The academic cost of international conflict

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Abstract

Countries involved in international armed conflicts pay a high price in terms of human capital. By leveraging the start of the Russo-Ukrainian war in 2022, I analyse causally the cost that Russia-based researchers had to pay in academic terms. I find that the start of the conflict brought along a penalty to academics based in Russia, who see their citations drop in a magnitude similar to the penalties found following paper retractions. This drop is heterogeneous by the origin of citations, with some regions where citations grow in the treatment period. I also find that Russian-based researchers struggle to publish their research in international journals, even if they maintain similar productivity levels as in the pre-war period. Emigration seems to alleviate the problem, although with some delay.

JEL Classification: I23, F51, O15, D74

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1 Introduction

International conflicts are one of the human-created events that have a higher cost in civilization, with long lasting consequences. The most sizeable ones are the lost of lives and the destruction of infrastructure, but there are many second-round effects that affect almost every layer of society. Poverty, instability and internal conflict in the areas affected by wars coexist with the fall of diplomatic relationships between combating nations (or groups of them), which might hamper collaboration and trade for many years. Given its international vocation, one of the most exposed fields to geopolitical tensions is the academic one.

This paper tries to understand the cost that the academics of a country directly involved in international conflict have to deal with in terms of recognition and productivity, by looking both at the change in behaviour of global academia towards one specific community, and the internal productivity shocks at the individual level. There are existing works looking at the impact on researchers' careers of individual actions, but the consequences of events at a broader level (e.g. country-wise) are vastly understudied.

I leverage the start of the full-scale conflict between Russia and Ukraine in February 2022[1] and the quick reaction to condemn the Russian attack and the sharp increase in anti-Russian rhetoric in the US and EU to understand whether these events had any impact on the outcomes of the Russian academic community and, if so, to quantify it. In other words, my goal is to causally explore the academic cost that a country faces when engaging in a conflict that is condemned by the majority of the countries with the strongest academic communities. I find that the Russian academia in economics experienced a backslash in their citation records and their publication output of between 6% to 10% on average, and that these drops can be causally attributed to the start of the conflict.

This study focuses on the field of economics, given its lower costs of entry (no expensive equipment or labs needed), high degree of internationality and the low number of authors per paper, which makes individual affiliations more salient.

This paper is connected to several strands of the literature. Given the determined reaction from the EU and US by taking a clear stance against Russia, and the calls for boycott, this paper relates to the literature on the academic backslash of perceived misdoing. Psychology research has shown that people react to improper behaviour by punishing others (Fehr and Gächter (2002)). In academia, this punishment takes the form of ceasing collaboration or refraining from citing or publish the work of someone. Lu et al. (2013), Azoulay et al. (2015) or Azoulay et al. (2017) have documented the existence of such behaviour in research and quantified it. They look at the effect of having misbehaved in research in the form of retractions, and they find a penalty on previous works of affected authors of around 10% lower citations after the incident.

These penalties also extend to misbehaviour outside of the academic sphere. Widmann et al. (2025) look causally at the effect of being accused of sexual misconduct, also finding a drop in citations of accused authors of around 5%, and medium-lasting career effects. In this spirit, one of the potential reactions of Western academia towards the Russian one after the start of the war could have been penalising it by ceasing citing them or even accepting manuscripts from Russian-affiliated authors. There is some anecdotal evidence of the latter, as in 2022 the Journal of Molecular Structures openly decided to reject manuscripts based on affiliations coming from Russian institutions[2]. My results also support this hypothesis as one of the possible mechanisms: Russian-affiliated authors have a lower rate of publications after the start of the war, even when they show no drop in productivity.

Another consequence of the documented perceived misdoing in the literature is the distancing of previous collaborators from affected researchers. Hussinger and Pellens (2019) find that they stop citing or collaborating with former peers who suffered a

[1]Also considered as the escalation of the Donbas conflict ongoing since 2014. Given the scale and notoriety in press of February 2022 events in comparison to those 8 years before, I focus on 2022.

[2]See original post here: (https://retractionwatch.com/2022/03/04/journal-editor-explains-ban-on-manuscripts-from-russian-institutions/)

scandal. In this context, authors might choose to distance themselves from the Russian academia to avoid being seen as someone who does not condemn the war.

A third potential motive of lower citations is a taste-shift. Yang and Zhou (2025) show that papers where the first author is Chinese are less cited than comparable papers with non-Chinese first authors, and attributes this to taste-based discrimination after discarding other factors. If Russian academia is now perceived more negatively after 2022, a similar reaction could be taking place.

Additionally, my paper is the first, to the best of my knowledge, to look at a granular level at the origin of citations at a wider level, that is, further than a case-analysis scenario. Taking advantage of this information, I am able to characterise the drop in citations relating it to geographical blocks to look for heterogeneity in the citing behaviour response. By doing this I find that some groups of countries responded slightly negatively to the full scale invasion, while others responded with a more notably positive bias towards Russian-affiliated scientists.

However, the main driver of the drop in citations seems to come from a combination of two factors: the difficulty of the Russian academia to publish in the international journals pulls down the amount of citations coming from inside Russia, and the relatively high endogamy of Russian academia acts as a multiplier of this effect. In other words, researcher-level penalisation from abroad does not seem to be the main driving force.

These results also fill a gap in the literature. Country self-citations have received attention in the literature, with Bakare and Lewison (2017)'s recent paper being a good attempt at measuring it. However, the connexion between this and exposure is limited. An example of this is Bornmann et al. (2018), who study the relationship between over-citing national peers on international recognition. My paper goes a step beyond this to connect country self-citations to the exposure they have to external shocks, in this case geopolitical tensions. To the best of my knowledge, mine is also the first paper to do this.

Finally, my work also adds to the growing literature on the interaction of geopolitics with the academic world. Before the Russia-Ukraine war, research on this was relatively scarce, mainly looking at the effect of sanctions. Kokabisaghi et al. (2019) and Dehghani et al. (2021) look at the case of Iran and the effect of sanctions imposed by the US on research and international collaboration that originate in that country, mainly finding that they had a mild negative effect on productivity. Recent work by Zhang et al. (2024) focuses on the conflict in Eastern Europe and analyses the influence of the war on the productivity of Russian academia and on its international links. They find that while international scientific collaboration was affected to some extent, the number of documents published in international scientific journals coming from Russia has sharply declined. They attribute this to internal factors, mentioning the statements published by international journals against the boycott of Russian science (Bobok (2022), Plackett (2022)). Although their study was comprehensive, the results could not be claimed as causal. Makkonen and Mitze (2023) use the same geographical setting to causally analyse the impact of economic sanctions against Russia, but look at the period 2014-2019 following the annexation of the Crimean peninsula. They also find a drop in the intensity of academic collaboration of Russia with EU countries compared to other countries, quantifying it at around 15%. My work adds to all these studies by studying the ongoing conflict with causal estimations, using much more granular data, and studying the effects at both the paper citations and the author publications level.

My analysis is two-fold: First, I want to understand whether the start of the war had any impact on the citations received by papers authored by Russian-affiliated academics. The reason to focus first on citations is that it allows for a clean estimation of causal effects, given that they are very well measured and the control group can be clearly defined. Results shows that, compared to other papers from the same journal issue, articles authored by Russian-affiliated authors suffered a drop in their citation records after the start of the war of, on average, 6%. This is in par with the results of the studies mentioned above. To understand the mechanisms behind this drop, I try to disentangle its geographical source. By leveraging the origin of the citing papers, I find that most of the drop seems to stem from national citations, that is, citations coming from articles published by Russian-based researchers themselves. Given that citations only appear when papers are published, one possible explanation for this is that the Russian-based academics are publishing less.

Thus, as a natural second step, it is interesting to understand whether there is also a production drop from Russian-affiliated authors. Moving from the paper-level to a second dataset at the author-level, I show that Russian-affiliated authors publish 9.4% less after the start of the war in academic journals, likely driving the previously mentioned drop in citations. This decrease in the amount of publications does not seem to be driven by a productivity drop and especially affects journals written in the English language. This might in turn affect their visibility and that of their past research.

It is important to emphasise one of the main additions of this paper, which is to add a layer of causality to existing studies on the impact of international conflict on academia. This allows to differentiate mere relationships from cause-effect links. This is crucial to be able to confirm whether results from previous studies are a consequence of the conflict and the accompanying sanctions or the continuation of a downward trend in the Russian academia, or a combination of the two (and, if so, to quantify precisely the effect of the former).

The rest of the paper is structured as follows: Section 2 will present the data sources and the transformations undertaken to prepare it for the analysis; section 3 covers the methodology and results of the paper-level analysis; section 4 looks at the heterogeneity at the geographical origin of citations; while section 5 presents the analysis at the author level. Finally, section 6 concludes.

2 Data

To study whether Russia-based academics faced any consequences due to their affiliation after the start of the war, I will use two different but complementary datasets: a paper-level and an author-level dataset. First, to quantify with a higher precision the causal effect of the start of the war in Russian academia, I use data about citations at the paper level. Doing so entails two clear advantages: Citations are the most widely used metric in the scientometrics literature and are accurately measured (Mingers and Leydesdorff (2015), Krauss (2024)). This allows me to build on stable grounds the first results of the study. At the same time, focusing on paper-level data it will be easier to ensure comparability of the treatment and control groups in terms of topic and quality, both factors affecting citations. This will allow for a cleaner identification of the treatment.

Secondly, I use data on academic production at the author level. This allows the analysis to be broader by looking not only at whether papers suffered a drop in citations, but also whether this was accompanied by a drop in the production of Russian-affiliated authors and whether emigration played any role. As I will discuss in section 4, a fall in citations might be caused by the inability of potential citing papers to be published. Publication counts by author can be used to compare treated authors with comparable control authors to test whether there was any negative effect among the treated group after the start of the war (also potentially affecting citations).

As mentioned above, the analysis is restricted to the field of economics. The reason behind this is many-fold. First, this is a field with a low entry barrier in terms of monetary investment. No expensive equipment is needed, nor is it dependent on funding to the extent that other fields of knowledge are. Secondly, papers in economics tend to have a small number of authors, thus making it more plausible to identify any effect based on authors' affiliation. This is also an advantage, because international collaboration is not a fundamental requirement for projects to be undertaken, unlike other fields which depend on it for bigger projects (which are the ones with a higher impact). Thirdly, economics is a very international field, meaning that research topics are not regional-specific, in turn making it more exposed to geopolitical tensions. Finally, and only as an added benefit, familiarity with the academic environment in economics gives me an edge in understanding the dynamics in the field.

2.1 Paper-level

The main data comes from the academic database Openalex, which is the successor to the Microsoft Academic Graph project. This database indexes all works by all authors in all disciplines, with a coverage of peer-reviewed journals similar to that of alternatives such as Scopus or Web of Science (Culbert et al. (2025)). The advantage of this database is the availability of any other non peer-reviewed works for the authors that will come in handy to disentangle whether any of the discovered effect might be driven by a drop in academic productivity.

My sample of interest are all papers published before 2022, in English language, in Q1 or Q2 economic journals[3] and that were no older than 20 years old in 2022. This sample contains papers whose production/publication should not have been affected by the conflict, that have a minimum level of quality and relevance, and that are not too old to have outdated methods or results; all of these being factors that might affect their citation patterns.

[3] As defined by the Scimago Journal Ranking (SJR), 2023

For each of the papers falling in my sample of interest, I have full information on their yearly citation records, their publication date, their authorship (including affiliation of the authors), and the journal in which they were published along with their corresponding volume and issue (for those journals that launch issues).

The treatment is defined by being in the year 2022 or later for those papers having at least one author based in a Russian institution. To be able to cleanly identify the effect, I further restrict the sample to papers published in the same issue of the same journal as the treated paper. By doing this, I keep the quality, relevance and topic close across treatment and control articles, which make them similar enough to reasonably expect that both would have fared similarly in the absence of any treatment. I also restrict the citation records to the period from 2017 onwards to ensure balanced post- and pre-treatment periods. The final sample consists of 122.001 observations at the paper-year level, encompassing 18.119 unique papers. The summary stats for the papers' data can be found in table 2.

It can be seen that most papers are published in Q1 journals, including about 25% of papers that are published in journals with a SJR index within the top 10%. The share of authors based in Russia for each article on average is small, but among those who contain at least one Russia-based author, this percentage increases to over 60%. and for each treated article we have on average 10 papers in the control group.

One potential problem my definition of the control group has is the lack of issue information, either because some journals have a rolling publication scheme or because this information is missing for some observations. To avoid this, I take advantage of the information on the volume of the journal where the article is published and construct an alternative definition of "issue" by giving each paper a unique journal-volume-month identifier. This alternative way of constructing the control group is, if anything, stricter than using the real journal-volume-issue, given the bimonthly nature of some journals. However, as will be seen in section 3, both approaches give similar results. To reduce potential noise coming from too many control observations per each treated unit, I also repeat the estimation after randomly sampling control units from the original control group, with similar results.

To further characterise the citation dynamics of my sample of interest, I download the universe of works that cite any of the articles contained in the treated or control groups from the first step. For each of these new articles, I have the same information as mentioned above. In a similar vein, I can characterise each paper on whether they have at least one Russian-affiliated author, and thus calculate the amount of citations coming from Russia (defined as citations from papers where at least one author is affiliated to a Russian institution) or from anywhere else in the world. From now on, I will call them *domestic* and *foreign* citations, respectively (Lancho Barrantes et al. (2012), Shehatta and Al-Rubaish (2019)).

Taking advantage of the data, I can further divide domestic citations into those coming from papers with at least one Russian-affiliated author that did not leave the country after the start of the war, and those from authors who left Russia after February 2022. I will call these *domestic-stayers* citations and *domestic-leavers* citations.

Table 1: Papers dataset: Summary stats and balance

Statistic	N	Mean	St. Dev.	Min	Max
Full sample – # papers: 18119					
Number of citations (yearly)	121,082	4.016	10.058	0	494
Publication year	122,001	2,014.915	4.823	2,002	2,021
Paper age	122,001	6.038	4.836	0	22
Number of authors	122,001	2.333	1.664	1	59
Share of Russia-based authors	122,001	0.051	0.198	0	1
In Q1	122,001	0.589	0.492	0	1
In top 10% (SJR)	122,001	0.244	0.429	0	1
Treated – # papers: 1320					
Number of citations (yearly)	9,124	3.640	9.104	0	174
Publication year	9,179	2,014.424	4.869	2,002	2,021
Paper age	9,179	6.444	4.951	0	22
Number of authors	9,179	2.547	2.937	1	59
Share of Russia-based authors	9,179	0.684	0.301	0.017	1
In Q1	9,179	0.530	0.499	0	1
In top 10% (SJR)	9,179	0.206	0.405	0	1
Control (1) – # papers: 16799					
Number of citations (yearly)	111,958	4.047	10.131	0	494
Publication year	112,822	2,014.955	4.817	2,002	2,021
Paper age	112,822	6.005	4.825	0	22
Number of authors	112,822	2.316	1.513	1	49
Share of Russia-based authors	112,822	0.000	0.000	0	0
In Q1	112,822	0.594	0.491	0	1
In top 10% (SJR)	112,822	0.247	0.431	0	1
Control (2) – # papers: 15096					
Number of citations (yearly)	101,077	4.225	10.686	0	494
Publication year	101,862	2,014.738	4.922	2,002	2,021
Paper age	101,862	6.205	4.928	0	22
Number of authors	101,862	2.309	1.452	1	36
Share of Russia-based authors	101,862	0.000	0.000	0	0
In Q1	101,862	0.619	0.486	0	1
In top 10% (SJR)	101,862	0.258	0.438	0	1

Notes: Summary stats of raw data on the sample of interest. Treated corresponds to papers with at least one Russia-based author. Controls corresponds to papers published in the same journal-issue(1)/ journal-month(2) as the treated ones. The number of observations reflects the number of paper-year combination available in the data.

2.2 Author-level

Finally, the third dataset that I will use in my analysis is at the author level. As explained before, running the analysis at this level allows me to estimate the causal effect of the war on the academic production of Russian-affiliated authors. At the same time, given the richness of the data, this effect can be further characterised between published papers and other works (working papers, books), where the difference of the two can be used as a proxy for changes in productivity to identify the mechanisms.

My sample of interest are authors who have published at least once in a Q1 or Q2 journal in economics since the year 2002. This is equivalent to the sample of authors that produced the papers studied in the first part of this work. Then, I retrieve from Openalex the full research production from these authors and construct for each of them the amount of works published each year, the amount of citations received and the topics they worked on, their academic age (defined as the difference between the date of their first work and the current year), as well as their affiliation trajectories.

Using this last piece of information, I reconstruct the migration status of authors that were affiliated to a Russian institution before the start of the war, identifying stayers and leavers. To construct this, some caution had to be taken, since an author can have more than one affiliation at a given point in time. Unlike in the analysis at the paper level where it suffices to observe one Russian affiliation, recovering the affiliation trajectories of authors requires identifying which was their main affiliation every year[4]. To do so, I adopt some (nested) rules: 1. If one of the affiliations of the author is a university, it will be given the main affiliation status. I do this because most universities require exclusivity of affiliation, meaning one cannot publish under the affiliation of another university while being employed there; 2. The institution where the researcher has been affiliated for longer will be his/her main affiliation; 3. The main affiliation in each year will be the most common one in that year across all published works by the author. This ensures that the selected main affiliation is the most representative one of the actual author status. Thus, all results at the author level leveraging information on affiliation are subject to these definitions of affiliation. If I inverted rules 2 and 3, my procedure will be more sensitive to moving individuals, but this would introduce a higher likelihood of false positives, which might bias my analysis. I acknowledge that this procedure might produce false negatives, but I consider the resulting reduction of the power of my estimation to be safer than a potential bias driven by false positives.

I also construct an identifier for authors to be considered as "stars" (Zucker and Darby (1996)) based on their percentile in the total amount of citations (alternatively, publications) over their career, considering them as such if they are in the top 5% or 10% of the distribution.

All these three datasets were constructed in a way that they are linkable to one another, thus allowing me to conduct analyses at the paper level while also exploiting information from the authors, or the other way around.

[4]Note that this does not apply to the paper-level analysis, since what the important information is the affiliation(s) written on that paper, regardless of whether this was the "main" one or not.

Table 2: Authors dataset: Summary stats and balance

Statistic	N	Mean	St. Dev.	Min	Max
Full sample – # authors: 3753					
Publications	28,021	59.461	77.340	1	1,311
Citations	28,021	600.304	2,269.252	0	82,693
Works per year	28,021	3.910	6.637	0	176
Publications per year	28,021	2.767	4.412	0	86
Working papers per year	28,021	0.709	3.106	0	147
Share of works in English	28,021	0.619	0.433	0.000	1.000
Citations per year	28,021	60.221	233.638	0	7,948
First paper year	28,021	2,001.517	15.679	1,951	2,022
Emigration from Russia	28,021	0.026	0.158	0	1
Treated – # authors: 1266					
Publications	9,490	61.684	75.492	1	770
Citations	9,490	539.144	1,796.694	0	24,795
Works per year	9,490	4.059	6.903	0	143
Publications per year	9,490	2.890	4.541	0	86
Working papers per year	9,490	0.699	3.092	0	140
Share of works in English	9,490	0.621	0.426	0.000	1.000
Citations per year	9,490	55.638	237.578	0	7,923
First paper year	9,490	2,001.591	15.687	1,951	2,022
Emigration from Russia	9,490	0.067	0.250	0	1
Control – # authors: 2487					
Publications	18,531	58.322	78.247	1	1,311
Citations	18,531	631.625	2,476.047	0	82,693
Works per year	18,531	3.834	6.495	0	176
Publications per year	18,531	2.704	4.344	0	70
Working papers per year	18,531	0.714	3.113	0	147
Share of works in English	18,531	0.618	0.437	0.000	1.000
Citations per year	18,531	62.568	231.565	0	7,948
First paper year	18,531	2,001.479	15.675	1,951	2,022
Emigration from Russia	18,531	0.000	0.000	0	0

Notes: Summary stats of raw data on the sample of interest. Treated are authors affiliated to a Russian institution before the start of the war. Controls are comparable authors based on academic performance (see section 5 for details). The number of observations reflects the number of author-year combinations available in the data.

3 The exposure cost

Citations are one of the first perceived signals of quality of a paper that a researcher can receive, along with the journal in which it is published. Teplitskiy et al. (2022) show that higher citation counts lead to a higher reader's attention and that this translates into higher influence on downstream research. In contrast, lower citation counts reduce the exposure of the article in the medium and long term, not only quantitatively but, as Teplitskiy et al. (2022) find, also quantitatively.

If the works of Russian-affiliated authors suffer a drop in their citation counts because of the start of the war, this drop will entail a fall in exposure of these authors. This would mean that other researchers will have a reduced probability of coming across papers written by these Russian-affiliated authors, and those who find them will read them with lower engagement as they would have, had there been no war.

In order to quantify this exposure drop, I focus on the drop in the citations count. To estimate the average treatment effects for the treated (ATT), I follow a differences-in-differences (DiD) strategy. Given the extreme skewness of the dependent variable (42.25% of the paper-year combinations show zero citations) I run a two-way fixed effects (TWFE) model using a quasi-maximum likelihood estimation (QMLE) based on the Poisson distribution, adding fixed effects at the paper and year levels.

$$\mathbb{E}(cites_{it}) = \exp(\beta \times treated_{it} + \mho(age_{it}) + \delta_i + \delta_t + \epsilon_{it}) \tag{1}$$

where δ_i and δ_t are the paper and year fixed-effects, respectively. To account for the citation growth over time, I include a set of dummies for the paper age ($\mho(age_{it})$), since it is arguably one of its biggest determinants apart from quality and topic popularity (both of which are controlled by the paper fixed effects[5]). Concretely, I follow Azoulay et al. (2015) and include 20 different dummies, the last one including all articles 20 years of age or older. The testable implication of my model is the existence of a drop in citations, that is, whether $\beta < 0$.

As shown in Wooldridge (2023), the usual assumptions for the identification of ATT hold when estimating a QMLE-Poisson using TWFE. The validity of this approach relies on the setting fulfilling all the necessary conditions to ensure unbiasedness. The treatment is by design non-staggered and it can be claimed that there was no anticipation of treatment: given that the data is at the yearly level, even if a minority of authors would have predicted the border violation and would have taken retaliation measures before it took place, these events would have nevertheless taken place in the year 2022, thus being properly captured in the model.

Conceptually, the parallel trends assumption also holds. Both treatment and control groups should be similar enough in their citation trajectories given that they are published in the same journal and at the same time, thus having a similar quality, scope, close topics and have been exposed to the same readers. This is not to say that two articles published in the same issue of one journal will have the same citation records over time, but rather that their evolution will be similar after controlling for

[5] This is because both are time-invariant information linked to each specific paper

paper-specific characteristics that make it stand out. At the same time, this selection of the control group also means that there should be no other reason apart from the start of the conflict for the treated group's citation record to deviate from the control group's path. In figure 1 they are also successfully tested empirically.

Lastly, the no-spillovers assumption seems reasonable in this context too. If the drop in citations is driven by the affiliation of the authors, there is no straightforward mechanism that might also affect papers in the control group.

Table 3: Baseline results

	(1)	(2)	(3)	(4)	(5)
Constant	1.235***				
	(0.0204)				
after × RU	-0.1141***	-0.1186***	-0.1154***	-0.1213***	-0.0622**
	(0.0442)	(0.0443)	(0.0304)	(0.0314)	(0.0291)
Russia-based	-0.0443	-0.0402			
	(0.0732)	(0.0732)			
after	0.3359***		0.3322***		
	(0.0130)		(0.0093)		
year fixed effects		✓		✓	✓
paper fixed effects			✓	✓	✓
age dummies					✓
Observations	121,082	121,082	107,294	107,294	107,294
Squared Correlation	0.00449	0.00583	0.84124	0.85327	0.89769
Pseudo R^2	0.00966	0.01249	0.67095	0.67400	0.70399
BIC	1,387,313.9	1,383,419.1	609,050.5	605,203.4	566,954.4

Notes: GLM Poisson model (conditional quasi-maximum likelihood). Dependent variable: Number of citations. The unit of observation is paper-year. Control group: papers published in the same journal-issue. Clustered std. errors at the paper level in parenthesis. *p<0.1; **p<0.05; ***p<0.01

The results from estimating equation 1 can be seen in table 3. Paper and year fixed-effects are gradually introduced across columns (1)-(4) and our coefficient of interest β is similar in all specifications[6]. As expected, the coefficient for the affiliation is not significant, hinting that there was no selection into treatment, thus increasing the confidence in the estimates. Once the age dummies are introduced in column (5) the coefficient shrinks, but it is still negative and significant. Note that the coefficients in these regressions have to be transformed to recover a percentage change following $\beta^{\%} = exp(\beta) - 1$, since I am using a Poisson distribution for estimation. For the preferred baseline specification (column 5) this translates into a drop of 6.42% in citations for those papers with at least one author based in Russia after the start of the war. Given the close similarity of the coefficients with their transformed percentage change, one

[6]The fall in observations when using paper fixed effects comes from the fact that the model drops units (papers) that receive no citations at all in the whole period of interest.

can interpret the rest of the coefficients found in the table and the rest of the paper as a very good approximation to a percentage change.

There seems indeed to be a drop in citation beginning in 2022 for Russia-based authors, with a size similar to that found in previous literature of academic penalties as a response to misdoing. However, this effect size is a lower bound estimate, since it reflects the drop for papers with at least one author. Table 4 shows some extensions of this definition of treatment.

Table 4: Heterogeneity results

	cites					
	(1)	(2)	(3)	(4)	(5)	(6)
after × RU	-0.0622**	-0.0182	-0.1157***	-0.0585	-0.0749**	-0.0507
	(0.0291)	(0.0411)	(0.0323)	(0.0438)	(0.0338)	(0.0445)
year f.e.	✓	✓	✓	✓	✓	✓
paper f.e.	✓	✓	✓	✓	✓	✓
age dummies	✓	✓	✓	✓	✓	✓
Treatment	> 0	> 0	half	half	first	first
Journals	all	top 10%	all	top 10%	all	top 10%
Observations	107,294	27,627	107,294	27,627	107,294	27,627
Squared Correlation	0.89769	0.90474	0.89780	0.90478	0.89772	0.90476
Pseudo R^2	0.70399	0.73964	0.70401	0.73965	0.70399	0.73965
BIC	566,954.4	166,191.1	566,929.1	166,186.4	566,958.6	166,187.6

Notes: GLM Poisson model (conditional quasi-maximum likelihood). Dependent variable: Number of citations. The unit of observation is paper-year. Control group: papers published in the same journal-issue. Clustered std. errors at the paper level in parenthesis. *p<0.1; **p<0.05; ***p<0.01

Column (1) is the preferred specification of previous table 3 for reference. Column (3) redefines treated papers to be those that have at least 50% of their authors affiliated to a Russian institution. As expected, the coefficient is higher, reinforcing the idea that the citation drop is indeed affiliation-driven. In column (5) I focus on treated papers defined as those where the first author is Russian-based, regardless of the percentage of the total number of authors they represent. The coefficient is not statistically significant from the one in column (1), thus advocating against visibility as one of the reasons behind the results.

I repeat the same exercise by looking only at better-published papers, defined as those published in journals within the top 10% in the impact factor distribution. Results for this sub-sample exercise are found in columns (2), (4) and (6), where the treated groups are defined, respectively, as those papers with at least one Russian-based author, at least half of them, or at least the first author. None of these coefficients seem to be statistically significant from zero, although they share the negative sign of the other estimations. This suggests that better quality research (understood as better published papers) seems to be more robust to external shocks.

3.1 Lead-and-lags estimator

Additionally, to fully capture the dynamics of the effect and to test for parallel trends, I run a leads and lags estimator, more commonly known as event study:

$$\mathbb{E}(cites_{it}) = \exp(\sum_{y} \beta_y \times RU_i \times \mathbb{1}(t = y) + \mho(age_{it}) + \delta_i + \delta_t + \epsilon_{it}) \tag{2}$$

To further test whether the parallel trends assumption holds, I run a cluster-robust Wald statistic on $H_0 : \beta_y = 0$ for $y = 2016, ..., 2020$, being unable to reject the null.

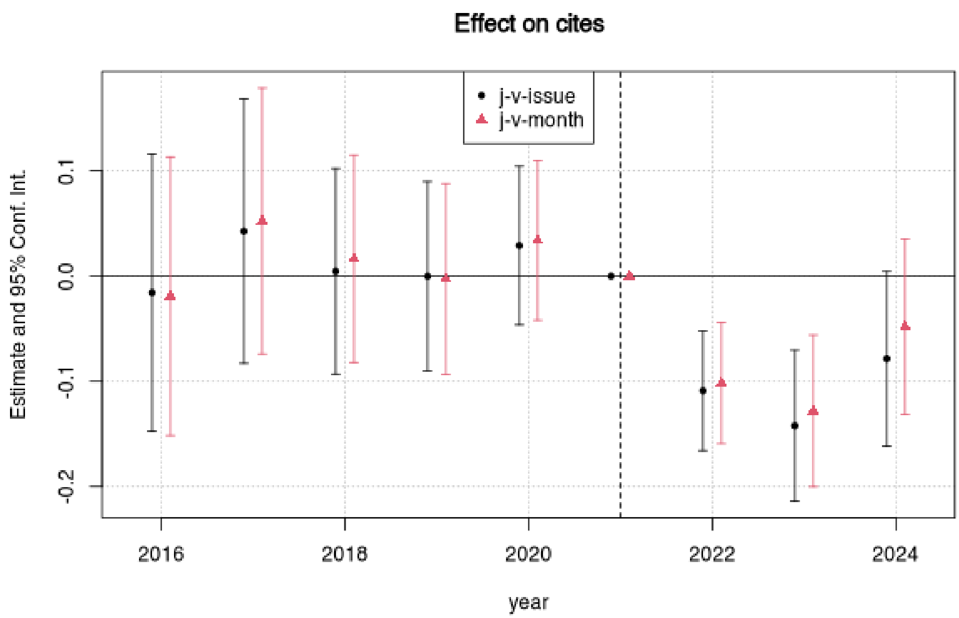


Figure 1: Leads-lags estimator: different control groups

Note: Leads-lags estimation results based on equation (2), using GLM Poisson model (conditional quasi-maximum likelihood). The unit of observation is paper-year. Control group: papers published in the same journal-issue or same journal-month. Standard errors clustered at the paper level. Reference year: 2021. 95% confidence intervals plotted around the point estimates.

The results of the leads-lags estimator can be found in figure 1. I show both results using the two alternative control groups, the one using journal-volume-issue (j-v-issue) and the one defined by the journal-volume-month (j-v-month). Parallel trends seem to hold across all specifications. Along with the previous discussion, this means that the parallel trends assumption holds visually, statistically, and conceptually.

The leads-lags results are useful to understand the dynamics of the drop. Citations seem to drop quite noticeably already in 2022 to around 10%, continue to drop in 2023, and reach the lowest point in comparison with the control group at around 13%. This drop is short-lived. Already in 2024, citation patterns of papers published by Russian-affiliated authors before 2022 recover to a level similar to that of the other papers published in the same journal issue. This fast recovery contrasts with the stark drop found in the first two years, but it can be related to previous findings in the literature. In their study of retractions, Azoulay et al. (2017) show that the authors' previous works suffer a drop of around 10% in the amount of citations after a retraction, and that the incidence of this effect depends greatly on whether the retraction was due to fraud or because of some honest mistake. In the case of the second, they find that the cost is much lower for those authors. The observed citation drop seems to follow a similar pattern to that of articles retracted because of honest mistakes.

Using this parallelism, it is possible to speculate on the motives behind the result. The penalisation that the Russian academia suffered looks like a reaction to the shock that the start of the war meant for most not closely related to the developments of the conflict. At the same time, the progressive recovery to pre-war levels can be connected to the realisation of the fact that individual researchers have no direct relationship with the conflict, and thus, as in the honest mistake case, their penalisation fades away. In sections 4 and 5, results suggest that this might be a plausible story but that it does not fully account for the drop.

The fact that a drop can be observed so early after the start of the conflict might be counter-intuitive, since the publication cycle is long (especially in the field of economics). However, citation takes place only at the end of this cycle, so there are two possible ways through which they might be affected: Under the assumption that some paper, authored by a Russian-affiliated author, is relevant for the work of some researcher, she may not cite this paper because of personal convictions (i.e. will to boycott Russian academia) or because she is not able to publish her research where she was citing this paper. Figure 2 serves as an illustration of this:

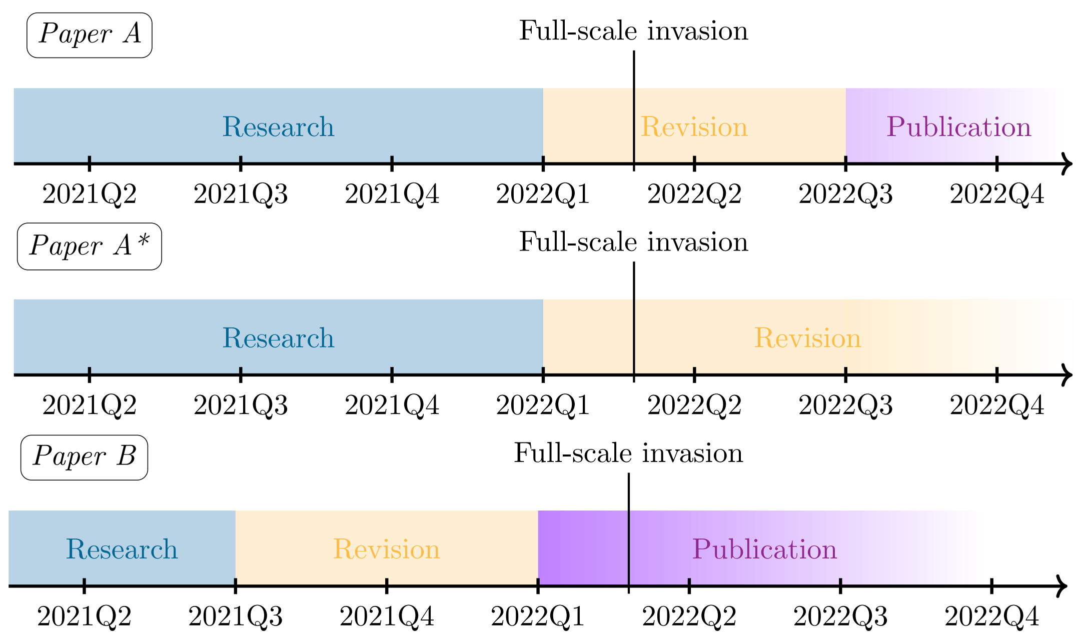


Figure 2: Timeline examples

All three papers in the figure represent cases with papers that consider citing some paper R authored by a couple of Russian-based authors. The timeline for Paper A represents the publication timing of a paper whose authors finished the research phase in late 2021 and submitted the work before the war started. After a (quite-short) revision period, their paper (luckily) was accepted and published in mid-2022. If the authors decided to take action boycotting the Russian academia, they might have removed their citation from the last version of the paper before sending the final version to the editor, thus affecting already in 2022 the amount of citations that paper R has. This contrasts with the timeline of paper B', where the authors have no more opportunity to adapt if they wanted to. Alternatively, the exact same paper A could be authored by Russian-based authors. If this were the case, after the start of the war, the authors might have suffered a productivity drop and delayed their response time, or they could have gotten a rejection if the journal to which they sent the paper decided to boycott Russian academia, as seen with paper $A*$. If this were the case, the citation that paper R would have received from paper $A*$ in Q3 2022 would have been delayed by months or would never have taken place.

4 The origin of citations

Characterising the drop in citations by the origin of the citing paper aids in further understanding the mechanisms behind the drop. Using the data on the universe of papers citing the papers that are included in both my treatment and control groups, I recalculate the amount of citations that each paper received from each geographical area by counting the publications citing that paper authored by researchers located in that area. Given the sparsity of the data at this level of granularity, calculating this quantity at the country-level, even if ideal, is not feasible. Thus, I define geographical areas following the classification by the United Nations Statistics Division[7], which divides the world into 24 different regions. I separate Russia from Eastern Europe to account for country self-citations separately. I also make sure that citations from papers authored by at least one researcher based in Russia are only counted as a Russian citation and not as a citation from any other region.

This procedure will, by construction, create several citation counts whose sum will exceed the original citation counts for each paper. This approach is followed because the objective of this exercise is to quantify separately whether there was any drop specific to each geographical citation flow.

Calculating the citations per geographical area creates new series of citations per paper that reflect the flows from the academia in that geographical area to that paper, thus allowing for the estimation of an ATT for each geographical group. To this end, I use equation 1 from section 3, redefining $cites_{it}$ as $cites^{n}_{it}$, where n is the geographical area from which the citations come from.

In figure A.6 I present the results for this estimation excluding from the map those regions with a non-significant coefficient at the 90% level. The full results can be found

[7] Standard Country or Area Codes for Statistical Use (M49): https://unstats.un.org/unsd/methodology/m49/

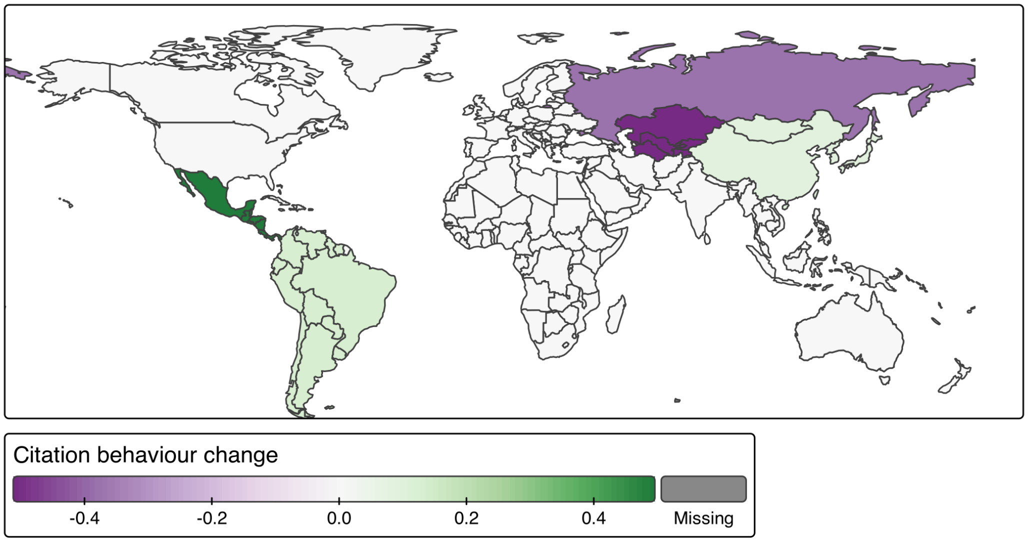


Figure 3: Citation change per geographical area

Note: Dependent variable: Number of citations coming from each geographical area. Estimation results based on equation (1), using GLM Poisson model (conditional quasi-maximum likelihood). The unit of observation is paper-year. Control group: papers published in the same journal-issue. Only significant estimates at the 90% confidence level coloured. Tables A.1, A.2, A.3, A.4 and A.5 in the appendix contain the full estimation results.

in the appendix in table **??**. It can be seen that there are two counteracting forces, with some groups of countries increasing their flow of citations towards papers authored by Russian-based researchers, while others reducing it dramatically, most notably Russia itself. However, most of the regions do not seem to respond strongly enough to find statistically significant results.

The citation drops observed in Russia might be related to a potential productivity drop of the Russian academia or/and to a negative reaction of Russian-based researchers towards the previous published works by their peers. A drop in the productivity of authors based in Russia in terms of their ability to publish new works is likely part of the story behind the drop. Conflict might have affected their mental well-being, government spending might have shifted away from their project, and, arguably more importantly, their research networks might have suffered. This will be checked in section 5.

An additional explanation for the drop comes from the possibility that authors are trying to send a signal to the rest of the academic community that they disagree with the war and stop citing their own peers, replicating the findings of Hussinger and Pellens (2019) where researchers try to distance themselves from the misbehaving authors. However, this is a rather unrealistic story, which would most likely only be applicable to those academics who left the Russian Federation after the start of the invasion.

Similar reasoning can be followed for the results for the Central Asian countries. Their drop in citations is likely closely related to that of the Russian one, given the close ties of the academic communities of these countries with the Russian academia. If the collaboration dependence is also very strong, a productivity drop in Russia might affect that of the Central Asian countries, since new projects arising from collaborations with the Russian academia might not prosper and get subsequently published.

The positive changes in citation patterns observed in Latin America and Eastern Asia can have two explanations in common. Firstly, an increase in collaboration from Russia-based authors will improve the visibility of their works in the foreign institutions where their collaborators are affiliated, thus fostering citations. Similarly, to improve the strength of these collaborations, it is possible that foreign institutions over-cite their Russian counterparts, using citation as a networking tool (Cronin and Shaw (2002)).

Secondly, geopolitical sympathies might motivate the change in citation flows. As the 2024 Pew Research Center report (Center (2024)) notes, Eastern Asia and some Latin America countries are among those who have a more positive view of Russia. Given that citation motives can have a high social component (Moravcsik and Murugesan (1975), Cronin and Shaw (2002)), these positive views might translate into a positive bias of their citation flows towards Russian-based researchers.

Finally, another factor that positively affects citation flows is the immigration of authors from Russia. Those incoming researchers will give greater visibility to previous work authored by them and their former peers among their new colleagues, potentially leading them to cite them. Similarly, the potential productivity increase for emigrants through a higher visibility in the Western academic world and a new research environment might lead them to publish more often and cite their former works or those of their former peers. Unlike the first option, which can take place quite fast after the migration takes place, this second channel could only be observed at a later stage, when researchers are more established in their new institutions. However, this positive effect through emigration is limited by the amount of leavers, which are a small percentage of the total academic population in Russia.

Even if the coefficients are not significant at standard levels, it is interesting to analyse the estimated direction of the effect for countries in Europe and North America, given that they are the ones with a more negative view of Russia and those whose governments are actively taking measures against the Russian government.

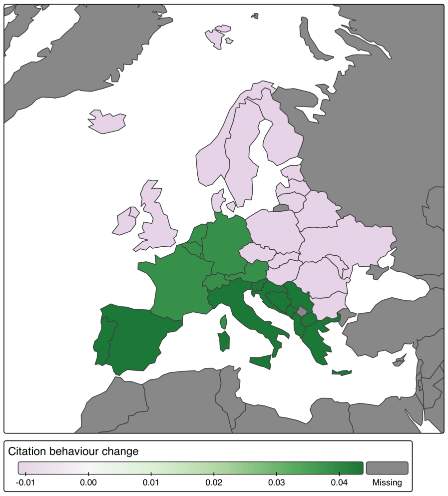


Figure 4: Citation change in Europe

Figure 5: Citation change in America

Note: Dependent variable: Number of citations coming from each geographical area. The unit of observation is paper-year. Control group: papers published in the same journal-issue. Left panel's colour scale adapted to the countries' subset. Tables A.4 and A.3in the appendix contain the full estimation results.

In figure 4 I present the results for Europe. It is noticeable how there seems to be a clear divide between North and Eastern Europe and South and Western Europe. Common patterns arise among the two groups: South and Western countries are those where Russia is viewed more favourable and who do not share a physical border with them. In addition, some of the Northern and Eastern countries have either been invaded at some point by Russia or have been under their political influence. The estimated coefficients show a positive reaction from Southern and Western countries and a negative reaction (but close to zero) from the rest, although none of them are statistically significant at conventional levels. The lack of significance might be a consequence of opposite signs in the direction of reaction between the different countries within each group. Comparing the results of Eastern and Northern Europe with those of North America (figure 5), in the second group the coefficient is very close to zero, while in the first group this coefficient is slightly negative. Again, this coefficient is also not significant at standard levels.

To further characterise the drop, I will focus on citations coming from Russia, by estimating again equation (1). I redefine $cites_{it}^{n}$ as either domestic or foreign citations. Domestic citations are those coming from papers with at least one Russian-affiliated author, and the rest are considered foreign citations. Among domestic citations, I differentiate between citations from papers authored by researchers who left Russia after the start of the war (domestic leavers) and those who did not leave the country (domestic stayers). Results of this estimation can be found in table 5.

Column (1) can be understood as the ATT for citations from any country. This is different from a weighted average of the coefficients presented in figures A.6, 4 and 5, but its lack of significance reflect the opposite behaviours studied above.

Table 5: Citations origin

	Foreign All (1)	All (2)	Domestic Stayers (3)	Leavers (4)
after × RU	-0.0234	-0.5368***	-0.6357***	-0.5419***
	(0.0305)	(0.0668)	(0.0851)	(0.1148)
paper fixed effects	✓	✓	✓	✓
year fixed effects	✓	✓	✓	✓
age controls	✓	✓	✓	✓
Observations	109,463	21,576	12,967	10,472
Squared Correlation	0.91322	0.39022	0.42100	0.32140
Pseudo R^2	0.71308	0.23188	0.20575	0.19691
BIC	571,743.5	50,018.4	34,056.3	22,787.2

Notes: GLM Poisson model (conditional quasi-maximum likelihood). Dependent variable: Number of citations. The unit of observation is paper-year. Control group: papers published in the same journal-issue. Clustered std. errors at the paper level in parenthesis. *p<0.1; **p<0.05; ***p<0.01

Column (2) shows that the biggest drop comes from domestic citations, as seen in figure A.6. As discussed above, there can be two (complimentary) reasons for this drop: A lower productivity or a signalling device. To test for the existence of the second, I further divide the domestic citations into those coming from domestic stayers and domestic leavers. If the main driver of the drop would be signalling, the coefficient for leavers should be bigger in absolute terms than that of stayers, since both have potentially experienced a similar productivity drop, but the second have more credible incentives to signal their disagreement. Columns (3) and (4) show that domestic citations coming from leavers and stayers are similar and that there is no statistically significant difference between the coefficients. Even more so, the coefficient for leavers is smaller than the one for stayers in absolute terms, hinting against signalling as a channel driving the results.

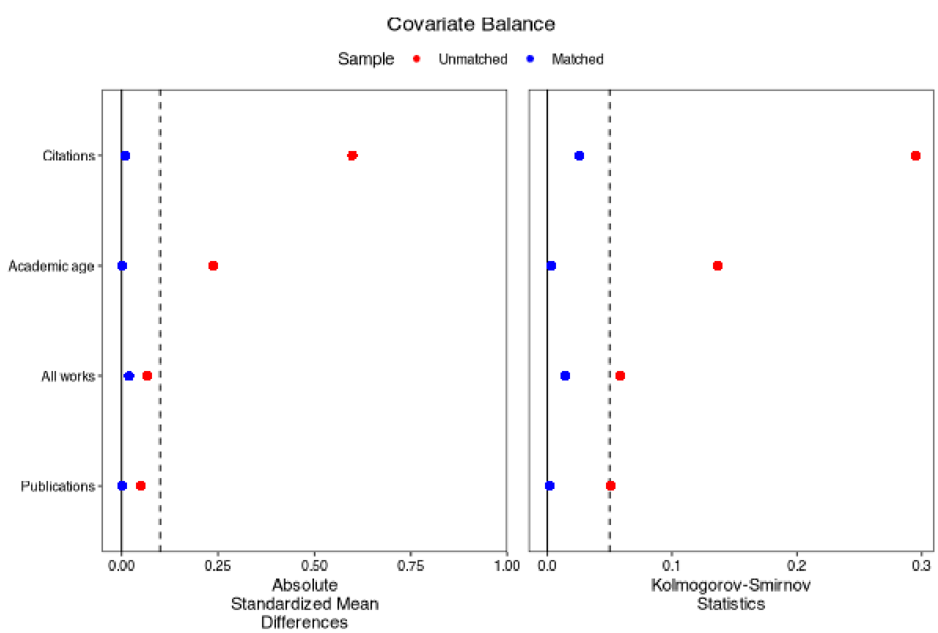
5 The production cost

The analysis at the author level unveils whether authors based in Russia suffered any backlash in their capacity to produce knowledge after the start of the war. In order to do this, a preliminary step is required to create a suitable control group.

Using the author-level data described in subsection 2.2, I define the treated observations as authors based in Russia after the start of the war in 2022. My goal is to run a DiD study, so I need to find a suitable control group which would resemble as good as possible at the time of treatment how the outcome of the treated authors would have evolved over time, had there been no war. Given that my outcome of interest is the number of works per author per year, I will look for non-Russia-based authors that have a similar production evolution in the recent years. To do this, I use a nearest-neighbour matching algorithm where I match treated authors with other authors with the same academic age and that have as close as possible current and past values of citation and production variables (meaning number of works in general and publications and working papers in particular). I use the `MatchIt` R package (Ho et al. (2011)), setting up the algorithm with replacement and using the Mahalanobis distance. To avoid noise coming from using only the year before the war, I match on the last 2-year average for the total number of works, the amount of publications in peer-review journals, and the citations for each author. Additionally, I make sure that only authors not related to Russia and with the same academic age as those affiliated with a Russian institution are compared. In my preferred specification, I match with a ratio of 2 control units per treated observation. Alternatively, I run the same exercise without replacement or using more or less control units and results are similar, but do not improve the balance compared to the preferred one in terms of mean differences or variance ratios.

In figure 6 it can be seen that the sample balance has improved substantially after the matching and that both the standardised mean differences and the KS-statistic fall within the acceptable range.

Figure 6: Matching balance



Notes: Standardized mean differences and Kolmogorov-Smirnov statistics between treated and control groups. Dotted lines indicate generally acceptable levels. Matching done for the year 2021 at the author level, using nearest-neighbour method with replacement. Treatment defined as being a Russian affiliated author after 2021. Control groups is composed of two comparable non Russian-affiliated researchers for each treated observation. Citations, publication and all works (publications, working papers and other outputs) data matched using the last two-years mean.

Using the results of this matching procedure, I identify the authors belonging to the control group, where all authors found a match, and 1.8% of the controls are used for more than one treated unit. In table 6 I show the balance statistics for both groups.

Table 6: Matching balance

	Means (T)	Means (C)	SMD	VR	eCDF mean	eCDF max	SPD
Raw data							
All works	4.7650	5.2230	-0.0676	0.0175	0.0029	0.0581	
Publications	3.2251	3.0080	0.0495	0.7643	0.0030	0.0509	
Citations	61.2129	223.8944	-0.5978	0.0889	0.0397	0.2950	
First paper	2002.2733	1998.5573	0.2371	0.8793	0.0521	0.1363	
Balanced data							
All works	4.7650	4.6509	0.0168	1.0431	0.0009	0.0150	0.0597
Publications	3.2251	3.2226	0.0006	1.0057	0.0001	0.0012	0.0040
Citations	61.2129	61.6912	-0.0018	1.0585	0.0006	0.0269	0.0272
First paper	2002.2733	2002.2800	-0.0004	1.0012	0.0007	0.0024	0.0061

Notes: Matching for 2021 using 2-year averages of the variables displayed, with a ratio of 2-to-1. Sample sizes: Treated – 1266, Controls – 2487 (ESS – 2441.36). Abbreviations: T – Treated group, C – Control group, SMD – Standardized Mean Difference, VR – Variance Ratio, SPD – Standardized Pair Distance

With the newly constructed control group, I run a similar DiD analysis as the one at the paper-level:

$$\mathbb{E}(works_{at}) = \exp(\beta \times treated_{at} + \delta_a + \delta_t + \epsilon_{at}) \tag{3}$$

where $treated_{at}$ takes the value one if the author is affiliated to a Russian institution in year t, thus taking into account exit from treatment. As stated in de Chaisemartin and D'Haultfœuille (2024) this could be problematic if one argues that treatment effects do not disappear once treatment is over (in this case, when the author leaves Russia), in other words, that there is memory in the treatment. However, given that the effect is expected to come through the affiliation the author exhibits rather than by the name (which are the two attributes readers see about the authors), it seems reasonable to assume out this memory.

Another potential issue of this estimation lies in the possible violation of the stable unit treatment value assumption (SUTVA). This assumption requires that there were no spillovers between treatment and control groups. Given that space for articles in journals is limited, a potential barrier to publication for Russian-based authors (regardless of whether this barrier is caused by external -rejection- or internal -productivity drop- factors) might in turn increase the chances of authors in the control group to publish their research. If this were the case, my estimates would be positively biased. However, not having used the field of expertise in the matching algorithm implies that control and treated authors, having very similar academic careers and outputs, do not necessarily compete with each other for the same spot in a journal, thus reducing the risk of SUTVA being violated. At the same time, Zhang et al. (2024) find drops in the amount of publications after the start of the war by Russian-affiliated scientists of a magnitude similar to mine. I acknowledge that the risk of SUTVA violation exists, but given the factors presented, I believe it not to be of first-order concern.

Table 7: Author production

Dependent variable	Works (1)	Papers (2)	Non-paper (3)	English (4)	Papers shr (5)	Eng. shr (6)
after × RU	-0.1503***	-0.0991**	-0.1002	-0.1149***	0.0605***	0.0393*
	(0.0469)	(0.0417)	(0.0980)	(0.0421)	(0.0189)	(0.0212)
author f.e.	✓	✓	✓	✓	✓	✓
year f.e.	✓	✓	✓	✓	✓	✓
Observations	24,967	24,803	17,349	24,801	19,698	19,698
Squared Corr.	0.63192	0.61697	0.34469	0.59500	0.33616	0.36333
Pseudo R^2	0.48940	0.41211	0.38214	0.43393	0.21233	0.21546
BIC	144,993.2	131,765.8	72,007.1	142,371.3	67,119.1	69,563.2

Notes: Columns (1)-(4): GLM Poisson estimation, columns (5)-(6): OLS estimation. The unit of observation is author-year. Clustered standard errors at the author level in parenthesis. *p<0.1; **p<0.05; ***p<0.01

Table 7 shows the results of estimating equation 3. Column (1) shows that Russian-affiliated authors see a drop in the amount of works they produce, as could be expected from the results of section 4. To further characterise this, I redefine the dependent variable in equation 3 to count either only published peer-reviewed papers or other non-peer-reviewed academic works[8]. The results of this estimation are shown in columns (2) and (3). The estimations point towards a significant drop in the amount of published papers while there does not seem to be a significant decrease in the amount of other works. This talks against the idea of a productivity drop among Russian-affiliated authors, since they continue to produce academic knowledge despite the start of the war. Observing these results along with those from column (4), where only works written in English language are included as the dependent variable, there seems to be a barrier for Russian-affiliated authors in access to international journals. This is further supported by the results of looking only at English-language journals and comparing them with non-English ones[9], where the first still show a significantly negative coefficient while the second is not significantly different from zero (albeit positive).

Columns (5) and (6) look at the weight of peer-reviewed papers and works published in English over the total of works of each author, respectively. Results show that the drop in the amount of peer-reviewed publications is not explained by a shift away from research from treated authors, given that the coefficient for the share of publications is non-negative. Something similar happens with the coefficient for the share of works published in English, which does not point towards a will of drifting away from the international research sphere.

[8]This includes mainly working papers, but also books and databases. Results are similar when looking only at working papers specifically or when including all other works non-peer-reviewed.

[9]Results not displayed in the main body, to be found in the appendix

One can argue that failing to account for emigration might create a bias, given that leavers might be fundamentally different from stayers. Although this could be indeed a concern, in table A.6 of the appendix it can be seen that defining treatment as ever being affiliated to a Russian institution returns similar effects, meaning results are not driven by this.

In addition, there are two potential shortcomings of this method in its current state. First, the DiD standard errors do not reflect the uncertainty coming from the matching algorithm, so results should be taken with a bit of caution, since they are subject to potentially larger standard errors once estimated. Second, the matching was done at year 2021, so potentially post-Covid effects might still be present. Nevertheless, running the matching exercise in 2019 instead creates very similar results, so timing should not be a source of great concern.

5.1 Does emigrating help?

To further identify the mechanism, one can zoom in towards the emigration decision of academics. There are two opposite forces affecting the immediate outcomes of a researcher: if affiliation is indeed a barrier impeding authors from accessing internationally published journals, emigration from Russia might alleviate the drop observed in table 7. At the same time, migration is a costly process, so one can expect to find a productivity drop among leavers compared to stayers, at least in the first periods after emigration. A third force plays a positive role in the medium run, given that leavers will arrive at less isolated academic communities that will enhance their productivity.

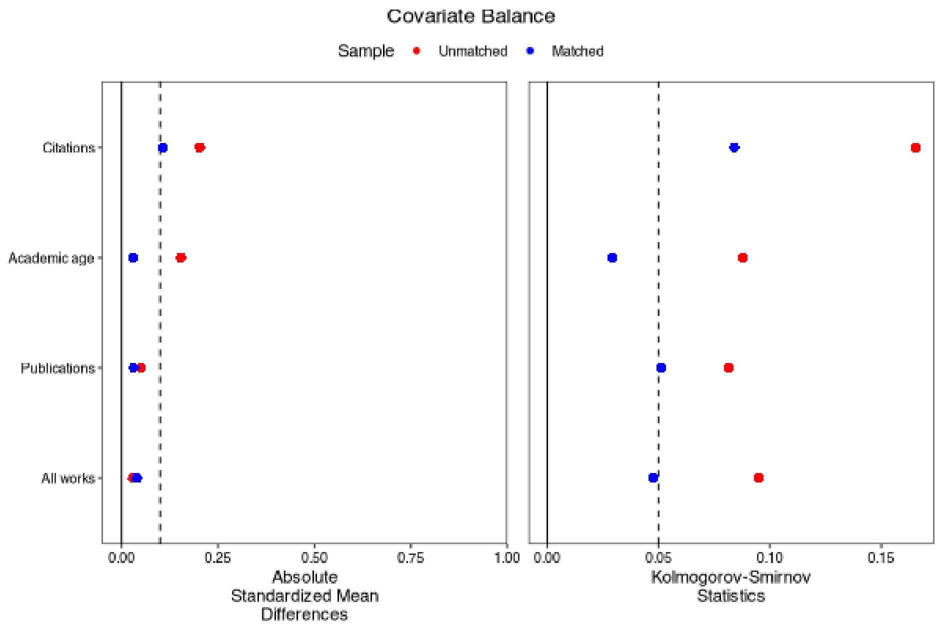
To study this, I run a set of exercises similar to those in table 7, but redefining the sample of interest to be only the treated units from the previous exercise, that is, researchers affiliated to a Russian institution before the start of the war. In this new framework, the new treated units are those who leave Russia and the control group are those comparable researchers who stay back in the country.The quality of the matching is lower (as seen in 7, given the small sample size and the fundamental differences between leavers and stayers, since the first will have better connexions abroad, which would also help their research.

With this new definition of treatment, the ATT is estimated taking into account the timing of entry into treatment (i.e. emigration). Following Sun and Abraham (2021), I calculate the cohort average treatment effect for the treated (CATT) as shown in equation 4, to then calculate the ATT as a linear combination of the CATTs for each relative time period, weighted by each cohort's relative share in the sample at that point in time. This estimation ensures that only never-treated observations enter the control group, avoiding the comparison of treated units with those not-yet treated.

$$\mathbb{E}(works_{at}) = \exp(\sum_{e}\sum_{l\neq -1}\gamma_{e,l}(\mathbb{1}\{E_i = e\} \times treated^l_{at}) + \delta_a + \delta_t + \epsilon_{at}) \tag{4}$$

E_i is a dummy variable taking value 1 if cohort e is treated. $treated^l_{it}$ are indicators taking value one at l periods from treatment. $\gamma_{e,l}$ captures the cohort-year specific

Figure 7: Matching balance for leavers vs. stayers



Notes: Standardized mean differences and Kolmogorov-Smirnov statistics between treated and control groups. Dotted lines indicate generally acceptable levels. Matching done for the year 2021 at the author level, using nearest-neighbour method with replacement. Treatment defined as researchers affiliated to Russia who emigrated after 2021. Control group formed by two comparable stayers for each treated observation. Citations, publication and all works (publications, working papers and other outputs) data matched using the last two-years mean.

effect, later aggregated to the CATT γ_e. As before, δ_a and δ_t are author and year fixed-effects.

Results of this estimation can be seen in table 8. The ATTs in the first row across all columns show that emigration has a very positive impact on researchers' academic outcomes. This is to be expected, and might be fundamentally reflect the strength of pre-war networks that these authors had, which allowed them to move in the first place.

It is also of interest to show the coefficients of the estimation by cohort, ie. the CATT. Early leavers, that is, those leaving right after the invasion, had time to establish themselves in their new institutions, having overcome the moving cost by the latest period in the data, 2024. Compared to their peers who never left Russia, they are more productive and able to publish more in international journals. For those researchers emigrating at a later point in time, coefficients are positive but statistically not significant, hinting towards the existence of some adaptation time and potentially a lower productivity while still in Russia.

Table 8: Leavers vs. stayers

	Works (1)	Papers (2)	Non-paper (3)	English (4)	Papers share (5)	English share (6)
ATT	0.4390***	0.2197*	0.9028***	0.3858***	-0.0638	0.0524
	(0.1664)	(0.1151)	(0.2905)	(0.1165)	(0.0777)	(0.0742)
leaving in 2022	0.3700**	0.3039*	1.617***	0.5950***	-0.0524	0.0875
	(0.1780)	(0.1724)	(0.5279)	(0.1975)	(0.0956)	(0.0815)
leaving in 2023	0.4233	0.2019	0.3676	0.2484	0.1105	0.2019*
	(0.3394)	(0.1732)	(0.3756)	(0.1569)	(0.1174)	(0.1156)
leaving in 2024	0.7743***	-0.0593	0.4235	0.0196	-0.5574***	-0.4580**
	(0.1726)	(0.2349)	(0.4057)	(0.2077)	(0.2136)	(0.2255)
author f.e.	✓	✓	✓	✓	✓	✓
year f.e.	✓	✓	✓	✓	✓	✓
Observations	2,556	2,542	1,916	2,542	2,108	2,108
Squared Correlation	0.60576	0.81340	0.51527	0.73337	0.37116	0.39096
Pseudo R^2	0.44559	0.46192	0.41767	0.47347	0.25659	0.27648
BIC	14,243.3	12,183.1	7,272.8	13,464.7	5,925.1	5,827.4

Notes: Columns (1)-(4): GLM Poisson estimation, columns (5)-(6): OLS estimation. The unit of observation is author-year. Clustered standard errors at the author level in parenthesis. *p<0.1; **p<0.05; ***p<0.01

6 Conclusion

This paper provides causal evidence on the academic cost of international conflict, focusing on the Russian academia in the field of economics after the 2022 full-scale invasion of Ukraine. Using granular data at both the paper and author levels, I quantify the costs in terms of exposure through citations and in terms of productivity.

Papers authored by Russian-affiliated researchers experienced a significant decline in citations of around 6% shortly after the onset of the war. This penalty is comparable in magnitude to those observed following scientific retractions or personal misbehaviour. While the channels of the penalties following these two events are very different, it is interesting to see that the size of the effect in both cases is similar, hinting towards a close resemblance of perceived misdoing, whether this is at the individual or at the collective level, and whether the affected researcher is at fault or unrelated to the source.

Furthermore, the analysis of citation flows by region of citation origin reveals that the sharpest decline in citations originates from domestic sources, consistent with the idea that reduced publication opportunities within Russia amplify the citation loss. Conversely, foreign citations show heterogeneous responses, with some regions even increasing their citation rates towards papers authored by researchers based in Russian institutions, possibly reflecting intensified collaborations or geopolitical alignments.

When looking at productivity, Russian-based authors faced a marked reduction in their ability to publish in international journals, particularly those written in English. By Comparing these estimations with those for other works production such as working papers of books, results point towards barriers to access the aforementioned journals rather than a fall in productivity. Emigration emerges as a mitigating factor: researchers who relocate abroad recover visibility and publication capacity, albeit with some lag, underscoring the role of mobility in buffering against isolation.

This paper is the first to look causally and at a granular level at this issue, and the results bring several takeaways. Firstly, if the academia of a country tends to be too insulated, not only will it do worse internationally (Ladle et al. (2012), Glänzel and Schubert (2005)), but also it is more exposed to reputational shocks not related to it.

They also hide potential second-round consequences that are unobservable in the current time frame. Citations are a common measure of a researcher's reputation, so a (sudden) drop in citations will bring about a fall in her reputation, which in turn will affect the future career of this researcher, in terms of the likelihood of future work to be well published, collaborations, visibility, grants, tenure/promotion, etc. (Petersen et al. (2014)). A similar argument can be made for the hiatus in publication for these researchers. Future work at a further point in time will help unveiling the full academic cost of international conflict, which also includes these second round effects.

While the evidence presented is related to a specific conflict, the mechanisms uncovered (affiliation-based barriers, reputational spillovers, and the importance of international integration) are likely relevant in other geopolitical crises. Interesting future avenues of research include the long-run consequences of these disruptions on careers, collaboration networks, and knowledge diffusion, as the short-term penalties documented here may translate into persistent gaps in global scientific exchange.

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A Robustness

A.1 Paper-level analysis

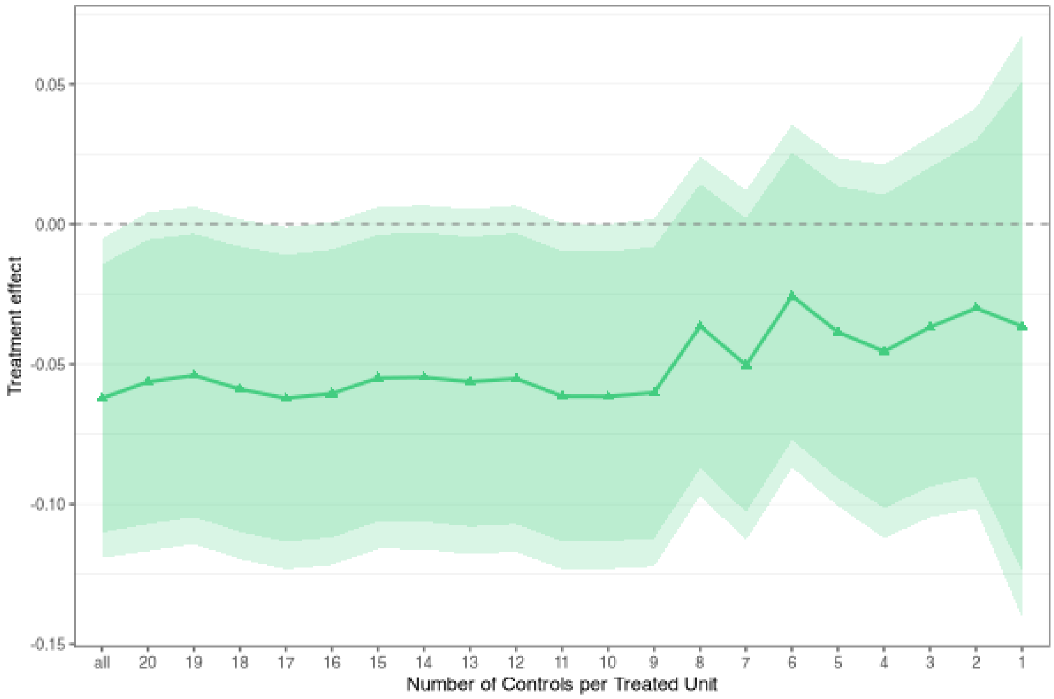

Figure A.1: Treatment effect by control group size (# papers)

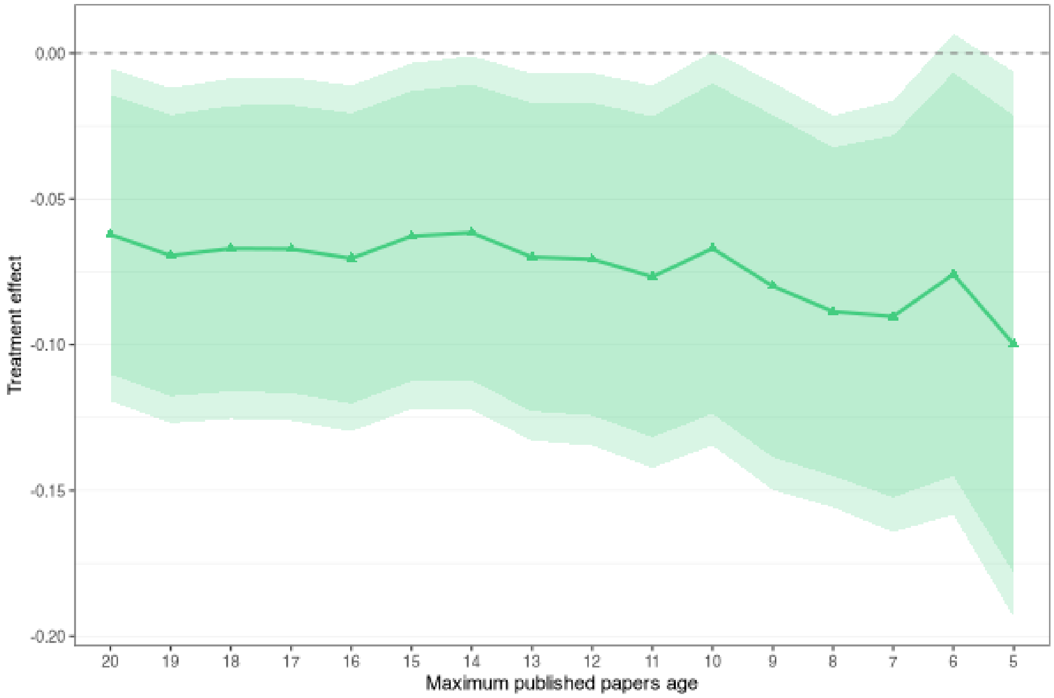

Figure A.2: Treatment effect by paper age horizon

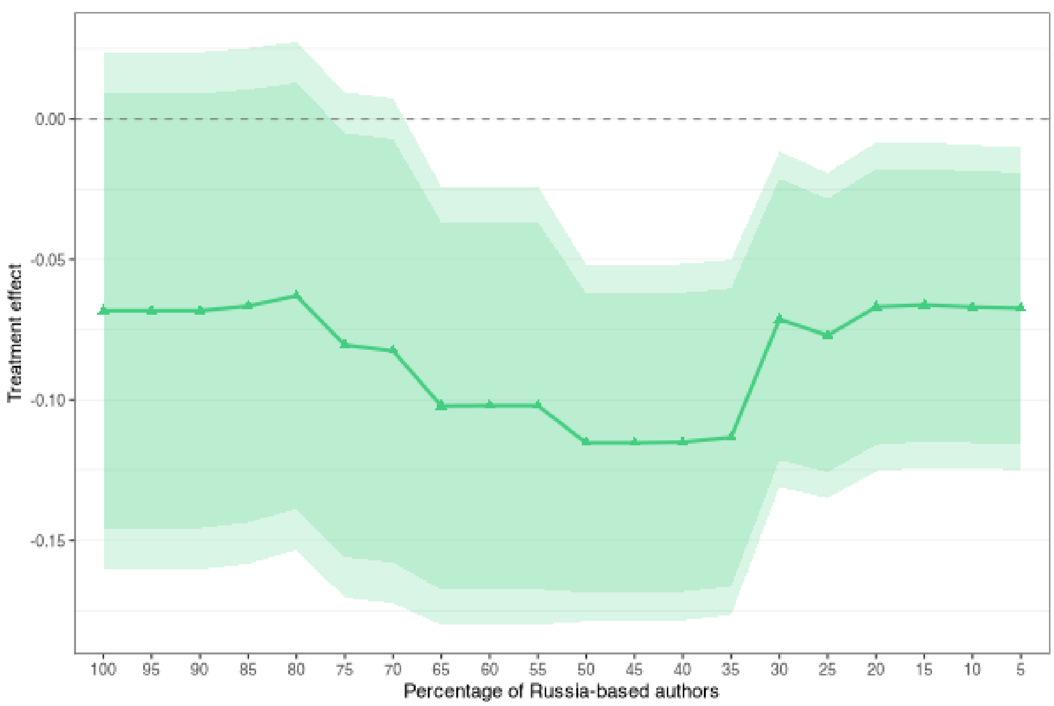

Figure A.3: Treatment effect by share of Russian-based authors

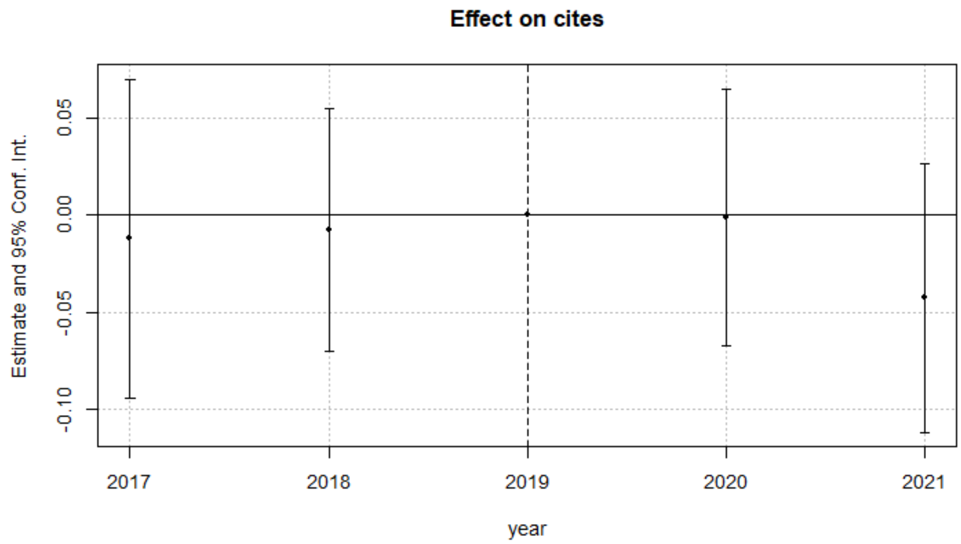

Figure A.4: Placebo exercise

Table A.1: Citation drop by origin of citations: Asia

	Central (1)	Eastern (2)	South-Eastern (3)	Southern (4)	Western (5)
after × RU	-0.7196***	0.0797*	0.0045	-0.0561	-0.0177
	(0.2413)	(0.0467)	(0.0854)	(0.0754)	(0.0775)
Observations	6,587	61,527	41,561	39,802	40,698
Squared Correlation	0.27939	0.84441	0.71060	0.79223	0.79475
Pseudo R^2	0.14580	0.57679	0.39244	0.46552	0.44771
BIC	17,364.9	280,295.4	151,983.6	149,210.7	147,871.7
paper fixed effects	✓	✓	✓	✓	✓
year fixed effects	✓	✓	✓	✓	✓

Notes: GLM Poisson model (conditional quasi-maximum likelihood). Dependent variable: Number of citations coming from each geographical area. The unit of observation is paper-year. Control group: papers published in the same journal-issue. Clustered std. errors at the paper level in parentheses. *p<0.1; **p<0.05; ***p<0.01

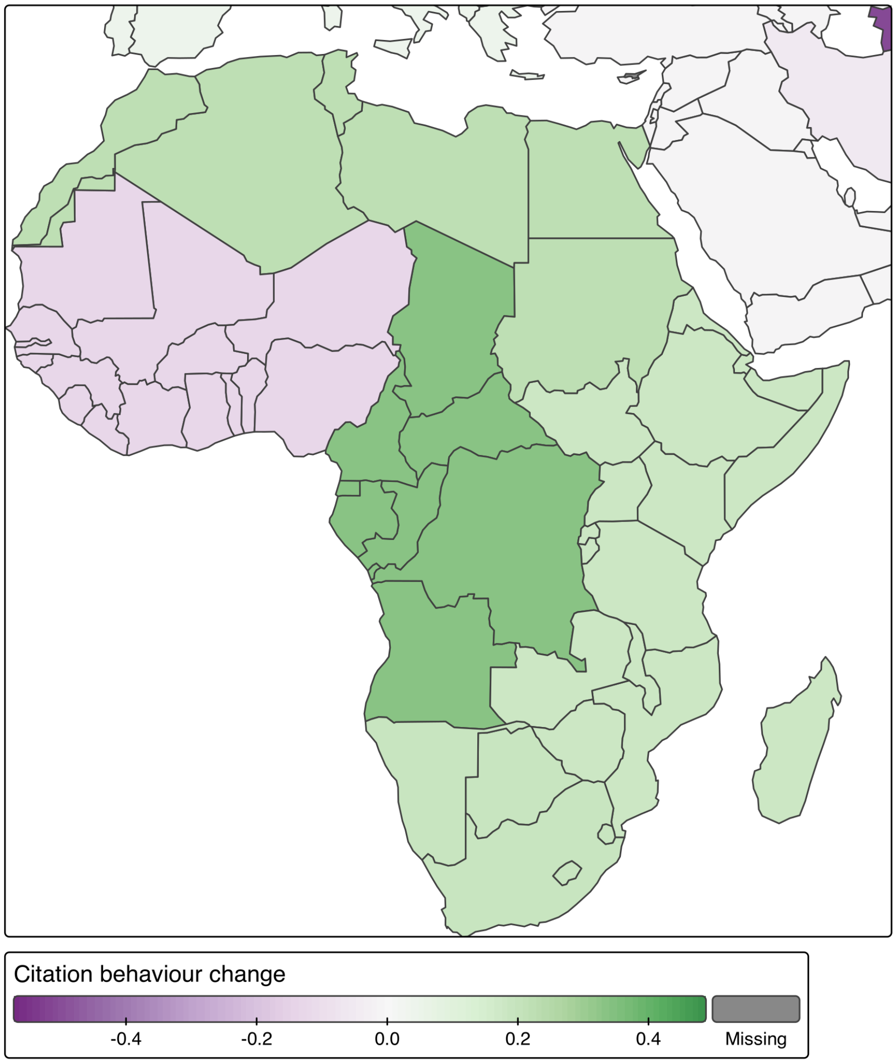

Figure A.5: Citation change per geographical area: Africa

Note: Dependent variable: Number of citations coming from each geographical area. Estimation results based on equation (1), using GLM Poisson model (conditional quasi-maximum likelihood). The unit of observation is paper-year. Control group: papers published in the same journal-issue. Only significant estimates at the 90% confidence level coloured. Table **??** in the appendix contains the full estimation results.

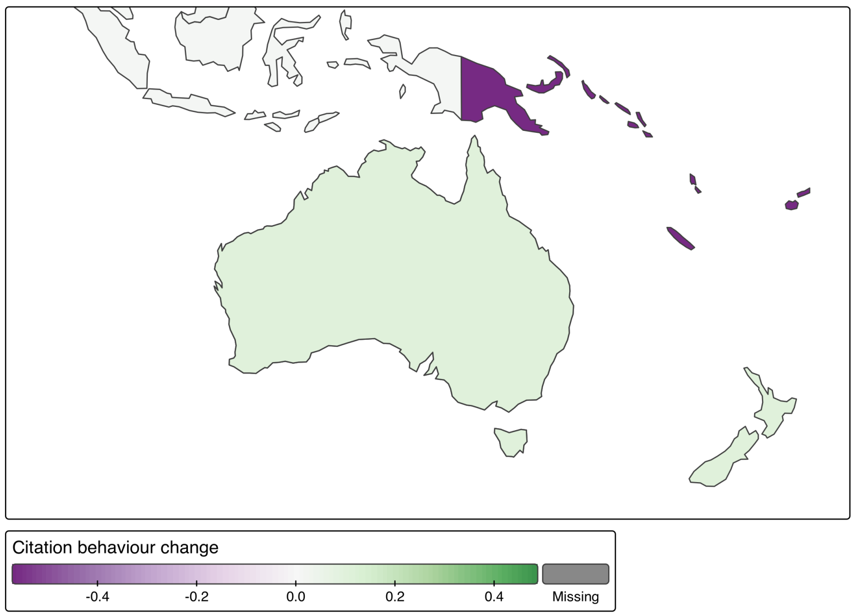

Figure A.6: Citation change per geographical area: Oceania

Note: Dependent variable: Number of citations coming from each geographical area. Estimation results based on equation (1), using GLM Poisson model (conditional quasi-maximum likelihood). The unit of observation is paper-year. Control group: papers published in the same journal-issue. Only significant estimates at the 90% confidence level coloured. Table **??** in the appendix contains the full estimation results.

Table A.2: Citation drop by origin of citations: Africa

	Eastern (1)	Middle (2)	Northern (3)	Southern (4)	Western (5)
after × RU	0.1600	0.2896	0.1999	0.1742	-0.1380
	(0.1861)	(0.5998)	(0.1873)	(0.1859)	(0.1530)
Observations	12,250	4,107	15,687	16,865	17,031
Squared Correlation	0.49334	0.60488	0.57544	0.59613	0.59254
Pseudo R^2	0.24183	0.39929	0.27388	0.28232	0.31747
BIC	34,848.4	11,481.1	47,121.4	50,243.0	53,522.5
paper fixed effects	✓	✓	✓	✓	✓
year fixed effects	✓	✓	✓	✓	✓

Notes: GLM Poisson model (conditional quasi-maximum likelihood). Dependent variable: Number of citations coming from each geographical area. The unit of observation is paper-year. Control group: papers published in the same journal-issue. Clustered std. errors at the paper level in parentheses. *p<0.1; **p<0.05; ***p<0.01

Table A.3: Citation drop by origin of citations: America

	Caribbean (1)	Central (2)	Northern (3)	South (4)
after × RU	-0.0492	0.4021**	-0.0061	0.1182
	(0.5578)	(0.1594)	(0.0426)	(0.0796)
Observations	2,347	12,880	64,227	34,607
Squared Correlation	0.17314	0.27686	0.86434	0.64966
Pseudo R^2	0.09803	0.14129	0.57300	0.28389
BIC	5,322.8	34,839.9	298,405.6	115,675.2
paper fixed effects	✓	✓	✓	✓
year fixed effects	✓	✓	✓	✓

Notes: GLM Poisson model (conditional quasi-maximum likelihood). Dependent variable: Number of citations coming from each geographical area. The unit of observation is paper-year. Control group: papers published in the same journal-issue. Clustered std. errors at the paper level in parentheses. *p<0.1; **p<0.05; ***p<0.01

Table A.4: Citation drop by origin of citations: Europe

	Eastern (1)	Northern (2)	Southern (3)	Western (4)	Russia (5)
after × RU	-0.0112	-0.0110	0.0426	0.0378	-0.4808***
	(0.0745)	(0.0540)	(0.0501)	(0.0473)	(0.0764)
Observations	36,249	59,538	54,769	54,083	21,122
Squared Correlation	0.58102	0.75290	0.75355	0.71189	0.42378
Pseudo R^2	0.27077	0.40612	0.37200	0.40622	0.23988
BIC	123,514.7	250,001.0	217,538.9	218,781.1	66,625.8
paper fixed effects	✓	✓	✓	✓	✓
year fixed effects	✓	✓	✓	✓	✓

Notes: GLM Poisson model (conditional quasi-maximum likelihood). Dependent variable: Number of citations coming from each geographical area. The unit of observation is paper-year. Control group: papers published in the same journal-issue. Clustered std. errors at the paper level in parentheses. *p<0.1; **p<0.05; ***p<0.01

Table A.5: Citation drop by origin of citations: Oceania

	Australia and New Zealand (1)	Melanesia (2)
after × RU	0.0983	-0.8615
	(0.0763)	(0.9911)
Observations	40,245	1,024
Squared Correlation	0.58457	0.42434
Pseudo R^2	0.28975	0.17677
BIC	139,801.4	2,445.0
paper fixed effects	✓	✓
year fixed effects	✓	✓

Notes: GLM Poisson model (conditional quasi-maximum likelihood). Dependent variable: Number of citations coming from each geographical area. The unit of observation is paper-year. Control group: papers published in the same journal-issue. Clustered std. errors at the paper level in parentheses. *p<0.1; **p<0.05; ***p<0.01

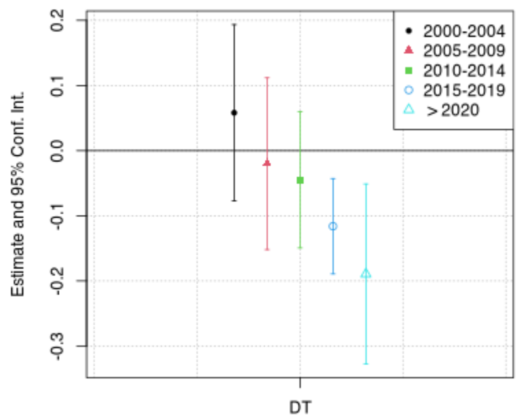

Figure A.7: Year of publication

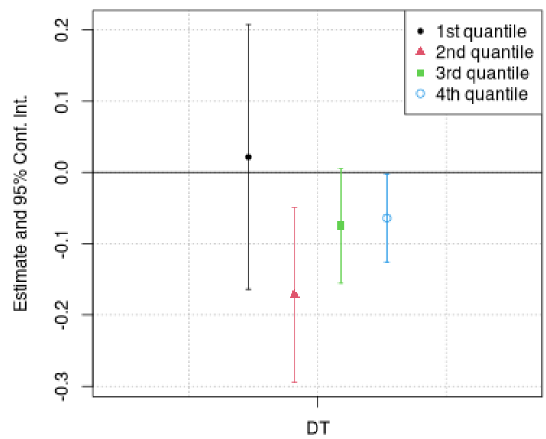

Figure A.8: Paper citations quartile

Table A.6: Author production

	Works (1)	Papers (2)	Non-paper (3)	English (4)	Papers share (5)	English share (6)
after × RU	-0.1448***	-0.1031**	-0.1236	-0.1258***	0.0583***	0.0387*
	(0.0468)	(0.0417)	(0.1007)	(0.0423)	(0.0187)	(0.0209)
author f.e.	✓	✓	✓	✓	✓	✓
year f.e.	✓	✓	✓	✓	✓	✓
Observations	24,967	24,803	17,349	24,801	19,698	19,698
Squared Correlation	0.63205	0.61707	0.34484	0.59520	0.33613	0.36332
Pseudo R^2	0.48937	0.41213	0.38220	0.43400	0.21230	0.21546
BIC	145,001.0	131,762.7	72,002.3	142,359.7	67,119.9	69,563.3

Notes: Columns (1)-(4): GLM Poisson estimation, columns (5)-(6): OLS estimation. The unit of observation is author-year. Clustered standard errors at the author level in parenthesis. *p<0.1; **p<0.05; ***p<0.01