliated with prominent partners, and find that entrepreneurial firms with more prominent associates go to initial public offering (IPO) faster than comparable firms without such prominent associates. Relatedly, Burton et al (2002) measure outcomes for new ventures with more prominent prior employers, finding that new firms coming out of more prominent firms are more likely to pursue innovative strategies and to attract external financing.

Although this literature provides many insights into the link between relationships and performance, some issues remain unresolved. First, Stuart and Sorenson (2007) highlight the difficulty in attributing an individual’s outcomes to their network structure and position. Second, the conditions under which a relationship with more elite actors is most beneficial to those less elite has not yet been explored.

2.3 Challenges in Measuring the Value of Relationships

The establishment of a causal link between relationships and outcomes is extremely difficult (Manski 1993; Mouw 2006), and researchers in this area face three major challenges. First is the problem of unobserved heterogeneity. Un-measurable features of an individual could drive both the relationships that the individual has, as well as outcomes. This would lead to a conflation of the impact of relationships on outcomes with underlying quality of the individual, particularly where relationship formation is strategic (Jackson and Wolinsky 1996). Second is the problem of reverse causality. In other words, outcomes could lead to relationship formation instead of the other way round. Third, a common problem in studies of this kind is selection on the dependent variable. An examination of outcomes of those who already have relationships makes it extremely difficult to both understand what happens to those who have relationships that do not survive to observation, and to define an accurate control group who are comparable on every dimension aside from having the relationships.

One approach to these challenges is to manipulate ties with more prominent affiliates, holding all else constant. In this study, I focus on evaluating the impact of an opportunity that is randomly presented to some less elite scientists to build relationships with more prominent affiliates. Under the consideration of such an opportunity as a relationship or a tie, I am able to measure the causal impact of ties with more
prominent affiliates, allowing for attrition of the tie and the possibility that it is never fully converted into an observable relationship. This allows for a realistic estimate of the role of relationships with more prominent affiliates, and a test of the following hypothesis:

**Hypothesis 1 (H1)** The presence of an opportunity to build relationships with more prominent affiliates improves performance.

### 2.4 Limits to Opportunities to Build Relationships

Given the observational evidence on the value of relationships with more prominent affiliates, the H1 of this study is that an opportunity to build relationships with more prominent affiliates plays a role in performance of those less elite. However, there is an argument to be made that the effects of an opportunity to build relationships with those more prominent may differ across subsets of the less elite population. Ties are costly to form and maintain (Burt 1995; Jackson et al 2008; Rivera et al 2010), and those more prominent have a dis-incentive to affiliating with lower status groups as it could negatively affect their own outcomes (Jones et al 2008). Therefore, it is plausible that even once given an opportunity to build a relationship, there are limits to the extent to which less elite scientists are able to take advantage of it. Relatedly, recent studies find that not everyone with a randomly assigned tie is able to activate, and benefit from, the relationship (Carrell et al 2013; Koning 2016).

Relationships form and endure if the benefits outweigh the costs. I argue that benefits of a relationship are contingent on the relevant knowledge and skills, or intellectual capital, of the potential partners and costs are contingent on the relevant social network, or social capital, of the potential partners. Thus, from the perspective of a less elite scientist, I posit that the impact of an opportunity to build relationships with more prominent affiliates depends on their relevant intellectual and social capital that they bring to the relationship.

**Intellectual Capital:** With relationships providing a way to access complementary knowledge and skills (Jones 2009; Anderson 2016), those with more relevant knowledge or skills are more likely to form and maintain relationships due to the perceived and actual benefits of a partnership. Scientists self-report that they form collaborations based on shared interests and complementary skills (Hara et al 2003), and inter-firm alliances are observed more often when information on the potential partner’s capabilities and resources is available (Gulati 1999), or when the stock of knowledge of the potential partner is greater (Ahuja 2000). With the local nature of many forms of knowledge (Nelson and Winter 1982; Levinthal 1997; Myers 2018), the potential partner’s stock of knowledge relative to the relationship or the problem the partnership is trying to solve is likely to affect the value they bring to the partnership.
Thus, the benefit of an opportunity to build relationships with more prominent affiliates will depend on the less elite scientist’s relevant intellectual capital.

**Social Capital**: Overlap of social networks of potential partners can reduce search and co-ordination costs of a relationship. Potential partners within the same social network have more access to information on each other, and ‘embedded’ relationships are more likely to be reliable and benefits from shared norms (Guliati 1995; Ahuja 2000; see Stuart and Sorenson 2007 for a review of embedded exchange). In settings with high uncertainty, such as the scientific setting, referrals and trust that come with embedded relationships are of particular importance in the formation and maintenance of relationships. Thus, the benefit of an opportunity to build relationships with more prominent affiliates will also depend on the less elite scientist’s relevant social capital.

In arguing that relevant intellectual and social capital of a scientist limit the benefit from an opportunity to build relationships with more prominent affiliates, I expect the following relationship to hold:

**Hypothesis 2a (H2a)** *A scientist’s relevant intellectual and social capital moderates the positive impact of the presence of an opportunity to build relationships with more prominent affiliates on performance.*

Given that H2a suggests limits to the impact of an opportunity to build relationships with more prominent affiliates, to the extent that those better positioned to leverage the opportunity are also those who are already better performing, inequality is increasing in the presence of such an opportunity. One setting in which this has been explored is that of the impact of globalization on low-income countries. Recent models support macro-level evidence of the impact of globalization on inequality within low-income countries (Kremer and Maskin 2006; Maskin 2015). Kremer and Maskin (2006) propose a skills matching model to explain this phenomenon. Specifically, the model proposes that workers of high-skill in a low-income country are able to benefit from globalization as they collaborate with high-income countries, but those with low-skill are not able to participate and thus are excluded from the benefits of globalization, summarized in the following quotation from Kremer and Maskin (2006):

‘The key insight is that the globalization of the production process may benefit only those in the developing country with a skill level sufficiently close to that of their rich country collaborators, thus marginalizing low-skill workers in the developing country.’

In addition to the level of skill, or intellectual capital, the earlier argument also implies that prior social capital determines who benefits from an opportunity to build relationships with more prominent
affiliates, and thus the levels of inequality following such an opportunity. As both of these are correlated with performance in the setting of African science, this leads me to my final hypothesis:

**Hypothesis 2b (H2b)** *The presence of an opportunity to build relationships with more prominent affiliates increases inequality amongst less elite scientists.*

### 2.5 Persistent Effects

Despite the predictions of the impact of an opportunity to build relationships with more prominent affiliates, these benefits could be transient. Relationships often don’t last forever. New relationships (Burt 2002), and those across geographic distance or between individuals with different status are challenging to maintain (Reagans and Burt 1998; Pfeffer 1983; Blau 1977; Rivera et al 2010; Jones 2008; Azoulay et al 2017; Ahmadpoor and Jones 2018). Thus, it is possible that any benefits arising from an opportunity to build relationships with more prominent affiliates is short-lived.

However, the study’s focus on African scientists may be one setting in which these kinds of relationships are long-lasting. African scientists can provide valuable and non-substitutable skills and access to more prominent affiliates from around the world. If this value outweighs the costs to maintaining the relationship, the relationship will persist. This ex-ante uncertainty about the persistence of relationships with more prominent affiliates in this setting provides an opportunity to learn about the dynamics of these kinds of relationships.

### 3 Empirical Approach

This study exploits a unique natural experiment that provided a group of less elite scientists the opportunity to build relationships with more prominent affiliates. This research design differs from extant research in two main ways. First, the natural experiment employed provides an arguably randomly allocated opportunity to some scientists to build relationships with more prominent affiliates, while prior research has focused on measuring existing relationships. Second, I create a sample of matched control scientists who did not receive the opportunity to build relationships with more prominent affiliates, but in every other way are observably similar prior to the event. This results in a matched sample consisting of scientists who are subject to the opportunity and those who are not in which to assess whether the opportunity to build relationships with more prominent affiliates affects performance, relative to outcomes of the control group. Analysis of the change in performance of an individual after the change in opportunity, compared to that of a control scientist, in a difference-in-differences framework also allows
me to avoid bias due to any constant, unobserved differences between scientists.

### 3.1 West and Central African Scientists

The setting for the empirical work is the science sector in West and Central Africa. The study’s focus on these scientists can be justified on substantive grounds. Scientific production levels in West and Central Africa are among the lowest in the world. Out of the 1,833,410 journal articles published and captured in the Scopus database in 2013, just 8,527 (0.46% of the global total) contained authors affiliated with mainland West or Central African countries. Not one university in West or Central Africa has ever been ranked in the top 800 research universities in the world\(^1\), and no scientist from this region has ever been awarded a Nobel prize in science.

As well as being less distinguished than their global counterparts, scientists from the region rely heavily on international connections to access resources necessary for scientific production. High quality training for scientists in the region is scarce, labs are poorly equipped and domestic funding for science is negligible. A survey on just under 500 West African scientists carried out by the author in 2017 found that just under 50% of respondents carried out their graduate studies abroad in Organization for Economic Cooperation and Development, or OECD countries, and that the predominant funders of science in the region are American and European funders, including the Wellcome Trust, the US National Institutes of Health (NIH), the Bill and Melinda Gates Foundation and the European and Developing Country Clinical Trials Partnership (EDCTP).

Given these contextual factors, any change in West or Central African scientists’ opportunities to build relationships with scientists from elsewhere in the world, particularly from OECD countries, provides the ideal conditions under which we would expect the hypotheses outlined above to hold. Furthermore, the focus on scientists in this study is of pragmatic importance due to the rich data available on individual level scientist performance and collaborative relationships. I focus on one such change in the remainder of the paper.

### 3.2 The 2014 West African Ebola Outbreak

I test the hypotheses through estimating the impact of the 2014 West African ebola epidemic on endemic country scientists. Ebola virus disease is characterized by severe and mostly fatal outcomes, and tends to affect populations within outbreaks of the disease. A rare and deadly disease spread through direct

\(^1\)https://www.usnews.com/education/best-global-universities/articles/methodology
contact with infected animals or people, there is no approved vaccination or treatment for the disease. Following its discovery in 1976 in what is now known as the Democratic Republic of the Congo, there have been around twenty outbreaks throughout Africa. In March 2014 the World Health Organization (WHO) reported the first cases of an ebola outbreak in Guinea, West Africa and by August 2014 the WHO had declared ebola a Public Health Emergency of International Concern (Figure 1). Two years later, when the last case was confirmed in 2016, the virus had spread to ten other countries, and over 30,000 cases and 11,000 deaths were attributed to the disease in the three countries at the epicenter; Guinea, Liberia and Sierra Leone. The epidemic had been the world’s largest and deadliest in recorded history, and was recognized as a catastrophic event throughout the world, with a WHO statement in 2014 recognizing that ‘the ebola epidemic ravaging parts of West Africa is the most severe acute public health emergency seen in modern times’.

While the disease swept through and devastated the endemic countries, around the world science was being touted as one of the potential solutions to the ghastly epidemic. With very little published research on the disease, a better understanding of the virus, its spread and mutations, and development and testing potential vaccinations and cures was one of the more hopeful avenues to keeping it under control.

Scientists around the world turned their research agendas to focus on the disease (Mutters et al 2018) and global funders increased funds available for such research, with an estimated USD $435 million spent in 2014 and 2015 on ebola alone (Fitchett et al 2016), the majority of which came from the US government2. A huge variety of foreign scientists took an interest in, started projects on, and many visited, the endemic countries. Scientists from Centers for Disease Control and Prevention attempted to track the epidemiology of the epidemic. Private sector scientists field tested drugs, vaccines and diagnostic technologies. And academics committed to reading the genome of the virus, and better understanding how to manage the burden of the epidemic on the already fragile health systems in the affected countries. The following quotation from one West African scientist that I interviewed illustrates the level of engagement of the international research community and the sudden attention given to endemic countries:

‘During ebola a lot of scientists came in. It was quite a chaotic environment. Ebola was exciting for the research community. It is dangerous, little research had been done, there is no approved treatment. Ebola had all the right reasons to attract international researchers to Sierra Leone.’

Many of these foreign scientists researching the ebola outbreak worked together with local researchers

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2 GFinder 2014 report
and made use of pre-existing institutions in order to efficiently gain access to populations, gather samples\(^3\), obtain local knowledge and streamline their own research process. The local scientists who were well embedded in the hospitals and laboratories as well as the government (which can have complex research clearance procedures) were in high demand as collaborators to the foreign researchers. A small group of scientists in the endemic countries suddenly found themselves at the epicenter of the subject of some of the most topical research at the time, and the two following quotes from West African scientists that I interviewed summarize the new ties that were formed between global and endemic country scientists during the epidemic:

‘You cant just go to a place to conduct research. They [the foreign researchers] were trying to attract locals therefore.’

‘You want someone on the ground who can help you to achieve your aim and make things happen.’

Not only did the endemic country scientists receive solicitations for collaboration, but the foreign scientists brought resources with them as well that they were accessible to scientists in the countries. For example, the Chinese Military Medical team built a USD $10 million Prevention and Control Centre for infectious diseases, cited to be a direct result of challenges that the visiting Chinese medical staff and researchers experienced during ebola. In addition to new laboratories, pre-existing infrastructure was strengthened, and a lot of scientific equipment was donated and brought to the endemic countries. One of the larger donations of equipment was negotiated by the team at the Broad Institute in the United States and their West African collaborators and Illumina sequencing technology and resulted in three Illumina Miseq genomic sequencers (each valued at around USD $100,000) to be donated to West African laboratories during the outbreak.

This international interest in the outbreak and affected countries generated new ties between endemic countries and global scientists and afforded scientists in endemic countries an opportunity to build relationships with more prominent affiliates from around the world.

### 3.3 Control Scientists

While it would be reasonable to expect that comparing the outcomes of endemic country scientists before and after the epidemic, i.e. before and after they were provided with the opportunity to build

\(^{3}\)samples that were frequently sent back to the researcher’s home country for analysis
relationships with more prominent affiliates, would give a causal estimate of the impact of the opportunity, there is still the concern that career age trends as well as general improvements in regional capacity could conflate the role that relationships play with improvements that may have occurred absent the opportunity. To alleviate this concern, I use a control group that consists of carefully matched group of scientists from non-endemic countries within the same region. The inclusion of these control scientists in the empirical framework allows to account for underlying trends in career age, field and regional changes. The next section describes how the treated and control scientists are selected and the empirical framework by which the impact of the epidemic is estimated.

4 Data, Measurement and Statistical Approach

I measure the impact of the ebola epidemic on endemic country scientists. Those scientists actively publishing in biomedical or social sciences and affiliated with endemic country institutions at the time of the epidemic are considered treated by the ebola epidemic.

In order to identify those scientists treated by the epidemic I use publication data in the Elsevier Scopus database to generate a comprehensive sample of scientists and associated publication history affiliated with endemic country institutions between 2010 and 2013.

The use of publication data in studies of this type (namely, in generating a plausible set of scientists in a particular location associated with their full publication record) comes with a couple of major challenges. First, generating a full scientist level publication record is complicated by the fact that scientists may have common names (for example, Smith J). Therefore it can be difficult to determine which Smith J published which paper, or a single scientist may go by more than one version of a name. Second, understanding where scientists are located given that an affiliation in a publication may not accurately represent the full time location of a scientist. In addition, a scientist needs to publish in order for the researcher to see their affiliation - which for the West African scientists is not always the case in each year. Fortunately, the first issue is resolved using the Elsevier Scopus publication database which provides an author identifier for each author in every publication contained in the database. The author identifier is developed using an algorithm that incorporates scientist name, coauthors and topic type and allows for scientists to change affiliations across publications. The second issue is resolved using a rule of thumb - if a scientist classifies her affiliation as being in a certain country in over 75% of her publications over a defined, multi year period, she is considered in this database as being based in that country in that time period.

Following the exclusion scientists who are never first or last author in the 4 years prior to the
outbreak (to exclude technicians) and those stop publishing before 2013 (to exclude those who re-
tired/deceased/those who moved before the outbreak hit) leaves 61 potential treated scientists from the
highly endemic countries: Sierra Leone, Liberia and Guinea.

I order to identify the effect of the epidemic I could examine changes in endemic country scientist’s
outcomes after the epidemic, relative to before. However, because the epidemic is mechanically correlated
with career age and calendar year, the specifications must include life cycle and period effects (Levin
and Stephan 1991). The control group that pins down the counterfactual age and calendar time effects
are those scientists in non-endemic, but similar, countries.

Publication data in the Elsevier Scopus database is again use to generate a sample of scientists
publishing in biomedical or social sciences affiliated with institutions in non-endemic West or Central
African countries at the time of the epidemic. The control scientists are culled from this sample of
scientists to generate a group of scientists who are observably similar prior to the epidemic (Table 1).
The control scientists are chosen using a coarsened exact matching procedure (Iacus et al 2011) so that
their average career age, productivity and research area, as well as international collaborations and
country level variables such as GDP per capita and number of scientists mirrors that of the treated
scientists. At least one match (and up to 18 matches for each scientist) is found for 52 (85%) of
the treated scientists. Combining the treated and control samples allows me to estimate the effect of
the epidemic in a difference-in-differences framework. This is a new dataset that follows the publication
history of African scientists. It is unique in being one of the first datasets on African scientists generated
in a systematic manner, and the only dataset of which I am aware that traces the publication of scientists
before and after a significant event in Africa.

I complement the quantitative analysis with 35 interviews with scientists from both West Africa
and OECD institutions, as well as site visits to both treated and control country sites. The interviews
range from 1 to 2 hours, with site visits ranging from a half day to a week. The primary purpose of the
interviews is to illuminate mechanisms of the impact of the ebola epidemic.

4.1 Measurement

Dependent Variables

I conduct two main analysis of scientist’s performance. In the first analysis, the dependent variables
are international collaborations. It is possible that an opportunity to build relationships results in
collaborative publications with more prominent, international scientists. Past studies have identified
evidence of the connection between international collaborations and research impact (Van Raan 1998;
Wagner and Leydendorff 2005; Jonkers and Tjissen 2008), and significant policy attention is placed on fostering international collaborations. While collaborations can result in improvements in publication rates, so can direct access to knowledge or resources. In the second part of the analysis, I use publication rates as the dependent variables as is standard in studies on scientists’ performance (Azoulay et al 2010; Ding et al 2010; Oettl 2012). A description of how the variables are generated is provided below.

**International Collaborations** Measurements of collaborations are generated using author written code parsing the affiliations of coauthors in the sample scientists’ publications. International collaborators are defined in this study if they are affiliated with an institution in an Organization for Economic Co-operation and Development (OECD) country. 63% of the global count of publications in 2013 contained authors affiliated with countries that are part of the OECD. The OECD makes up 35 of the world’s most developed countries⁴, and hosts 18% of the world’s population. With over 53 times the volume of publications per capita as for West or Central African scientists, the scientific ecosystems in OECD countries are known to be the central locations for the majority of scientific research. Collaborations with more prominent, OECD based scientists are measured in two main ways. The number of publications in a given year with at least one OECD coauthor, and the number of new OECD coauthors in a given year with whom the sample scientist had not previously coauthored a publication with.

**Publication Rates** Measures corresponding to the rate of publication include the number of publications each year a scientist is an author on, with each publication weighted by its journal impact factor (JIF) - a measure of the frequency with which the average article in a journal has been cited in a particular year. Key word searches of the title, abstract and keywords in each publication in a given year for a sample scientist gives publication outcomes in a given research area. One ideal measure is the number of ebola publications in a given year authored by sample scientists. However, very few sample scientists publish in ebola before the epidemic making the empirical model difficult to run. I therefore use a measure of the number of tropical disease publications, of which ebola is included. Furthermore I measure the number of non-ebola publications to ascertain if the observed increase in ebola publications is a switch from other topics, or additional publications to their usual stock.

**Independent Variables**

**Endemic country location** The before after treatment approach hinges on the expectation that a scientist’s post-epidemic collaborations or publications differs from her pre-epidemic collaboration or publications, and that this difference depends on her location at the time of the epidemic. To capture whether there is a change in performance as a function of location in 2014, I construct a dummy variable that takes the value of 1 if the scientist is affiliated with the endemic country in over 75% of

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⁴https://www.topteny.com/top-10-highly-developed-countries-in-the-world/
their publications in the 4 year period prior to the epidemic.

Some descriptive evidence supports the use of endemic country location as the determinant of the presence of the opportunity build relationships during the ebola epidemic. Figure 2 shows that following the start of the epidemic in 2014, endemic country scientists in the sample are much more likely to publish in ebola related research with OECD coauthors than comparable control scientists in non-endemic countries. Together with qualitative evidence on the impact of the epidemic on the attention given to endemic country scientists, this provides the foundation for the definition of the treated group in the study.

Relevant Intellectual and Social Capital

To ascertain a scientist’s relevant intellectual capital prior to the epidemic I construct a dummy variable that takes a value of 1 if over 50% of the scientist’s publications are in neglected tropical disease related areas prior to the epidemic. As ebola is a neglected tropical disease it is reasonable to assume that the knowledge required to research ebola is closely related to that to research neglected tropical disease.

To measure a scientist’s relevant social capital, I generate a dummy variable indicating whether the scientist has all of their publications coauthored with OECD coauthors prior to the epidemic. As the definition of elite in this study is those scientists affiliated with OECD country institutions, this can be considered as an overlapping social network, or relevant social capital, for the endemic country scientists in this experiment.

Post Epidemic Period

The post treatment variable considers the years 2014-2018 in the data as post epidemic. Generally, there is a lag period of around a year between when scientific work is carried out and when the publication appears in a journal. However, interviews uncovered that during the ebola outbreak journals fast-tracked the relevant publications and published them in real time. Some scientists even noted that they worked with the journals to provide updates as the research went on. For this reason, the year that the epidemic started, 2014, is considered the first year when an effect could be seen.

4.2 Statistical Approach

In order to identify the effect of the ebola epidemic on endemic country scientists, I compare an endemic country scientist’s outcomes after the epidemic relative to before, using a scientist fixed effect specification. The estimating equation (equation 1) relates endemic country scientist $i$’s outcomes in year $t$ to

\[^5\text{as the data was collected in 2018, data of publications in 2018 is incomplete}\]
the epidemic.

\[ E[y_{it}|X_{it}] = \exp\left[ \beta_0 + \beta_1 \text{AFTER}_\text{EPIDEMIC}_{it} \times \text{ENDEMIC}_\text{COUNTRY}_{it} \
+ f(\text{AGE}_{it}) + \delta_t + \gamma_i \right] \]  

Where \( y \) is the outcome measure, \text{AFTER}_\text{EPIDEMIC} denotes an indicator variable that switches to one the year the ebola epidemic began (2014). \text{ENDEMIC}_\text{COUNTRY} denotes an indicator for if the scientist is affiliated with an institution in an ebola endemic country. \( f(\text{age}) \) corresponds to a flexible function of the scientist’s career age and \( \gamma_l \) stands for a full set of calendar year indicator variables to account for the fact that aggregate research activities may vary over time. \( \delta_i \) correspond to scientist fixed effects, consistent with my approach to analyze changes in the scientist’s output following the epidemic. Standard errors are clustered at the level of the country.

The dependent variables are mostly counts, and are skewed and non-negative, with 54% of the scientist year observations in the data corresponding to years of no publication output at all. Therefore following tradition in the study of scientific and technical change, I present quasi-maximum likelihood (QML) estimates based on the fixed-effects Poisson model developed by Hausman et al (1984).

5 Results

5.1 Sample Characteristics

Table 2 provides details on the location of study scientists, and the descriptive statistics in Table 3 pertain to the set of 52 + 250 matched treated and control scientists. The covariates of interest are measured at the time of the epidemic (end of 2013). A number of the covariates are balanced by construction, due to the coarsened exact matching procedure, for instance, the career age and collaboration patterns of scientists, but I also find balance of other key covariates that was not guaranteed by the matching. Two features of the sample of scientists are worth pointing out. Around 50% of scientists had collaborated with OECD scientists in the year prior to the outbreak, and less than than 8% of endemic country scientists had experience in ebola related research.

The estimation sample includes observations 5 years before and 4 years after the epidemic. The result is a balanced panel dataset with 2,718 scientist \( \times \) year observations.
5.2 The Effect of an Opportunity to Build Relationships with More Prominent Affiliates (H1)

To test hypothesis 1, I begin by graphically examining whether the opportunity to build relationships with more prominent affiliates during the ebola epidemic affected the international collaborations and publication rate of endemic country scientists. Figure 3 descriptively presents that scientists in endemic countries experience a boost in their collaborations with OECD country scientists, and in their publication rate following the outbreak. This descriptive evidence is consistent with the basic hypotheses: that an opportunity to build relationships with prominent affiliates results in increases in international collaborations and publication rates. However, this raw comparison does not include any adjustment for career age or calendar year, and could be driven by differences in the baseline of scientists. I control for these differences using the scientist fixed effect treatment model described above.

Table 4 presents the core results estimating the specification presented in equation 1. Consistent with the raw data, I find strong support for H1, that an opportunity to build relationships impacts the number of international collaborations (columns 1 and 2) and publication rates (column 3), as indicated by the estimates for AFTER_EPIDEMIC × ENDEMIC_COUNTRY being positive and significant. I find a sizeable 75% increase (significant at the 1% level) in the annual number of journal impact factor (JIF) weighted publications authored by scientists in ebola endemic countries following the epidemic (Table 4 column 3). Columns 4 and 5 of Table 4 suggest that the ebola publications are substitutes to the research that the endemic country scientists are doing prior to the epidemic.

5.3 The Moderating Effect of Intellectual and Social Capital (H2a)

I then test hypothesis 2a, that the impact of an opportunity to build relationships with more prominent affiliates is greater for those with relevant intellectual and social capital.

Table 5 implies the moderating effect of intellectual capital on an opportunity to build relationships with more prominent affiliates. I split the sample of treated and control scientists into those for whom the majority of their publication record prior to the epidemic is in neglected tropical diseases, and the rest of the sample, and run the same specification on the two samples separately. The results in the table illustrate that those endemic country scientists with a publication record in tropical disease research are the most affected by the epidemic. Furthermore - columns 2, 4, 6 and 8 illustrate that those without such a record in tropical disease research experience a negative impact from the epidemic.

Table 6 provides evidence of the moderating effect of social capital on an opportunity to build
relationships with more prominent affiliates. I split the sample into those who have significant experience publishing with OECD coauthors, and those who don’t, prior to the epidemic. The results in table 6 illustrate that those endemic country scientists with a significant OECD collaboration record experience a greater positive impact of the epidemic than those without. While this could be because of a variety of reasons, one reason is a referral from OECD scientists. A scientist based in the United States illustrates how her coauthored publications with her West African collaborator prior to the epidemic played a role in the connections her collaborator made during the epidemic:

‘I got a lot of calls from people at medical schools in the US who wanted to be involved because they thought it [ebola research] was cool. I think I got more calls than [West African collaborator]. People saw that I had the American looking name so (thought) I must be in charge.’

Finally, I ascertain if there is a benefit to having both relevant intellectual and social capital together, and so split the sample into those scientists with both neglected disease experience and OECD coauthoring record prior to the epidemic, and those without. Table 7 shows that the benefit of both types of capital is significant - and greater than each capital separately.

5.4 The Effect of an Opportunity of Within Group Inequality (H2b)

Tables 5, 6 and 7 all illustrate increasing inequality within endemic countries following the epidemic. Not only do the tables provide evidence that those with prior tropical disease research experience and OECD networks are the most affected by the epidemic, they also show that those endemic country scientists without experience are either not at all, or negatively affected by the epidemic. This negative finding was explored in interviews, and scientists without relevant capital said that they stalled their research projects during the epidemic for safety concerns. To further explore consequences of the epidemic on within treatment group inequality, Table 8 splits the sample into those who have high pre-epidemic productivity and low pre-epidemic productivity, and runs the regression on these two groups separately. Those with a higher pre-epidemic productivity are the only scientists in the endemic countries to have a positive impact of the epidemic.

5.5 Longer Term Impacts

I explore the persistence of these effects in Table 9. Using a reduced sample of treated and control scientists who publish with OECD coauthors in the three years following the epidemic, I run cross
sectional logit regressions to estimate average differences in outcomes of these scientists in the years 2017 and 2018 between endemic country and control country scientists. I find that although the increase in JIF weighted publications is not sustained, the endemic country scientists are more likely to be last author on international projects following the epidemic (Table 9 column 2). Furthermore, the collaborations with more prominent scientists generated during the epidemic are more likely to lead to a second co-authored publication together than comparable collaborations generated by non endemic country scientists in the same time period (Table 9 column 3). A West African scientist I interviewed confirmed these longer term impacts of the epidemic on his career:

‘My ebola papers took me to bigger journals. I had not published in the Lancet before. It was ebola that took me to the Lancet... I am an editor for PlosOne now because of my publications (during ebola)’.

5.6 Alternative Mechanisms and Robustness Checks

It may be that the endemic countries also increased their investment in science around the time of the epidemic, and so the observed effect could be in part driven by this, biasing the result of the impact of the opportunity to build relationships with more prominent affiliates. I examine two sources of data on science and R&D funding in West and Central African countries to better understand if this is driving the results. First, I examine the Policy Cures online database on neglected disease R&D funding. A comprehensive annual survey of global funders, including governments, provides data on the global levels of spending into neglected disease R&D. Not one endemic country features as a global neglected disease R&D funder between 2007 and 2017 and so levels are not obviously increasing from these endemic countries. Second, I examine the UNESCO Institute for Statistics database on gross domestic expenditure on R&D per year. Again - none of the endemic countries have any data between 2007 and 2018, and so levels again are not obviously increasing from these endemic countries. With numerous reports, and qualitative evidence, confirming that that levels of R&D spending by African governments are extremely low, or negligible and have not changed since the epidemic - together this provides supports that the effect is not driven by a change in domestic R&D spending in endemic countries. Relatedly, none of the endemic countries released national science and technology strategy documentation since the epidemic, and so there is no clear evidence that science is supported to a greater degree. Field work confirmed that the support of science and R&D, either financially or otherwise, is still nascent in endemic countries.

I probe the robustness of the main results, that endemic country scientists experience increases in publication outcomes following the epidemic, in Table 10. I run difference-in-differences regressions.
with the outcome of JIF weighted publications per year and present the coefficient of the interaction
ENDEMIC_COUNTRY \times AFTER_EPIDEMIC. I estimate a placebo experiment using a placebo epidemic year for the full sample in Table 10 column 2. Using just the pre-epidemic time period I use an event date of 2010. Reassuringly, the effect of being in an endemic country in a placebo epidemic year is statistically insignificant. Next I examine the possibility that the result is being driven by more senior scientists, or more productive scientists. In Table 10, column 3 and 4 I estimate the specification without the inclusion of scientists who have more than 10 years of experience at the time of the epidemic (column 3), and who have more than 5 publications in the four years before the epidemic (column 4). I find that the results are robust to the removal of these groups.

6 Discussion

Global science is dominated by a handful of elite scientists (Crane 1965; Crane 1972; Zuckerman 1988; Furman et al 2002). For those outside of this elite invisible college, relationships with more prominent affiliates may be one way to get ahead. In this paper I propose that opportunities to build relationships with more prominent affiliates can improve performance, but that existing intellectual and social capital moderates the extent to which scientists can leverage such an opportunity to their advantage. Given that not everyone benefits equally from such relationships, I further propose that such opportunities can lead to increasing inequality amongst less elite groups.

To test this proposition I make use of a unique natural experiment. The 2014 West African ebola epidemic randomly provided the opportunity to build such relationships for scientists in countries most affected. Scientists from around the world flooded into endemic countries looking for collaborators and research project assistance, and paid unique attention to the work and environment of scientists in these locations. I measure international collaborations and publication rates for different types of endemic country scientists as compared with scientists in similar countries that weren’t affected by the epidemic. The size of the effect is large. Endemic country scientists with relevant intellectual and social capital produced 285% more journal impact factor weighted publications a year following the epidemic, and generated an average of almost five more collaborations a year with scientists from OECD country institutions. Longer term, these new collaborations are maintained. However, those scientists in endemic countries without relevant intellectual or social capital experienced no, or negative, effects of the epidemic. This results in increasing inequality within endemic country scientists as compared to non-endemic countries.

This manuscript provides rare causal evidence for a mechanism hypothesized to overcome stratification in global science. With prior literature focusing on understanding the benefits accruing to high
status scientists, ‘the rich get richer’, evidence of the transferability of these benefits to less elite affiliates is limited. This paper uncovers the causal role that opportunities to build relationships with more prominent affiliates play in the outcomes of a group of less elite scientists. The finding that an opportunity can only be leveraged for advantage by less elite scientists with relevant intellectual and social capital has important implications for our understanding of network based advantage and the design of social interventions. The findings of this study are consistent with prior research that finds that peer effects are hard to replicate in field experiments (Carrell et al 2013; Koning 2016). These studies find that provision of a randomly assigned peer group has limited effect due to the unequal likelihood of actually using the tie. Together with the findings from this study, this implies implications for policy measures aiming to promote development for groups outside of the elite, as well as strategic measures implemented by those less elite.

The findings from this research have their limits. Pragmatically, the study is limited by the short time period available following the epidemic, and relies on publication outcomes, which may be a noisy reflection of true scientific capacity. Relatedly, the study is not able to unpack whether the results, and particularly the persistent effects, are driven by actual improvements in scientific capacity, or changes to the perceived quality of work. While this study is not able to tease these apart from each other, this is an important avenue for future research.

That said, I interpret the empirical results as providing support for the insights in the theoretical framework. Although focused on scientists, the results provide more general insights about stratified systems. With ‘outsiders’ prevalent in almost every setting, a better understanding of how relationships with ‘insiders’ can impact their performance is of first order importance in increasing overall productivity of a system. Given that the theoretical model underpinning the value of relationships with more prominent affiliates assumes uncertainty about the less elite, whether the same value is observed outside of the scientific setting and entrepreneurial firms is a question for future research.

Since Merton’s seminal work (Merton 1968) on stratification in science, scholars have had an interest in the mechanisms driving such stratification. While we know that those at the ‘top’ or the exclusive elite benefit from their elite position, we know surprisingly little about how those less elite can overcome the disadvantages of cumulative advantage. This study is a first step towards understanding the role of inter-status relationships in the trajectory of those less elite.
References


Burt, R.S., 1995 Structural Holes: The Social Structure of Competition Harvard University Press

Burt, R.S. 2002 Bridge Decay Social Networks 24(4): 333-363

Burt, R.S., 2010 Neighbor Networks: Competitive Advantage Local and Personal Oxford University Press


Coleman, J.S., 1988 *Social Capital in the Creation of Human Capital* American Journal of Sociology 94: S95-S120


Granovetter, M.S., 1973 *The Strength of Weak Ties* The American Journal of Sociology 78(6): 1360-1380


Gulati, R., 1999 *Network Location and Learning: The Influence of Network Resources and Firm Capabilities on Alliance Formation* Strategic Management Journal 20: 397-420


Jackson M.O., et al., 2008 *Social and Economic Networks* Volume 3 Princeton University Press, Princeton


Hasan, S., Koning, R., 2019 *Prior Ties and the Limits of Peer Effects on Startup Team Performance* Strategic Management Journal (forthcoming)


McNamee, S. Willis, C., 1994 *Stratification in Science: A Comparison of Publication Patterns in Four Disciplines* Knowledge: Creation, Diffusion, Utilization 15: 396-416


Myers, K., 2018 *Managing the Rate and Redirection of Science: Evidence from NIH Data* Working Paper

Nelson, R., Winter, S., 1982 *An Evolutionary Theory of Technical Change* Cambridge, Ma, Beknap Harvard


Pfeffer, J., 1983 *Organizational Demography* Research in Organizational Behavior

Reagans, R.E., Burt, R.S., 1998 *Homophily, Legitimacy, and Competition: Bias in Manager Peer Evaluations* Annual meetings of the American Sociological Association


Simcoe, T.S., Waguespack, D.M, 20111 *Status, Quality and Attention: What’s in a (Missing) Name?* Management Science 57(2): 274-290


Stuart, T.E., Sorenson, O., 2007 *Strategic Networks and Entrepreneurial Ventures* Strategic Entrepreneurship Journal 1: 211-227


Figures and Tables

Figure 1: 2014 West Africa ebola outbreak - cases by country

Note: This figure represents official World Health Organization statistics of number of total cases (suspected, probable, confirmed) by end of outbreak in 2016.
Figure 2: Mean Number Ebola Publications Authored by Sample Scientists

(a) Ebola publications with OECD coauthors

Note: Average number of ebola publications co-authored between OECD scientists and sample scientist per year are calculated for endemic country and control country sample scientists and plotted above. The lighter gray bars correspond to mean ebola publications for endemic country scientists, and the darker black bars correspond to mean ebola publications for control country scientists. The ebola epidemic struck in 2014.
Figure 3: Outcomes for Endemic Country Scientists vs Non Endemic, Control Country Scientists Following Ebola Epidemic

(a) Publications with OECD coauthors
(b) Number new OECD coauthors
(c) Journal Impact Factor (JIF) weighted publications
(d) Tropical disease publications

Note: Raw averages of outcomes each year are calculated for endemic country scientists and control country sample scientists and plotted above. The solid lines correspond to mean outcomes for endemic country scientists, and the dashed correspond to mean outcomes for control country scientists. The vertical dotted line illustrates the year that the ebola epidemic struck (2014).
Table 1: Details of West and Central African Countries Included in Analysis

<table>
<thead>
<tr>
<th>Country</th>
<th>Number of ebola cases (confirmed and suspected) (2014-2016)</th>
<th>GDP per capita</th>
<th>Population (in millions)</th>
<th>Number biomedical or social scientists in country at time of ebola outbreak</th>
<th>Number of those scientists working on ebola during outbreak with foreigners</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treated</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sierra Leone</td>
<td>14,124</td>
<td>788</td>
<td>6.2</td>
<td>28</td>
<td>12</td>
</tr>
<tr>
<td>Guinea</td>
<td>3,814</td>
<td>550</td>
<td>12.0</td>
<td>27</td>
<td>10</td>
</tr>
<tr>
<td>Liberia</td>
<td>10,678</td>
<td>461</td>
<td>4.4</td>
<td>6</td>
<td>3</td>
</tr>
<tr>
<td>Control</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nigeria</td>
<td>20</td>
<td>3,185</td>
<td>178.5</td>
<td>3,327</td>
<td>36</td>
</tr>
<tr>
<td>Ghana</td>
<td>0</td>
<td>1,462</td>
<td>26.4</td>
<td>726</td>
<td>11</td>
</tr>
<tr>
<td>Cameroon</td>
<td>0</td>
<td>1,426</td>
<td>22.8</td>
<td>455</td>
<td>4</td>
</tr>
<tr>
<td>Senegal</td>
<td>1</td>
<td>1,071</td>
<td>14.6</td>
<td>434</td>
<td>12</td>
</tr>
<tr>
<td>Cote d’Ivoire</td>
<td>0</td>
<td>1,646</td>
<td>20.8</td>
<td>359</td>
<td>7</td>
</tr>
<tr>
<td>Benin</td>
<td>0</td>
<td>825</td>
<td>10.6</td>
<td>397</td>
<td>1</td>
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<tr>
<td>Burkina Faso</td>
<td>0</td>
<td>720</td>
<td>17.4</td>
<td>306</td>
<td>4</td>
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<tr>
<td>Mali</td>
<td>8</td>
<td>766</td>
<td>15.8</td>
<td>133</td>
<td>10</td>
</tr>
<tr>
<td>Togo</td>
<td>0</td>
<td>646</td>
<td>6.9</td>
<td>105</td>
<td>0</td>
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<tr>
<td>Gabon</td>
<td>0</td>
<td>10,067</td>
<td>1.7</td>
<td>88</td>
<td>12</td>
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<tr>
<td>Congo, Republic</td>
<td>0</td>
<td>3,100</td>
<td>4.6</td>
<td>86</td>
<td>6</td>
</tr>
<tr>
<td>Gambia, The</td>
<td>0</td>
<td>423</td>
<td>1.9</td>
<td>78</td>
<td>1</td>
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<tr>
<td>Congo, Democratic Re-</td>
<td>0</td>
<td>475</td>
<td>69.4</td>
<td>89</td>
<td>7</td>
</tr>
<tr>
<td>public</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Niger</td>
<td>0</td>
<td>441</td>
<td>18.5</td>
<td>53</td>
<td>0</td>
</tr>
<tr>
<td>Central African Republic</td>
<td>0</td>
<td>379</td>
<td>4.7</td>
<td>23</td>
<td>1</td>
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<tr>
<td>Angola</td>
<td>0</td>
<td>5,936</td>
<td>22.1</td>
<td>12</td>
<td>0</td>
</tr>
<tr>
<td>Guinea-Bissau</td>
<td>0</td>
<td>586</td>
<td>1.7</td>
<td>12</td>
<td>0</td>
</tr>
<tr>
<td>Mauritania</td>
<td>0</td>
<td>1,270</td>
<td>3.9</td>
<td>7</td>
<td>0</td>
</tr>
<tr>
<td>Chad</td>
<td>0</td>
<td>1,053</td>
<td>13.2</td>
<td>7</td>
<td>0</td>
</tr>
</tbody>
</table>

Note: Details of the countries included in the sample before the matching procedure are given in the table. The column ‘number biomedical or social scientists in country at time of ebola outbreak’ provides numbers of all possible treated and control scientists in each country on which the matching procedure will take place. This full set of possible study scientists is identified as those publishing in the scopus database prior to 2014 and publishing at least once after 2012 (to exclude retired scientists). Further inclusion criteria is that scientists publish at least three times during their entire publication history and are first or last author at least once on a publication (to exclude lab technicians). Their country of residence is determined as a rule of over 75% of their affiliations being based in a particular country between 2010 and 2014.
<table>
<thead>
<tr>
<th>Country</th>
<th>Number scientists in study sample</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Treated</strong></td>
<td></td>
</tr>
<tr>
<td>Sierra Leone</td>
<td>25</td>
</tr>
<tr>
<td>Guinea</td>
<td>21</td>
</tr>
<tr>
<td>Liberia</td>
<td>6</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>52</td>
</tr>
<tr>
<td><strong>Control</strong></td>
<td></td>
</tr>
<tr>
<td>Mali</td>
<td>62</td>
</tr>
<tr>
<td>Congo, Democratic Republic</td>
<td>53</td>
</tr>
<tr>
<td>Togo</td>
<td>50</td>
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<tr>
<td>Gambia, The</td>
<td>38</td>
</tr>
<tr>
<td>Niger</td>
<td>33</td>
</tr>
<tr>
<td>Central African Republic</td>
<td>9</td>
</tr>
<tr>
<td>Guinea-Bissau</td>
<td>5</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>250</td>
</tr>
</tbody>
</table>

Note: This study sample is a sub-set of the sample provided in Table 1 that are matched using a coarsened exact matching procedure based on covariates such as country specific features, and researcher specific features such as career age and publication record.
### Table 3: Summary Statistics for Study Scientists the Year Prior to the Ebola Epidemic

<table>
<thead>
<tr>
<th></th>
<th>Control Scientists (N = 250)</th>
<th></th>
<th>Treated Scientists (N = 52)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>mean</td>
<td>median</td>
<td>std. dev.</td>
<td>min.</td>
</tr>
<tr>
<td>career age</td>
<td>9.56</td>
<td>7</td>
<td>5.85</td>
<td>4</td>
</tr>
<tr>
<td>any publication</td>
<td>0.59</td>
<td>1</td>
<td>0.49</td>
<td>0</td>
</tr>
<tr>
<td>num. publications</td>
<td>0.84</td>
<td>1</td>
<td>0.91</td>
<td>0</td>
</tr>
<tr>
<td>cum. num. publications</td>
<td>6.91</td>
<td>5</td>
<td>5.95</td>
<td>1</td>
</tr>
<tr>
<td>num. JIF weighted publications</td>
<td>0.80</td>
<td>0.41</td>
<td>1.05</td>
<td>1</td>
</tr>
<tr>
<td>cum. num. JIF weighted publications</td>
<td>6.72</td>
<td>4.32</td>
<td>7.33</td>
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<tr>
<td>any publication last author</td>
<td>0.088</td>
<td>0</td>
<td>0.28</td>
<td>0</td>
</tr>
<tr>
<td>num. publications scientist is last author</td>
<td>0.10</td>
<td>0</td>
<td>0.37</td>
<td>0</td>
</tr>
<tr>
<td>any publication in tropical diseases</td>
<td>0.24</td>
<td>0</td>
<td>0.43</td>
<td>0</td>
</tr>
<tr>
<td>num. publications in tropical diseases</td>
<td>0.32</td>
<td>0</td>
<td>0.67</td>
<td>0</td>
</tr>
<tr>
<td>cum. num. publications in tropical diseases</td>
<td>3.04</td>
<td>1</td>
<td>4.84</td>
<td>1</td>
</tr>
<tr>
<td>any publication in viral hemorrhagic fever in 3 years prior</td>
<td>0.008</td>
<td>0</td>
<td>0.089</td>
<td>0</td>
</tr>
<tr>
<td>any publication with OECD coauthors</td>
<td>0.48</td>
<td>0</td>
<td>0.50</td>
<td>0</td>
</tr>
<tr>
<td>num. publications with OECD coauthors</td>
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<td>0</td>
<td>0.79</td>
<td>0</td>
</tr>
<tr>
<td>num. new OECD coauthors</td>
<td>4.65</td>
<td>3</td>
<td>4.74</td>
<td>0</td>
</tr>
</tbody>
</table>

Note: The sample consists of 302 Central and West African scientists who were actively publishing at the time of the ebola outbreak. All statistics are measured using scientist level data gathered from the scopus database, and measurements are made prior to the epidemic (at the end of 2013).
Table 4: Impact of Ebola Epidemic on Endemic Country Scientists

<table>
<thead>
<tr>
<th></th>
<th>(1) pubs with OECD</th>
<th>(2) new OECD coauthors</th>
<th>(3) JIF weighted pubs</th>
<th>(4) tropical disease pubs</th>
<th>(5) non-ebola pubs</th>
</tr>
</thead>
<tbody>
<tr>
<td>AFTER EPIDEMIC × ENDEMIC COUNTRY</td>
<td>0.25 (0.21)</td>
<td>0.94* (0.48)</td>
<td>0.56*** (0.16)</td>
<td>0.75 (0.47)</td>
<td>-0.31*** (0.068)</td>
</tr>
<tr>
<td>Number of scientists</td>
<td>285</td>
<td>283</td>
<td>301</td>
<td>188</td>
<td>301</td>
</tr>
<tr>
<td>Number of scientists × year observations</td>
<td>2,565</td>
<td>2,547</td>
<td>2,709</td>
<td>1,692</td>
<td>2,709</td>
</tr>
</tbody>
</table>

[a] Estimates stem from fixed effects Poisson specifications with dependent variables being counts of outcomes per scientist per year. All models incorporate a full suite of calendar year, age bracket and scientist fixed effects. Exponentiating the coefficients and differencing from one yield numbers interpretable as elasticities. For example, the estimates in column (3) imply that the endemic country scientists publish 100x(exp[0.56]-1) = 75% more journal impact factor (JIF) weighted publications following the epidemic. The number of observations varies slightly across columns because the conditional fixed effects specification drops observations corresponding to scientists for which there is no variation in activity over the entire observation period.

[b] Heteroskedastic robust standard errors, clustered at the country level, are given in parentheses. *, **, *** denote statistical significance at p-values of 0.1, 0.05 and 0.01 respectively.
Table 5: Breakdown of Impact of Ebola Epidemic on Endemic Country Scientists by Pre-Epidemic Intellectual Capital

<table>
<thead>
<tr>
<th></th>
<th>(1) pubs with OECD</th>
<th>(2) new OECD coauthors</th>
<th>(3) JIF weighted pubs</th>
<th>(4) tropical disease pubs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tropical Disease</td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>Record</td>
<td>0.67*</td>
<td>1.22*</td>
<td>1.04**</td>
<td>0.86*</td>
</tr>
<tr>
<td></td>
<td>(0.40)</td>
<td>(0.71)</td>
<td>(0.41)</td>
<td>(0.47)</td>
</tr>
<tr>
<td>No Tropical Disease</td>
<td>-0.64***</td>
<td>-0.10</td>
<td>-0.64**</td>
<td>-0.09</td>
</tr>
<tr>
<td>Record</td>
<td>(0.24)</td>
<td>(0.13)</td>
<td>(0.25)</td>
<td>(0.82)</td>
</tr>
</tbody>
</table>

Number of scientists × year observations

<table>
<thead>
<tr>
<th></th>
<th>Tropical Disease</th>
<th>No Tropical Disease</th>
</tr>
</thead>
<tbody>
<tr>
<td>ENDEMIC COUNTRY</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AFTER EPIDEMIC</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

[a] The sample is divided into two sub-samples: those who have published more than 50% of their publications in the four years before the epidemic in neglected tropical disease subject areas in columns 1,3,5,7, and the rest of the sample in columns 2,4,6,8. The same specification is run on each sample.

[b] Estimates stem from fixed effects Poisson specifications with dependent variables being counts of outcomes per scientist per year. All models incorporate a full suite of calendar year, age bracket and scientist fixed effects. The number of observations varies slightly across columns because the conditional fixed effects specification drops observations corresponding to scientists for which there is no variation in activity over the entire observation period.

[c] Heteroskedastic robust standard errors, clustered at the country level, are given in parentheses. *, **, *** denote statistical significance at p-values of 0.1, 0.05 and 0.01 respectively.
Table 6: Breakdown of Impact of Ebola Epidemic on Endemic Country Scientists by Pre-Epidemic Social Capital

<table>
<thead>
<tr>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>pubs with OECD</td>
<td>new OECD coauthors</td>
<td>JIF weighted pubs</td>
<td>tropical disease pubs</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>OECD collab. record</td>
<td>no sig. OECD collab. record</td>
<td></td>
<td>OECD collab. record</td>
<td>no sig. OECD collab. record</td>
<td></td>
<td>OECD collab. record</td>
<td>no sig. OECD collab. record</td>
</tr>
<tr>
<td>AFTER EPIDEMIC × ENDEMIC COUNTRY</td>
<td>0.34* (0.20)</td>
<td>0.12 (0.30)</td>
<td>1.21*** (0.38)</td>
<td>0.34 (0.70)</td>
<td>0.63*** (0.18)</td>
<td>0.47* (0.21)</td>
<td>1.19** (0.55)</td>
</tr>
</tbody>
</table>

Number of scientists 191 94 189 94 190 111 116 72
Number of scientists × year observations 1,719 846 1,701 846 1,710 999 1,044 648

[a] The sample is divided into two sub-samples: those who have published with OECD based collaborators in all of their publications in the four years prior to the epidemic in columns 1,3,5,7, and the rest of the sample in columns 2,4,6,8. The same specification is run on each sample.

[b] Estimates stem from fixed effects Poisson specifications with dependent variables being counts of outcomes per scientist per year. All models incorporate a full suite of calendar year, age bracket and scientist fixed effects. The number of observations varies slightly across columns because the conditional fixed effects specification drops observations corresponding to scientists for which there is no variation in activity over the entire observation period.

[c] Heteroskedastic robust standard errors, clustered at the country level, are given in parentheses. *, **, *** denote statistical significance at p-values of 0.1, 0.05 and 0.01 respectively.
Table 7: Breakdown of Impact of Ebola Epidemic on Endemic Country Scientists by Pre-Epidemic Intellectual and Social Capital

<table>
<thead>
<tr>
<th></th>
<th>(1) pubs with OECD</th>
<th>(2) new OECD coauthors</th>
<th>(3) JIF weighted pubs</th>
<th>(4) tropical disease pubs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tropical Disease and OECD Coauthor Record</td>
<td>Tropical Coauthor</td>
<td>Tropical Coauthor</td>
<td>Tropical Coauthor</td>
<td>Tropical Coauthor</td>
</tr>
<tr>
<td>Rest of Sample</td>
<td>Record</td>
<td>Record</td>
<td>Record</td>
<td>Record</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AFTER EPIDEMIC × ENDEMIC COUNTRY</td>
<td>0.80**</td>
<td>-0.12**</td>
<td>1.62***</td>
<td>0.35</td>
</tr>
<tr>
<td></td>
<td>(0.40)</td>
<td>(0.056)</td>
<td>(0.56)</td>
<td>(0.36)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>1.35***</td>
<td>0.033</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.44)</td>
<td>(0.14)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>1.17**</td>
<td>0.33</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.60)</td>
<td>(0.33)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of scientists</td>
<td>89</td>
<td>196</td>
<td>88</td>
<td>195</td>
</tr>
<tr>
<td>Number of scientists × year observations</td>
<td>801</td>
<td>1,764</td>
<td>792</td>
<td>1,755</td>
</tr>
</tbody>
</table>

[a] The sample is divided into two sub-samples: those who have both published more than 50% of their publications in the four years prior to the epidemic in neglected tropical disease, and only with OECD based collaborators in the four years prior to the epidemic in columns 1,3,5,7, and the rest of the sample in columns 2,4,6,8. The same specification is run on each sample.

[b] Estimates stem from fixed effects Poisson specifications with dependent variables being counts of outcomes per scientist per year. All models incorporate a full suite of calendar year, age bracket and scientist fixed effects. The number of observations varies slightly across columns because the conditional fixed effects specification drops observations corresponding to scientists for which there is no variation in activity over the entire observation period.

[c] Heteroskedastic robust standard errors, clustered at the country level, are given in parentheses. *, **, *** denote statistical significance at p-values of 0.1, 0.05 and 0.01 respectively.
<table>
<thead>
<tr>
<th></th>
<th>(1) pubs with OECD</th>
<th>(2) new OECD coauthors</th>
<th>(3) JIF weighted pubs</th>
<th>(4) tropical disease pubs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>high productivity</td>
<td>low productivity</td>
<td>high productivity</td>
<td>low productivity</td>
</tr>
<tr>
<td>AFTER EPIDEMIC × ENDEMIC COUNTRY</td>
<td>0.33 (0.20)</td>
<td>-0.028 (0.27)</td>
<td>0.94** (0.43)</td>
<td>0.96 (0.68)</td>
</tr>
<tr>
<td>Number of scientists</td>
<td>177</td>
<td>108</td>
<td>177</td>
<td>106</td>
</tr>
<tr>
<td>Number of scientists × year observations</td>
<td>1,593</td>
<td>972</td>
<td>1,593</td>
<td>954</td>
</tr>
</tbody>
</table>

[a] The sample is divided into two sub-samples: those who have published more than the sample median journal impact factor (JIF) weighted publications in the four years prior to the epidemic in columns 1,3,5,7, and the rest of the sample in columns 2,4,6,8. The same specification is run on each sample.

[b] Estimates stem from fixed effects Poisson specifications with dependent variables being counts of outcomes per scientist per year. All models incorporate a full suite of calendar year, age bracket and scientist fixed effects. The number of observations varies slightly across columns because the conditional fixed effects specification drops observations corresponding to scientists for which there is no variation in activity over the entire observation period.

[c] Heteroskedastic robust standard errors, clustered at the country level, are given in parentheses. *, **, *** denote statistical significance at p-values of 0.1, 0.05 and 0.01 respectively.
Table 9: Persistent Impact of Ebola Epidemic on Endemic Country Scientists

<table>
<thead>
<tr>
<th>(1) publishing with OECD coauthors</th>
<th>(2) last author on OECD co-authored publication</th>
<th>(3) second publication with new OECD coauthor generated in 2014-2016</th>
<th>(4) later period publication with new OECD coauthor generated in 2014-2016</th>
<th>(5) having a hit publication</th>
</tr>
</thead>
<tbody>
<tr>
<td>ENDEMIC COUNTRY</td>
<td>-0.00386</td>
<td>1.202*</td>
<td>0.724**</td>
<td>0.427</td>
</tr>
<tr>
<td></td>
<td>(0.749)</td>
<td>(0.635)</td>
<td>(0.290)</td>
<td>(0.646)</td>
</tr>
</tbody>
</table>

Number of scientists 106 106 106 106 106

[a] Using a reduced sample of those who published in 2014-2016 with OECD coauthors and have the characteristics to be involved in epidemic science should it affect their country, estimates stem from cross-sectional logit specifications with dependent variables being dummy of outcomes post 2016 per scientist. All models incorporate controls for age bracket and full suite of scientist level covariates (same as used for matching procedure) on productivity, research area, and international collaborations. Coefficients can be interpreted as log odds. Exponentiating the coefficient gives the odds ratio. So - for model (2) the likelihood of being a last author on an OECD co-authored publication is exp(1.202) = 3.3 times more for those in endemic countries than the control countries.

[b] Heteroskedastic robust standard errors, clustered at the country level, are given in parentheses. *, **, *** denote statistical significance at p-values of 0.1, 0.05 and 0.01 respectively.
Table 10: Sensitivity Checks

<table>
<thead>
<tr>
<th></th>
<th>(1) benchmark specification</th>
<th>(2) placebo test without senior scientists</th>
<th>(3) without most productive scientists</th>
<th>(4) without most productive scientists</th>
</tr>
</thead>
<tbody>
<tr>
<td>AFTER EPIDEMIC × ENDEMIC COUNTRY</td>
<td>0.56*** (0.16)</td>
<td>0.25 (0.21)</td>
<td>0.36** (0.16)</td>
<td>0.65*** (0.19)</td>
</tr>
<tr>
<td>Robustness</td>
<td></td>
<td>only pre-period</td>
<td>without senior scientists</td>
<td>without most productive scientists</td>
</tr>
<tr>
<td>Number of scientists</td>
<td>301</td>
<td>292</td>
<td>194</td>
<td>263</td>
</tr>
<tr>
<td>Number of scientists × year observations</td>
<td>2,709</td>
<td>1,168</td>
<td>1,746</td>
<td>2,367</td>
</tr>
</tbody>
</table>

[a] Estimates stem from fixed effects Poisson specifications with dependent variables being counts of journal impact factor (JIF) weighted publications per scientist per year. All models incorporate a full suite of calendar year, age bracket and scientist fixed effects. The number of observations varies slightly across columns because the conditional fixed effects specification drops observations corresponding to scientists for which there is no variation in activity over the entire observation period.

[b] Heteroskedastic robust standard errors, clustered at the country level, are given in parentheses. *, **, *** denote statistical significance at p-values of 0.1, 0.05 and 0.01 respectively.