Accelerated Science:

Evidence from Pandemic-Era Economics Research*

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Abstract

This paper examines how the COVID-19 pandemic reshaped the production and diffusion of economic research. Using a novel linked dataset that connects NBER working papers to OpenAlex bibliometrics and Altmetric traces, I track how pandemic-focused scholarship moved through academic, media, and policy channels. COVID-related papers accumulated citations nearly twice as rapidly in their first two years, moved through publication about six months faster, and received substantially more policy and media attention. These advantages, however, were front-loaded: citation rates converged within five years, and COVID papers were less likely to appear in top journals. Papers released earliest in the crisis captured a pronounced first-mover advantage. Pandemic papers were also shorter, cited fewer references, and scored markedly lower on indices I construct that summarize research documentation, empirical thoroughness, and differentiation within the literature. Those effects are particularly pronounced for the papers released earliest in the pandemic. Together, the results reveal a distinct mode of scholarship defined by speed, salience, and abbreviated execution—an accelerated science that expanded visibility but altered how research was produced and where it was shared.

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1 Introduction

The COVID-19 pandemic reshaped working environments across nearly every profession, but its effects on academic knowledge production remain incompletely understood. For economists, the crisis disrupted established routines while simultaneously creating unprecedented opportunities. Reduced commuting and an abundance of urgent policy questions fueled a surge in research output, particularly on pandemic-related topics. Evidence from Bloom et al. (2025) and Burdett et al. (2024) documents broad shifts in work patterns, while Carr et al. (2021) and Amano-Patiño et al. (2020) highlight the surge in academic productivity within economics. Kruger et al. (2023) further show that this expansion was concentrated in COVID-related scholarship. The result was a flood of working papers addressing health, labor markets, inequality, and public finance—areas where economics could offer immediate guidance.

This raises a fundamental question: *how did crisis conditions reshape the production and diffusion of economic research*? The pandemic offered a unique opportunity to study how scholarly systems adapt under conditions of acute urgency. Did accelerated production timelines alter observable research practices? How did attention flow differently across academic, media, and policy channels? And did the surge of pandemic-focused work displace contemporaneous research on other topics? Answering these questions clarifies how academic systems respond to crisis conditions and how those responses become visible in publication and citation patterns.

To address this question, I move beyond prior studies that emphasize counts of papers or aggregate citation counts. I construct the first comprehensive linked dataset connecting the universe of NBER working papers to two complementary sources: OpenAlex bibliometric records and Altmetric traces of policy and media engagement. This linkage enables a unified view of how research travels through scholarly and public domains. I then characterize pandemic scholarship along four dimensions: (i) *citation trajectories*—the shape, timing, and persistence of scholarly attention; (ii) *publication dynamics*—journal placement patterns and time-to-publication, which reveal how institutions managed the speed–selectivity tradeoff; (iii) *visibility allocation*—media and policy mentions that trace how research reached non-academic audiences; and (iv) *production practices*—observable features of each paper that serve as proxies for how research was executed. To capture these practices systematically, I construct three composite indices that summarize how papers document their empirical design, invest in methods and data, and position themselves within the literature. Together, these measures provide a framework for describing research practices across papers, but do not make broader claims about overall research "quality."

The evidence reveals a consistent pattern. COVID-related papers followed a distinct trajectory: they accumulated citations nearly twice as fast in their first two years, moved through publication roughly six months faster, and attracted substantially more media and policy attention than comparable non-COVID work. These advantages, however, were concentrated early. Citation rates converged within five years, and pandemic papers were significantly less likely to appear in top journals. Papers released at the pandemic's onset captured the greatest visibility across all channels, reflecting a pronounced first-mover advantage. COVID-related work was also shorter, cited fewer references, and scored lower on indices I construct that summarize research documentation and empirical thoroughness, indicating that accelerated timelines translated into leaner execution and compressed reporting practices.

On one hand, the surge of pandemic-related work could have displaced other research by drawing on a finite pool of scholarly and editorial attention—crowding out contemporaneous work on unrelated topics as journals, seminars, and media outlets concentrated on COVID questions. On the other hand, the crisis might have expanded the total visibility of economics, mobilizing new audiences and creating temporary capacity in both publication and media channels. Using regression discontinuity estimates, I find that attention expanded rather than reallocated: COVID research drew exceptional visibility without measurable displacement of other work, suggesting that crisis-driven attention can temporarily broaden the overall reach and capacity of the discipline.

Whether the first papers released during the pandemic would ultimately fare the best was not ex-ante obvious. Early papers could have enjoyed a powerful first-mover advantage: when uncertainty was highest and information scarce, these analyses set the baseline for policy and academic discussion, anchoring the terms of debate and accumulating enduring visibility. Yet, the same urgency could have produced a penalty rather than a premium as early work written under informational constraints might have been superseded as better data and methods became available, leading later research to dominate. This paper provides evidence consistent with the former; the earliest pandemic papers were not only the most widely covered in media and policy venues but also the most heavily cited by other economists.

How the crisis would reshape research practices was also uncertain. The urgency and novelty of COVID-19 might have spurred economists to innovate: to build new datasets, adopt unfamiliar methods, or reach beyond their usual literatures to address unprecedented questions. Yet time pressure and the demand for rapid insights could have constrained such experimentation, prompting researchers to streamline analyses, shorten validation steps, and reduce the depth of methodological development. The evidence presented in this paper reveals that constraint dominated: pandemic papers were produced more quickly, with lighter empirical validation and methodological innovation. Furthermore, this result is most pronounced for the first papers released during the pandemic.

Existing evidence on how the pandemic reshaped research helps situate these questions. The COVID-19 pandemic sparked a large literature on how crisis conditions altered academic productivity and who was able to participate in that shift. Barber et al. (2021) document declines in research output in finance, while Amano-Patiño et al. (2020) show that within economics, publication activity actually rose— driven largely by already-active and senior scholars. In contrast, Kruger et al. (2023) highlight how much of this surge reflected a reallocation of attention toward pandemic-relevant topics. Meanwhile, Cui et al. (2022) emphasize that these aggregate increases masked widening inequalities, as women—especially those with caregiving responsibilities—faced greater disruptions. Complementary evidence from Viglione (2020) and Deryugina et al. (2021) confirms that parental responsibilities limited women's participation in the pandemic-era publication surge. Together, these studies reveal how the pandemic amplified pre-existing disparities in research activity. This paper extends that discussion by shifting focus from individual-level productivity gaps to the structure of pandemic-era economics research itself—documenting how topic choice, diffusion patterns, and research practices changed when attention, data, and policy demand were jointly reshaped.

A second strand of work examines how best to measure the influence and value of research. Traditional approaches emphasize citation counts and journal placement as core metrics of impact, and recent work links citations to broader scientific and social benefits (e.g. Yin et al., 2021). However, short-horizon citation measures are ill-suited to a setting in which attention was both front-loaded and topic-specific. The pandemic shifted which questions were immediately salient and created a temporary surge in publication that inflated citation opportunities. In response, a growing literature on alternative metrics argues for incorporating media coverage, policy use, and online engagement when assessing how research circulates beyond academia (Erdt et al., 2016). This paper contributes to that discussion by combining citation trajectories, journal outcomes, and Altmetric-based measures of media and policy visibility. In doing so, it shows how crisis-driven advantages in early attention and dissemination can coexist with faster decay and different publication placements–providing a more holistic view of research impact.

This paper makes three contributions. First, it documents how crisis conditions altered the temporal structure of research production and diffusion, revealing a mode of scholarship characterized by accelerated timelines, front-loaded attention, and rapid decay. Second, it provides integrated empirical evidence across multiple channels—citations, journals, media, and policy—demonstrating how pandemic research circulated differently within and beyond the academy. Third, it introduces a novel data infrastructure linking bibliometric, Altmetric, and full-text features, and develops new paper-level indices that summarize how research is documented, executed, and positioned within the literature. Together, these contributions establish that crises produce systematically different modes of scholarship, leaving distinct traces in bibliometric, institutional, and textual records.

Understanding these dynamics matters for both scholarship and institutional design. Documenting how research production responds to crisis conditions illuminates whether accelerated timelines systematically alter observable research practices, how visibility gets allocated across channels under urgency, and whether such patterns reflect conscious institutional adaptation or emergent constraints. Prior work has shown that pandemic disruptions had uneven effects across researchers (Kitchener, 2020; Hasna et al., 2020), raising questions about whether crisis-driven scholarship exacerbates or mitigates existing inequalities. More broadly, characterizing the traces that different production modes leave in the academic record provides empirical foundations for designing systems that can respond to future emergencies while maintaining transparency about the tradeoffs involved.

The remainder of the paper is organized as follows. Section 2 provides background on the pandemic-era surge in economic research including authorship and output patterns. Section 3 describes the data sources and empirical framework, including the construction of the linked NBER–OpenAlex–Altmetric dataset and the paper-level indices summarizing research documentation, empirical thoroughness, and differentiation within the literature. Section 4 presents the main results, detailing how pandemic-focused research differed in citation trajectories, publication outcomes, media and policy visibility, and observable research practices. Section 5 concludes.

2 Background

The pandemic triggered an unprecedented shift in economic research production. NBER working paper releases more than doubled at the onset of COVID-19, with May 2020 marking the peak: one in four papers published that month focused directly on the pandemic. Of the nearly 1,600 NBER papers released in 2020, 19% were COVID-related, a share that fell to 12% in 2021. Across the pandemic period as a whole, monthly output remained about 17% above pre-pandemic baselines, as shown in Figure 1. The vertical gray lines in the figure align the series with the WHO's March 11, 2020 declaration and the formal end of the emergency, anchoring the timing of the surge to global milestones.

Not all economists responded equally to the crisis. Roughly 17% of NBER authors produced at least one COVID-related paper, and those who did were already among the field's most active researchers before 2020. Compared to peers who continued publishing on non-COVID topics, these authors had produced about 50% more papers and accumulated 50% more citations in the pre-pandemic period. During the pandemic, they devoted nearly one-fifth of their total output to COVID-related questions—a share that rose to 26% among economists based at top-50 departments. Figure 2 illustrates this divergence in productivity between COVID and non-COVID authors during the pandemic era. Appendix figure A.1 shows that the rise in pandemic-related scholarship was driven almost entirely by a sharp rise in empirical papers.

COVID authors were, on average, more senior and more likely to be male. Nearly 80% of pandemic-related papers came from full professors, and female representation among COVID authors was 16%, below the 20% observed for pre-pandemic NBER authors. Collaboration dynamics shifted modestly. Average team size rose from 2.9 to 3.1 authors per paper for papers unrelated

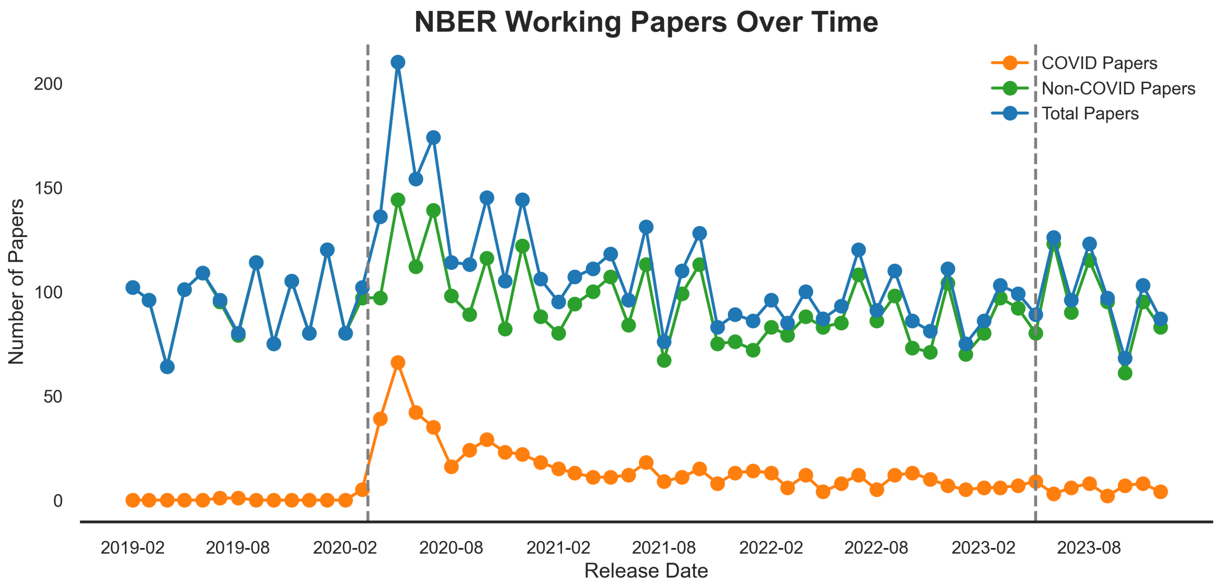


Figure 1: Monthly NBER working paper output, 2019–2023, split between COVID-related papers (orange), non-COVID papers (green), and the total (blue). Vertical dashed lines mark the WHO's March 11, 2020 pandemic declaration and the official end of the emergency in May 2023. The figure shows a sharp surge in total working paper output at the onset of the pandemic, driven largely by COVID-related work, followed by a gradual normalization as COVID papers declined and non-COVID output returned to pre-pandemic levels. Appendix Figure A.3 present the 2020 working paper output as a percent of the 2019 average.

to the pandemic and 3.5 authors for pandemic-related work, suggesting that crisis conditions encouraged larger, often more interdisciplinary, teams. Appendix figures A.3 and A.4 present trends in the number of authors per paper and which demographic groups drove the rise in working papers during the pandemic. Reading Figures 1 and 2 together, the pandemic-era surge reflects both a level shift in overall output and a compositional shift toward already high-productivity researchers working in slightly larger teams. These descriptive patterns echo prior evidence that the pandemic's effects on research production were unevenly distributed (Amano-Patiño et al., 2020; Kruger et al., 2023; Kitchener, 2020). The COVID boom in economics was large, rapid, and concentrated among already-active researchers.

3 Data and Methods

3.1 Data

I draw on three complementary datasets that together trace research from its initial release through scholarly diffusion and public visibility. The core of the analysis is the universe of NBER working papers released since 2015, which I scrape and compile directly from the NBER website and link to OpenAlex bibliometric records and Altmetric engagement data. The NBER series captures much of the applied economics research produced by U.S.-based authors. Because NBER releases new papers weekly, it offers a near–real-time window into where scholarly attention and perceived policy relevance shift during moments of crisis. The frequency and depth of these releases make the corpus especially valuable for tracking pandemic-era production patterns, collaboration dynamics, and

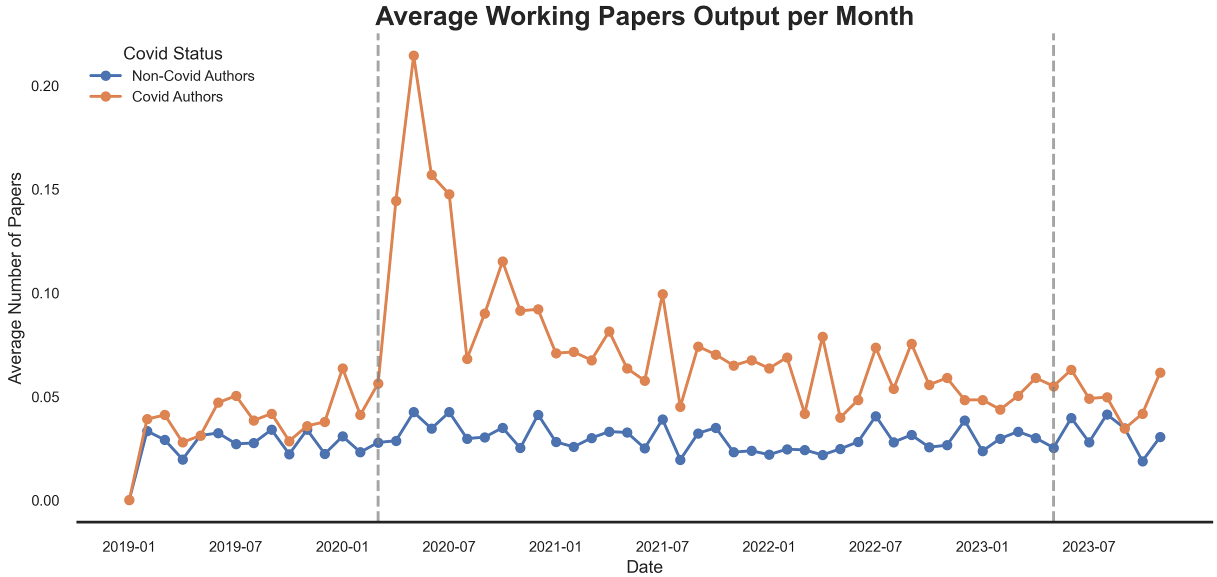


Figure 2: Average monthly NBER working paper output per author, comparing those who wrote at least one COVID-related paper (orange) to those who did not (blue). Vertical dashed lines mark the WHO's March 11, 2020 pandemic declaration and the official end of the emergency in May 2023. COVID authors sharply increased their output at the onset of the pandemic, peaking in mid-2020, before gradually converging back toward pre-pandemic levels. Non-COVID authors maintained relatively stable output throughout.

subsequent diffusion. From NBER, I collect information on titles, abstracts, authors, topics, working groups, and release dates, as well as structural features of each paper such as length, reference counts, equation counts, and other observable characteristics.

I merge these data with OpenAlex, which aggregates records from Crossref, SSRN, arXiv, RePEc, NBER, and institutional repositories to enable large-scale bibliometric analysis. From OpenAlex I obtain citation counts by year, journal acceptance and publication outcomes, and publication dates. These data make it possible to follow how working papers transitioned into journal articles, how citations accumulated over time, and how these patterns differed between COVID and non-COVID research.

Finally, I link a subset of papers to Altmetric records. Altmetric tracks attention outside traditional scholarly channels including tweets, news coverage, policy-document mentions, blogs, and Wikipedia references, providing a complementary signal of policy relevance and public engagement. This dimension was particularly salient during the pandemic, when policymakers, journalists, and the public sought rapid evidence. By joining Altmetric data to NBER release dates and OpenAlex citation trajectories, I construct a unified record of both urgency-driven visibility and longer-run scholarly engagement.

Each of these sources provides a distinct perspective on pandemic-era scholarship but also introduces limitations. NBER posting privileges are invitation-only, so the series overrepresents senior, U.S.-based researchers and underrepresents early-career scholars and non-U.S. institutions. Altmetric data, in turn, exist only when a paper can be matched by identifier and has at least one recorded mention. Despite these caveats, the merged dataset offers a detailed picture of how economics research, especially COVID-focused work, circulated through academic, media, and policy outlets.

3.2 Study Design

To examine how crisis conditions influenced research production and diffusion, I combine descriptive evidence with quasi-experimental variation. The analysis leverages newly extracted textual and bibliometric features of NBER working papers together with measures of attention and publication outcomes. The core empirical strategy is a two-way fixed effects regression estimated by OLS, comparing papers released before and after the WHO's March 11, 2020 pandemic declaration while distinguishing COVID-related papers from other work by the same authors. The baseline specification is:

$$y_{it} = \alpha + \beta_1 \,\mathrm{Post}_i + \beta_2 \,\mathrm{COVID}_i + \lambda_t + \gamma_a + X_i^\top \delta + \varepsilon_{it}, \tag{1}$$

where y_{it} denotes an outcome such as citations or publication placement for paper i by author a in month t. Post_i equals one if the paper was released on or after March 11, 2020, while COVID_i equals one if the paper explicitly addressed COVID-19. The model includes month fixed effects (λ_t) to absorb time-varying common shocks, author fixed effects (γ_a) to compare researchers to their own pre-pandemic levels, and additional controls X_i for journal, discipline, and team size.

The author fixed effects specification requires restricting the sample to economists who published papers across all three categories: pre-pandemic, non-COVID (papers released during the pandemic but not about COVID), and COVID papers (papers written during the pandemic and about COVID). This restriction ensures that the γ_a terms absorb unobserved author heterogeneity by leveraging within-author variation in topical choice. While this limits external validity to a subset of "switcher" economists, it provides the cleanest identification of the COVID topic premium. Authors who specialized exclusively in COVID topics may differ systematically in ways that confound topical effects with selection. To address concerns about generalizability, I supplement the author fixed effects design with journal fixed effects specifications estimated on the full sample. This approach incorporates authors who specialized exclusively in COVID topics and those who didn't write about the pandemic at all while controlling for outlet standards and other observables. The similarity of results across both designs indicates that the descriptive patterns are robust to sample restrictions.

The β_1 coefficient on Post_i captures how non-COVID papers fared after the pandemic began, holding author identity and other controls constant. Because the onset of the pandemic was an exogenous shock to the research environment, this coefficient effectively functions as a regression discontinuity estimate. The coefficient β_2 captures the incremental effect of writing on COVID-related topics during the pandemic period. To identify the immediate impact of the pandemic declaration on non-COVID work, I also estimate a regression discontinuity (RD) design centered on March 11, 2020, the date of the WHO announcement. This specification uses the full sample of authors, rather than only those who wrote both COVID and non-COVID papers, and compares papers released in narrow windows before and after the declaration. The RD design provides a sharp test of whether the announcement itself disrupted attention to ongoing research or generated short-run crowding-out effects.

The empirical strategy prioritizes transparent description of how pandemic research circulated differently. Author fixed effects ensure that comparisons isolate the role of topical focus by holding constant researcher-level attributes. The RD design complements this by examining the immediate response to the pandemic announcement, when potential spillovers would be most acute. Together, these approaches characterize the production and diffusion patterns that emerged under crisis conditions.

Several features of the setting and empirical design merit acknowledgment. Topical choice was not random: researchers who pivoted to COVID topics may have differed in ways that fixed effects cannot fully capture. The sample restriction and inclusion of author fixed effects help mitigate this concern but do so only partially. Although the specification structurally resembles a difference-in-differences design, it should not be given a strong causal interpretation. The absence of pre-pandemic COVID papers precludes direct tests of parallel trends, and the pandemic itself affected all economists simultaneously, leaving no true control group untouched by the shock. These constraints are inherent to studying a global event rather than limitations of the analysis.

This descriptive approach builds on recent work characterizing pandemic effects on scholarship (Kruger et al., 2023). It reveals how quickly the profession reoriented toward urgent topics, how attention evolved across channels and over time, and how observable research practices varied with production speed. These patterns provide empirical foundations for understanding how knowledge systems respond to external shocks and for thinking about how funders, journals, and researchers navigate the tradeoffs between timeliness and rigor. The evidence establishes what pandemic scholarship looked like across multiple measurable dimensions, offering a baseline for evaluating whether and how academic institutions should adapt to future crises.

3.3 Empirical Specification and Robustness

Citation data present well-documented empirical challenges: they are zero-heavy, highly skewed, and severely overdispersed, with variance-to-mean ratios exceeding 500 in this sample. Recent work demonstrates that log-transforming such counts can bias estimates and complicate interpretation (Chen and Roth, 2024). I therefore compare two canonical approaches for count data: negative binomial (NB) regression and quasi-Poisson regression with robust standard errors (Cameron and Trivedi, 2013; Hilbe, 2011; Gardner et al., 1995). The negative binomial model is generally preferred for highly dispersed citation data because it allows variance to grow roughly with the square of the mean, better accommodating heavy tails. Quasi-Poisson retains the Poisson mean structure and inflates variance linearly, which can be too restrictive when dispersion accelerates with the mean (Bornmann and Daniel, 2008; Seglen, 1992).

Appendix figure B.5 compares residual diagnostics for the two count-data models. The quasi-Poisson specification fits slightly better near the center of the distribution, but the Negative Binomial model performs much better in the tails and produces more conservative inference for highly cited papers. Given this performance and its more flexible variance structure, I adopt the Negative Binomial as the primary specification. The main text reports Negative Binomial estimates, while the appendix presents parallel quasi-Poisson results. Substantive conclusions are consistent across models, with only small differences in magnitude, affirming that the patterns documented in the paper are not driven by distributional assumptions.

3.4 How I Measure Research Documentation and Differentiation

I construct three paper-level indices using OCR-extracted full-text features that summarize how research is documented and positioned relative to other papers in the same field and year. The *Reporting & Design Composition (RDC)* index aggregates signals of how transparently papers describe their design, uncertainty, and robustness. The *Methods & Data Composition (MDC)* index captures identifiable investments in methodological innovation and data construction. The *Differentiation & Integration Composition (DIC)* index summarizes how papers are situated within the literature based on textual similarity and citation-pattern signals. These measures are descriptive rather than evaluative: they quantify documentation and positioning without making claims about overall “quality” or intellectual importance.

What the indices measure. **RDC** (*Reporting & Design Composition*) captures documentation practices that make empirical reasoning explicit and verifiable. It records whether a paper (i) states a formal identification strategy (e.g., randomized experiment, IV, RD, DiD, synthetic control); (ii) reports design-specific validity diagnostics (e.g., pre-trend tests for DiD, McCrary or bandwidth diagnostics for RD, first-stage and overidentification checks for IV, or modern staggered-adoption DiD references); (iii) specifies uncertainty quantification (robust or clustered standard errors, with clustering level stated); (iv) includes dedicated robustness sections or tables; and (v) reports interpretable measures of precision (confidence intervals or exact p-values).

MDC (*Methods & Data Composition*) captures identifiable efforts to extend or enrich research through new methods or data. It combines three dimensions: (i) *method adoption*, including the use of new estimators, explicit method-introduction claims, or adaptation of emerging approaches (for example, large-language-model or self-supervised techniques, when present); (ii) *data construction*, encompassing the creation of new datasets, linkages, scraping, digitization, hand-coding, or the use of restricted or proprietary data; and (iii) an *orientation term* that quantifies topical or methodological breadth. The orientation term is computed as the Shannon entropy of normalized keyword frequencies extracted from the paper's text. Specifically, if p_k denotes the share of tokens belonging to keyword k among the paper's 1,000 most frequent keywords, the entropy term is

$$H = -\sum_k p_k \log(p_k),$$

normalized to a [0, 1] scale within field-year cells. Higher entropy values indicate a more diverse topical or methodological vocabulary. For example, a paper whose keywords are evenly distributed across "instrumental variables," "panel data," and "survey experiment" would receive a higher orientation score than one dominated by a single term such as "difference-in-differences." This component is rescaled to the 0–100 index range and enters the composite with a small weight (10 percent of the MDC score), serving as a secondary indicator of conceptual or methodological breadth rather than a primary determinant of the index.

DIC (*Differentiation & Integration Composition*) characterizes how a paper is positioned relative to other work in the same field and year, using comparative text and citation features. It incorporates seven components: (i) *textual similarity*, penalizing overlap in vocabulary or phrasing with other papers in the same field-year based on cosine similarity of term-frequency vectors; (ii) *citation concentration*, measured by the Herfindahl index of the reference list, which increases when a small number of sources account for a large share of citations; (iii) *local citation density*, capturing "shotgun" citation clusters defined as five or more consecutive citations within a single sentence or clause; (iv) *sectional clustering*, measuring the extent to which citations are concentrated in a small share of the paper's paragraphs rather than distributed throughout; (v) *recency*, rewarding citation of work published within the past three years relative to the paper's release date; (vi) *cross-field engagement*, measured as the share of citations directed to journals, working groups, or JEL codes outside the paper's primary field; and (vii) *lexical rarity*, defined as the mean inverse document frequency (IDF) of the paper's top 500 non-stopword tokens within its field-year corpus, rewarding the use of less common conceptual language. A self-citation penalty is applied when more than 10% of all references cite the authors' own prior work. All DIC components are normalized within field-year cells to ensure comparability across disciplines and time.

These indices describe how papers are executed and positioned, not whether they are better or more influential. RDC reflects transparency in design and reporting; MDC captures methodological and data-related investment; and DIC measures how distinctively and integratively a paper connects to the surrounding literature. Together, they trace the *production-side anatomy* of research: how economists documented, innovated, and situated their work under varying conditions of time pressure and topic salience, offering a reproducible and scope-limited picture of how empirical scholarship adapted during the pandemic.

How the metrics are combined. Each subcomponent is capped and the overall score is mapped to a common 0–100 scale. Let Transp, Uncert, Robust, and DesignSpec denote the four RDC sub-scores; Method, Data, and Orient the three MDC sub-scores; and DIC a weighted average of normalized comparative signals:

$$\mathrm{RDC} = 0.35\,\mathrm{Transp} + 0.20\,\mathrm{Uncert} + 0.25\,\mathrm{Robust} + 0.20\,\mathrm{DesignSpec}$$

$$\mathrm{MDC} = 0.45\,\mathrm{Method} + 0.45\,\mathrm{Data} + 0.10\,\mathrm{Orient}$$

For DIC, each component is standardized within field-year cells and rescaled to the unit interval $[0, 1]$ using a clipped z-score transformation to prevent a few outliers from dominating the index.[1] For variable x_i in field-year cell c, the transformed value is:

$$\tilde{x}_i = \min\left\{1,\ \max\left[0,\ \Phi\left(\frac{x_i - \mu_c}{\sigma_c}\right)\right]\right\},$$

where μ_c and σ_c denote the mean and standard deviation of x within cell c. This z-to-unit transformation maps each variable to $[0, 1]$ while preserving relative ordering. Let overlap, herfindahl, $\mathrm{group}_{\geq 4}$, and shotgun denote penalty components (higher values indicate lower differentiation); recent, outside, and lexrar denote bonus components (higher values indicate greater integration or novelty); and selfcite denotes a penalty for excessive self-citation. Then

$$\begin{aligned}\mathrm{DIC}_{\mathrm{raw}} = {}& 1.5(1 - \mathrm{overlap}) + 1.0(1 - \mathrm{shotgun}) + 1.0\,\mathrm{recent} + 1.0\,\mathrm{outside} \\ & + 0.5(1 - \mathrm{herfindahl}) + 0.5(1 - \mathrm{group}_{\geq 4}) + 0.5\,\mathrm{lexrar} + 0.5(1 - \mathrm{selfcite}).\end{aligned}$$

The resulting weighted sum is normalized to a 0–100 scale by dividing by the sum of all component weights (6.5) and multiplying by 100. RDC and MDC rely primarily on within-paper textual and structural features (e.g., identification statements, diagnostics, uncertainty quantification, data-linkage language), whereas DIC uses cross-paper normalization to characterize how each paper differentiates itself within its field-year context.

While the weights would ideally be recovered from a prediction problem, given that the objective function is unclear, the weights here were produced by submitting the various indices to an LLM and asking which the weights assigned to each should be given discipline norms. Appendix sections C.4 and C.3 present the results for equal weighted indices. They affirm that the results presented in section 4.4 are robust to the choice of weights. The composite indices positively correlate modestly with journal selectivity ($\rho \approx 0.16$ for RDC and MDC), indicating that while more selective outlets tend to feature somewhat more elaborated documentation and methodological investment, the indices capture variation largely orthogonal to journal prestige.[2] This supports their interpretation

[1] The transformation maps standardized values to $[0, 1]$ using the standard normal cumulative distribution function $\Phi(\cdot)$. Values beyond roughly ± 3.3 standard deviations are clipped to 0 and 1, limiting the effect of extreme observations while preserving within-cell variation.

[2] Table C.11 presents the journal ranks used for estimating the correlation.

as paper-level measures of research practice rather than proxies for outlet rank. The indices translate visible signals of reporting, methods, and positioning into a framework for understanding shifts in research practices during the pandemic.

4 Results

This section characterizes how pandemic research was produced and how it circulated. The analysis reveals four consistent empirical patterns. First, COVID-focused papers exhibited distinctive attention trajectories: citations accumulated nearly twice as fast in early years but decayed more quickly, converging with non-COVID work within five years. Second, COVID papers moved through publication substantially faster and received disproportionate media and policy visibility, with the earliest releases capturing a pronounced first-mover advantage. Third, these papers were shorter, cited fewer references, and scored lower on the indices summarizing documentation and empirical thoroughness, patterns concentrated among the most rapidly published work. Finally, while pandemic-related research expanded the total volume of scholarly and public attention, its effects were front-loaded and transitory. Together, these results show how crisis conditions compressed research timelines, amplified early visibility, and produced a distinctive mode of accelerated science.

4.1 Scholarly Citations

This section begins by examining how the pandemic affected the distribution of scholarly attention across topics. Table 1 reports estimates from negative binomial regressions of total citation counts. Each specification includes author and journal fixed effects, with time and discipline fixed effects added progressively across columns.

Table 1: Negative Binomial Regression Results: Number of Citations

	Dependent Variable: Number of Citations		
	(1)	(2)	(3)
Post	-1.0894***	0.1069	0.1202
	(0.0430)	(0.1168)	(0.1157)
About COVID	1.2366***	0.8969***	0.9698***
	(0.0611)	(0.0556)	(0.0573)
Author FE	✓	✓	✓
Journal FE	✓	✓	✓
Time FE		✓	✓
Discipline FE			✓
N	5,888	5,888	5,888

Notes: Table reports coefficients from negative binomial regressions of citation counts for NBER working papers released between January 2019 and May 2023. Coefficients are log incidence rate ratios (IRRs); positive values indicate higher expected citation rates. Standard errors, in parentheses, are clustered by release date. *Post* equals one for papers released on or after March 11, 2020; *About COVID* equals one for papers explicitly addressing COVID-19. Author, journal, time, and discipline fixed effects control for persistent heterogeneity at the corresponding levels. Significance: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

COVID-related papers accumulated citations more than twice as rapidly as contemporaneous non-COVID work, reflecting a sharp concentration of scholarly focus on pandemic-relevant topics. By contrast, non-COVID papers released during the pandemic received citation counts similar to pre-pandemic work by the same authors, indicating that ongoing research activity was largely unaffected. Together, these patterns point to an expansion rather than a reallocation of attention: researchers continued to engage with existing work while rapidly absorbing and citing new COVID-related research. Appendix tables B.8, B.9, and B.10 affirm that these results are robust to both the choice of bandwidth the cutoff for all three outcomes. Figure 3 extends this analysis by plotting annual citation rates for COVID papers as a percentage of citations to the same authors' pre-COVID and contemporaneous non-COVID papers. The figure shows that COVID papers were cited at many times the normal rate in their first two years, but this advantage declined steadily over time. By the fifth year after release, citation rates for COVID and non-COVID work had largely converged, illustrating how crisis-driven attention was intense but short-lived, compressing the typical life cycle of scholarly impact.

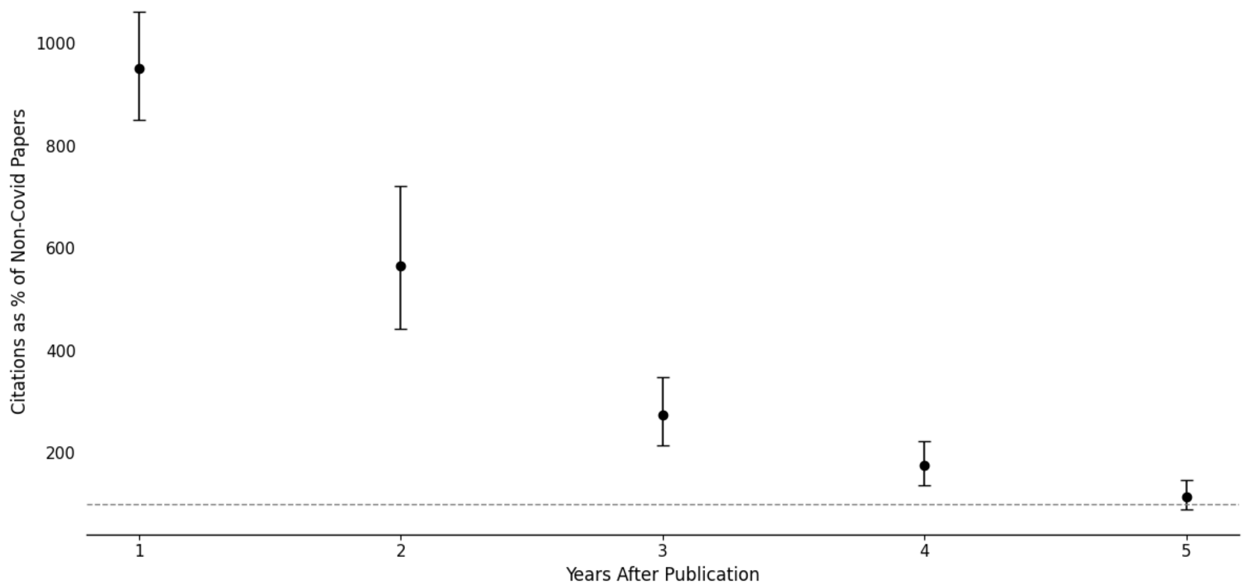


Figure 3: Citation trajectories for COVID-related papers relative to non-COVID papers, expressed as a percentage of non-COVID citation counts. Estimates shown for each year after publication with 95% confidence intervals. COVID papers accumulated citations nearly ten times faster in year one, but this advantage declined rapidly, converging toward non-covid and pre-covid papers by year five. The pattern documents front-loaded attention dynamics characteristic of crisis-driven research.

COVID papers received citations extremely quickly in their first two years—nearly ten times the rate of non-COVID papers. This early advantage declined steadily, and by the fifth year after publication, citation rates had largely converged. The pattern shows that attention to pandemic research was front-loaded and short-lived, in contrast to the slower and more sustained citation growth typical of non-pandemic work. These results are robust to model specification or the choice of the dispersion parameter. Appendix section B presents the robustness results.

While figure 3 captures relative citation intensity by comparing COVID papers to each author's pre- and non-COVID work, Figure 4 traces how citations evolved over time within each group. It reveals that COVID scholarship was unique in showing negative year-over-year citation growth: citation counts surged immediately after release but then declined sharply in subsequent years. Most papers, by contrast, continue to grow for the first few years before stabilizing. This effect is even more stark among the most cited papers. Appendix figure A.2 depicts the corresponding plot for the top 25% most cited papers by year. Together, the two figures show that pandemic research not only drew unusually high initial attention but also underwent unusually rapid rise and decline in citations. Both of these nuances are lost when strictly using aggregate citation counts.

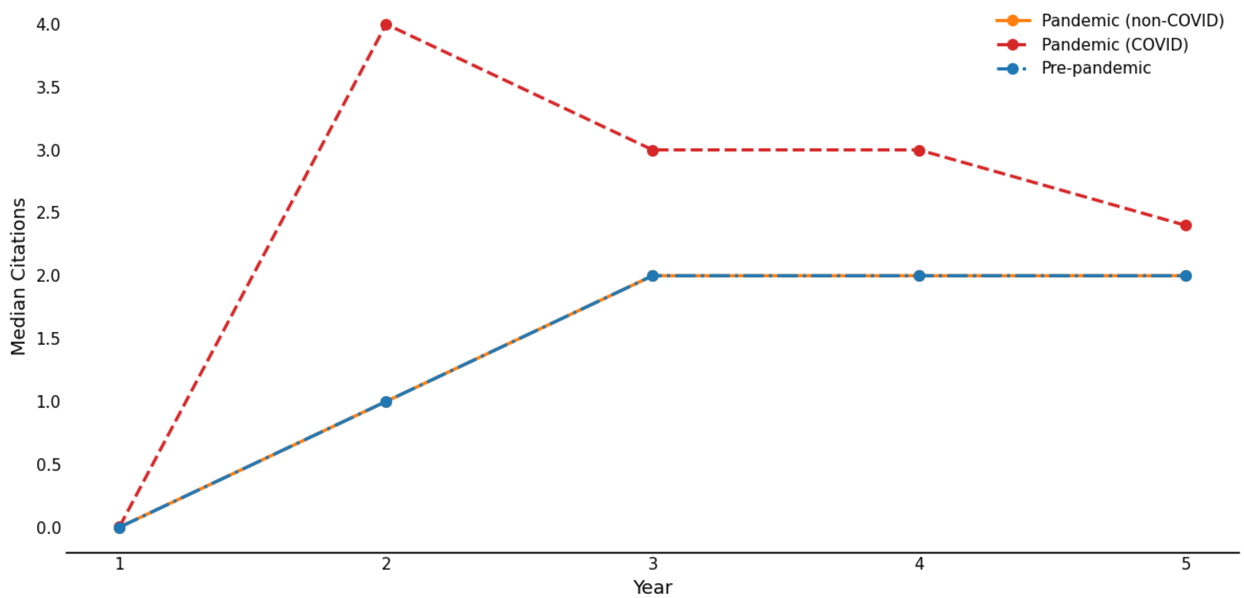


Figure 4: Median citation trajectories for COVID and non-COVID papers. The figure plots the median number of citations each year after release, comparing pandemic (COVID), pandemic (non-COVID), and pre-pandemic papers. Non-COVID work shows a gradual, steady increase in citations over time, consistent with cumulative scholarly uptake. COVID papers, by contrast, exhibit a sharp early spike followed by decline. The divergence highlights the difference between crisis-driven research that peaks rapidly and the slower, compounding influence typical of non-pandemic work.

4.2 Publication Outcomes

I next examine how pandemic conditions affected the publication process itself. Publication venues and timelines offer an independent view of how journals and review systems managed the surge of research produced during the crisis. Table 2 reports logistic regression estimates for journal placement and OLS estimates for time to publication, capturing both where papers were published and how quickly they moved through review.

COVID papers were substantially less likely to appear in the most selective journals. The probability of publication in a Top 5 economics journal was about 75% lower than for comparable non-COVID work, and publication in Top 50 outlets was roughly 35% lower. Even when considering high-impact interdisciplinary and policy-oriented journals, the likelihood of publication fell by nearly 30%. At the same time, COVID papers moved through review and publication dramatically faster, appearing in print on average 175 days earlier than other papers. Because publication time is endogenous to journal choice, this acceleration likely reflects a combination of journal-side expedience and author-side selection: researchers may have favored faster, less selective outlets to disseminate urgent findings quickly. Together, these results suggest that pandemic research advanced through the publication pipeline at greater speed but at the cost of placement in the most competitive journals, a pattern consistent with scholars prioritizing rapid dissemination to inform policy during a crisis.

Table 2: Publication Outcomes by Pandemic Timing and COVID Focus

	Acceptance (1)	**Top 5** (2)	**Top 50** (3)	**High-Impact** (4)	**Days to Pub.** (5)
Post	0.3414**	0.1074	0.1548	0.1717*	6.2053
	(0.1800)	(0.1820)	(0.0990)	(0.1000)	(36.621)
About COVID	0.6949**	−1.9904***	−0.5476***	−0.4790***	−174.9201***
	(0.1050)	(0.3780)	(0.1160)	(0.1190)	(36.234)
Discipline FE	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓
N	9,607	9,607	9,607	9,607	2,855

Notes: Columns 1–4 report logit coefficients; column 5 reports OLS coefficients. Dependent variables measure: (i) acceptance into any peer-reviewed journal, (ii) publication in top 5 economics journals, (iii) publication in top 50 economics journals, (iv) publication in high-impact outlets (economics, interdisciplinary, or policy journals), and (v) days from NBER release to journal publication. *Post* equals one for papers released on or after March 11, 2020; *About COVID* equals one for papers explicitly addressing COVID-19. Discipline and time fixed effects control for field-specific norms and temporal shocks. Standard errors clustered by release date. Sample includes all NBER working papers released January 2019–May 2023. Significance: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

For non-COVID papers released during the pandemic, the evidence for displacement is weak. Column 1 suggests modestly higher overall acceptance rates post-pandemic, while columns 2–4 show no systematic change in top-journal placement, and column 5 indicates no shift in time to publication. These null effects imply that the rapid dissemination of COVID work did not crowd out contemporaneous research on other topics. Part of this stability potential reflects the expansion of journal capacity during the crisis, as some outlets created COVID-specific issues. It may also reflect the composition of the NBER sample: non-COVID papers in this dataset are generally aimed at more selective journals, so if authors systematically directed their COVID papers toward lower-ranked or faster-turnaround outlets, the two groups would not have competed directly for publication space. To discern the dominant effect, in section 4.4 I compare papers submitted to the same journal on indices I construct.

4.3 Media and Policy Engagement

Citation counts and journal placements measure circulation within academic channels. I next examine whether pandemic research reached policy and public audiences differently. Table 3 reports negative binomial estimates for media mentions and policy document citations.

COVID-related papers received substantially more attention in both channels: approximately 60% more media mentions and more than 50% more policy citations across model specifications. Papers released post-pandemic but not focused on COVID showed no systematic shift in media or policy visibility, indicating that topic rather than timing drove attention reallocation. These patterns document how visibility was allocated across channels during the crisis. COVID papers reached media and policy audiences substantially more often than non-COVID work, revealing a systematic reallocation of attention toward pandemic-relevant research in non-academic channels. Whether this attention translated into policy influence or public understanding lies beyond what bibliometric data can measure. What is measurable is that COVID research appeared more frequently in venues where policymakers and journalists engage with academic work.

A remaining question is whether heightened attention to COVID papers displaced visibility for other research. The *Post* coefficients in Table 3 provide initial evidence, but that analysis

Table 3: Media Mentions and Policy Citations by Pandemic Timing and COVID Focus

	Media Mentions			**Policy Citations**		
	(1)	(2)	(3)	(4)	(5)	(6)
Post	0.184**	−0.156	−0.020	0.122*	0.058	−0.008
	(0.073)	(0.196)	(0.193)	(0.070)	(0.191)	(0.183)
About COVID	0.596***	0.484***	0.538***	0.625***	0.564***	0.516***
	(0.107)	(0.110)	(0.107)	(0.103)	(0.106)	(0.107)
Author FE	✓	✓	✓	✓	✓	✓
Time FE		✓	✓		✓	✓
Discipline FE			✓			✓
N	3,500	3,500	3,500	3,500	3,500	3,500

Notes: Negative binomial regressions predicting counts of media mentions (columns 1–3) and policy citations (columns 4–6) for NBER working papers released between January 2019 and May 2023. Coefficients are log incidence rate ratios (IRRs); positive values indicate higher expected counts. *Post* equals one for papers released on or after March 11, 2020; *About COVID* equals one for papers explicitly addressing COVID-19. Author, time, and discipline fixed effects control for heterogeneity at the corresponding levels. Standard errors clustered by release date. Significance: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

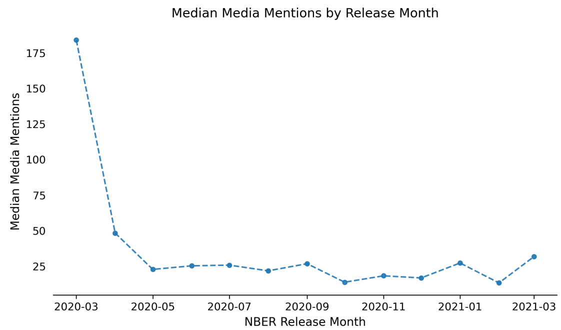
restricts to authors who wrote both COVID and non-COVID papers. Table 4 implements a sharper test using regression discontinuity around the WHO declaration of a global pandemic, comparing all non-COVID papers released just before and after the pandemic declaration. Across citations, policy mentions, and media engagement, the estimates show no systematic decline. This null result indicates that attention to COVID topics expanded the total visibility of economics research rather than reallocating fixed attention away from other work.

Table 4: Treatment Effects Across Outcomes

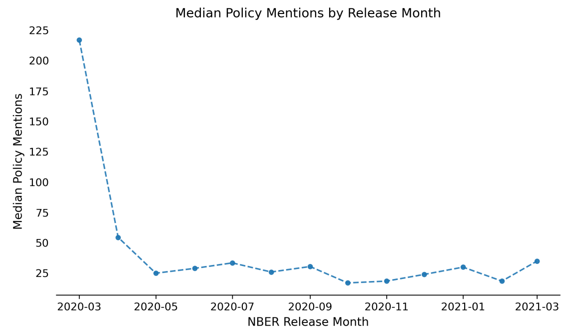
	Citation Count	**Policy Mentions**	**Media Engagement**
	(1)	(2)	(3)
Post	0.294	-0.011	0.004
	(0.198)	(0.290)	(0.299)
Discipline FE	✓	✓	✓
Release-month FE	✓	✓	✓
N	675	422	422

Notes: Each column reports estimates from a regression discontinuity design centered on March 11, 2020. The sample is restricted to non-COVID NBER working papers released within a three-month symmetric window around this date. The citation specification is estimated using a median (quantile, $\tau = 0.5$) regression, though results are robust to using a mean regression ($Post = 0.302$, SE $= 0.196$, $p = 0.123$). Outcomes capture different channels of research visibility: citations, policy mentions, and media engagement. All models include discipline and release-month fixed effects, and standard errors are clustered by release week.

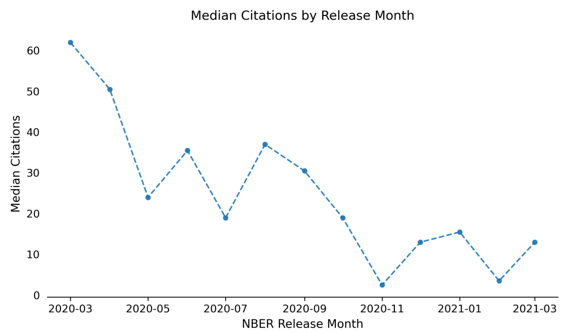
These patterns establish how pandemic research circulated across channels. COVID-focused work accumulated citations rapidly but exhibited faster decay, moved through publication more quickly while appearing less often in top journals, and reached media and policy audiences disproportionately. The evidence documents a systematic reallocation of attention during the crisis, with front-loaded visibility in all channels and strong advantages for papers released earliest.



(a) Media Mentions



(b) Policy Citations



(c) Scholarly Citations

Figure 5: Median outcomes for COVID papers by NBER release month within the first year after the pandemic declaration. All three channels—media mentions, policy citations, and scholarly citations—declined sharply with release timing, documenting strong first-mover advantages for research released earliest in the crisis.

4.4 Observable Research Features and Practices

The preceding sections showed that pandemic research circulated differently—spreading faster, receiving intense but short-lived attention, and reaching publication more quickly. I now turn to the research itself. To examine whether accelerated timelines corresponded to differences in how studies were conducted and presented, I assemble detailed paper-level features using OCR-based text extraction and structured parsing of full documents, linked to bibliometric metadata and Altmetric records. This section analyzes these characteristics directly and through composite indices that summarize transparency and methodological breadth.

Document structure. I begin this analysis with results for a selection of paper features. Table 5 reports differences in four measurable features of NBER working papers: total length, pages before the appendix, number of equations (a proxy for theoretical or econometric density), and number of references (a proxy for connectedness to the existing literature). Each regression includes author, discipline, and release-timing fixed effects, comparing the same author's work before and after the onset of the pandemic. Together, these measures provide a descriptive view of how crisis conditions may have reshaped the form and documentation of economic research.

Among non-COVID papers released during the pandemic, structural features barely changed: papers were about one page shorter (a negligible 1.9% reduction), with reference counts and equation density holding essentially steady. None of these results are statistically different from 0. COVID-

Table 5: Effects on Document Features: Post and COVID-Related Topics

	Number of Pages	**Pages Before Appendix**	**Number of Equations**	**Number of References**
Post	-1.129	-1.863	3.542	0.416
	(1.941)	(1.425)	(2.333)	(4.026)
About COVID (β)	-5.236**	-4.111***	-4.388*	-9.824**
	(2.064)	(1.516)	(2.481)	(4.282)
Author FE	✓	✓	✓	✓
Discipline FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
N	3,540	3,540	3,540	3,540
Pre-COVID Mean	59.300	44.580	15.693	34.152

Notes: OLS with controls for primary discipline, release month, release year, and author name. Standard errors in parentheses. *, **, *** indicate $p < 0.1$, $p < 0.05$, and $p < 0.01$, respectively. Pre-COVID mean is computed among observations with `post`=0 after dropping rows missing any outcome.

related papers, however, were 8.8% shorter, devoted 9.2% fewer pages to pre-appendix content, and cited roughly ten fewer references, a 29% reduction, relative to pre-covid papers. These papers were leaner across every dimension, consistent with production timelines that favored speed and directness over expansive documentation.

Physical features capture broad contours of research output, but they leave open a more granular question: when economists compressed production timelines, what specific practices changed? To answer this, I construct three composite indices that summarize how research was documented, executed, and positioned within the literature.

The *Reporting and Design Composition (RDC)* index measures transparency in empirical design and documentation. It records whether a paper states an identification strategy, reports design-specific validity checks (e.g., pre-trend tests for difference-in-differences, McCrary tests for regression discontinuity, or first-stage diagnostics for instrumental variables), specifies how uncertainty is quantified, and includes explicit robustness discussions. The *Methods and Data Composition (MDC)* index captures methodological and data-related investments, aggregating signals of new estimator use, data construction or linkage, and topical or methodological breadth. Finally, the *Differentiation and Integration Composition (DIC)* index describes how a paper positions itself relative to related work, combining text and citation features to reward recency, cross-field engagement, and lexical distinctiveness while penalizing citation concentration, large undifferentiated citation clusters, and excessive self-citation. Together, these indices offer a reproducible, scope-limited view of how economists documented, developed, and situated their research under varying production conditions, without attempting to evaluate quality or contribution. Section 3.4 offers a more comprehensive description of the construction of these indices.

Table 6 reports two complementary designs. Columns (1)–(3) include author fixed effects, comparing each researcher's COVID-era papers to their own pre-pandemic work. Columns (4)–(6) include journal fixed effects, comparing papers published in the same venues before and after the pandemic to hold editorial standards constant. This second specification is especially informative given the earlier finding that COVID papers were published more quickly and in lower-ranked journals: it tests whether the lower RDC and MDC scores simply reflect differences in where papers were published, or whether even within the same journals, COVID-era research exhibited distinct documentation and methodological patterns. All specifications control for discipline and release timing, and each index is scaled 0–100 for comparability.

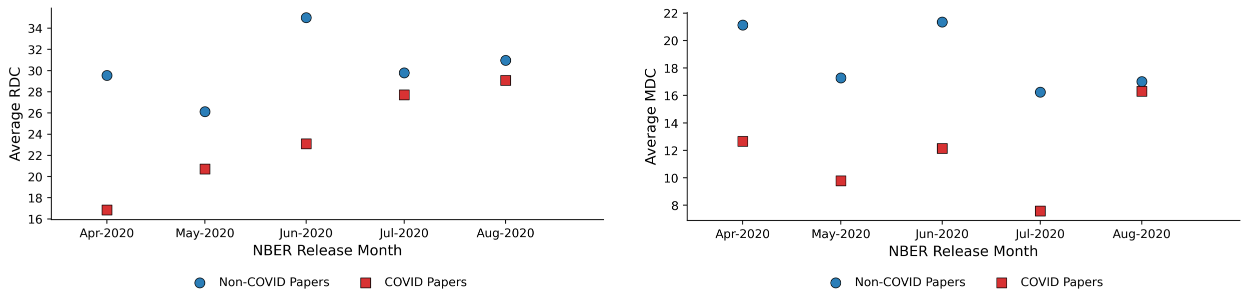
Table 6: Effects on Research Indices: Author & Journal Specifications

	Author Reg			**Journal Reg**		
	(1) RDC	(2) MDC	(3) DIC	(4) RDC	(5) MDC	(6) DIC
Post (β)	-0.788	-0.202	0.331	-0.726	-2.075***	0.315
	(1.007)	(0.704)	(0.813)	(0.748)	(0.521)	(0.595)
About COVID (β)	-3.998***	-4.117***	0.001	-5.155***	-4.873***	0.486
	(1.145)	(0.801)	(0.925)	(0.866)	(0.603)	(0.688)
Author FE	✓	✓	✓			
Discipline FE	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Journal FE				✓	✓	✓
N	6,857	6,857	6,857	6,369	6,369	6,369
Pre-COVID mean	27.956	17.803	53.485	27.956	17.803	53.485

Notes: OLS regressions predicting the three composite indices—Reporting and Design Composition (RDC), Methods and Data Composition (MDC), and Differentiation and Integration Composition (DIC). Columns (1)–(3) use author fixed effects; columns (4)–(6) use journal fixed effects. Standard errors are in parentheses below coefficients. *, **, *** indicate $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively. Pre-COVID means computed on observations with `post`=0 after dropping rows missing any outcome.

COVID-related papers score 14–18% lower on the RDC index, indicating leaner documentation with fewer reported diagnostic tests, robustness exercises, and explicit statements about statistical uncertainty. The decline is even larger for the MDC index, at 23 to 27%, reflecting fewer newly introduced estimation techniques, less evidence of data construction or linkage, and reduced use of novel or customized empirical approaches when projects were completed under shorter timelines. By contrast, non-COVID papers released during the pandemic show no meaningful change. Holding author or journal constant, their documentation and methodological practices remained stable. The DIC index also shows no systematic difference, indicating that COVID papers resembled other work in their framing. Authors drew on similar sources, referenced comparable literatures, and maintained the same degree of cross-field engagement as before the pandemic. This stability is itself informative. Faced with time pressure and rapidly evolving questions, economists largely relied on the theoretical and empirical traditions they already knew rather than expanding into unfamiliar literatures. The null result therefore highlights an important feature of crisis-era research: the production process adapted to urgency, but the theoretical frameworks, empirical approaches, and reference networks that structured economic research remained largely unchanged. Together, the three indices show that pandemic research differed most clearly in execution. Economists working under compressed timelines documented their analyses less fully and invested less in developing new data or methods, yet the theoretical frameworks, empirical strategies, and reference patterns that guided their work remained largely consistent with pre-pandemic research.

These effects were concentrated in the first wave of pandemic scholarship. Figure 6 tracks monthly RDC and MDC scores during the pandemic's early months, showing that COVID papers released in April 2020 scored markedly lower than contemporaneous non-COVID work, but the gap narrowed quickly. By mid-summer, scores for COVID papers had largely converged to those of other research, driven by improvements within the COVID literature itself rather than changes in non-COVID work. The earliest papers, produced when uncertainty was greatest and data scarcest, were the ones most affected by compressed production timelines. As the immediate crisis eased and revision cycles lengthened, later COVID papers reincorporated the design statements, diagnostic checks, and methodological details that had been truncated in the initial rush to produce timely evidence.



(a) Reporting & Design Composition (RDC)

(b) Methods & Data Composition (MDC)

Figure 6: Monthly binned scatter of indices by topic, Apr–Aug 2020. Blue circles: non-COVID papers; red squares: COVID papers. Points show monthly means; axes are in index units (0–100). COVID papers start lower on both dimensions but approach non-COVID levels by mid-summer, consistent with increasing incorporation of transparent reporting and method/data investments over time. Appendix figures C.7a and C.7b plot the medians.

Taken together, the document features and indices reveal a consistent picture of how economists adapted their research practices under crisis conditions. The pandemic saw papers that were shorter, less elaborated in design, and less methodologically intensive, reflecting the compression of research timelines and limited access to new data. These differences, however, narrowed quickly as scholars adjusted to the new environment. By mid-2020, COVID papers resembled other work along most observable dimensions of transparency and empirical thoroughness, suggesting a rapid institutional and professional recalibration. Appendix Sections C.4 and C.3 report results based on equal-weighted indices. The consistent estimates indicate robustness to alternative weighting schemes.

Viewed alongside the preceding evidence on diffusion and visibility, these findings suggest that crisis conditions reshaped the full research cycle from production through dissemination. The same pressures that accelerated publication and heightened early attention also shaped execution: projects were completed more quickly, published sooner, and initially presented with less methodological depth. The earliest papers, which received the greatest attention across academic, media, and policy outlets, also scored lowest on the reporting and methods indices, reflecting the tradeoff between speed and elaboration rather than differences in quality. Yet these changes proved transitory. As timelines normalized, both the pace and form of scholarship converged toward pre-pandemic patterns, even as the early surge in visibility left lasting traces in the field's collective focus. Overall, the evidence depicts a discipline that adapted flexibly to crisis demands—temporarily prioritizing speed and salience, but ultimately returning to its prior equilibrium in method, presentation, and attention.

5 Conclusion and Limitations

This paper examines how the COVID-19 pandemic reshaped the production and diffusion of economic research, tracing how economists adapted their work under conditions of urgency and uncertainty.

Using linked data on NBER working papers, journal placements, citation trajectories, media and policy mentions, and OCR-based indices of research practices, I document how pandemic-era scholarship differed from work produced under normal circumstances. COVID-related papers drew extraordinary attention in their first year, receiving citations many times faster than comparable non-COVID work, moved through publication roughly six months sooner, and appeared more frequently in policy documents, media coverage, and other public platforms. At the same time, they were less likely to appear in the most selective journals, exhibited steeper citation decay, and scored 15–25% lower on indices of empirical thoroughness. These differences were most pronounced among the earliest papers, which received the greatest attention across academic, media, and policy outlets but also displayed the leanest designs and data work.

By mid-2020, however, these gaps had largely narrowed as research timelines lengthened and revision cycles expanded, suggesting that the compression of research practice was a short-lived feature of the first months of crisis response.

Taken together, these results describe a distinctive mode of scholarship that emerged under crisis conditions—defined by accelerated production, concentrated early attention, and systematic links between speed and observable research practices. Crisis-driven work moved differently through academic and public channels than research produced under standard timelines, revealing how the research system as a whole adjusted to an exceptional period of global demand for evidence. Whether this adaptive mode ultimately served society well is a question that lies beyond what bibliometric and textual data can answer; it depends on outcomes this paper cannot observe, including how effectively the research informed policy or shaped lasting intellectual directions. What can be measured, however, is that the profession temporarily recalibrated its pace and procedures to meet those demands, leaving clear and measurable traces in how studies were designed, executed, and disseminated.

The analysis focuses on NBER working papers, which mainly represent the work of senior, U.S.-based economists and less of early-career researchers or smaller subfields. Therefore the findings should be interpreted with that scope in mind. The five-year window provides a view of early citation and publication dynamics but may not reveal which projects will ultimately have sustained influence. The outcomes I measure—citations, media and policy mentions, and indices of research practices—speak to attention and execution rather than ultimate intellectual or policy impact. Some papers may have shaped debates in ways that leave little bibliometric trace, while others may have generated visibility I do not observe.

Future extensions could broaden this analysis in several directions. Incorporating SSRN data would expand the sample and allow richer comparisons across career stages and subfields.[3] Cross-disciplinary comparisons—with medicine, public health, or political science, where rapid-response research is more institutionalized—could reveal whether the patterns observed here reflect economics-specific norms or general features of crisis scholarship. Comparing across historical shocks, like the 2008 financial crisis, natural disasters, or other public health emergencies, would clarify whether front-loaded attention and speed–rigor tradeoffs are recurring features of urgent research. Finally, following the career trajectories of pandemic-era authors could illuminate whether early visibility produced lasting professional benefits or quickly faded once attention shifted.

Alternative interpretations remain possible. Lower placement rates in top journals may reflect deliberate rerouting toward faster or more specialized outlets rather than rejection. Rapid citation decay could reflect the natural lifecycle of policy-oriented work designed for immediate relevance. The relationship between publication speed and methodological depth may partly reflect selection, as

[3] SSRN blocks scraping and does not provide their metadata free-of-cost which prohibited use of their data in this project.

the most urgent questions were often addressed first with whatever data and methods were available. These explanations do not contradict the findings but emphasize that the observed patterns reflect real tradeoffs under time pressure rather than failures of rigor.

The results also point to practical lessons for institutions that support research during crises. Funding agencies might formalize rapid-response mechanisms distinct from standard grant cycles, recognizing that different tempos of research serve different purposes. Journals could make expedited review tracks more transparent, clarifying how they balance speed with depth of evaluation. Universities and departments might refine how they assess crisis-era work, acknowledging its distinctive timelines and objectives. Such adjustments would not lower standards but would make explicit how rigor and responsiveness can coexist when research is conducted under exceptional conditions.

The pandemic demonstrated that economic research is remarkably adaptive. Faced with unprecedented global uncertainty, economists produced work that moved faster, reached wider audiences, and temporarily altered both the pace and the form of scholarly communication. Those adjustments left measurable marks on how studies were written, reviewed, and cited, yet the profession quickly reestablished its pre-crisis equilibrium. What remains to be understood is not whether research changed—it clearly did—but what those changes meant for the questions economists pursued, the policies they informed, and the ideas that endured once the crisis passed.

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A Background on the Pandemic

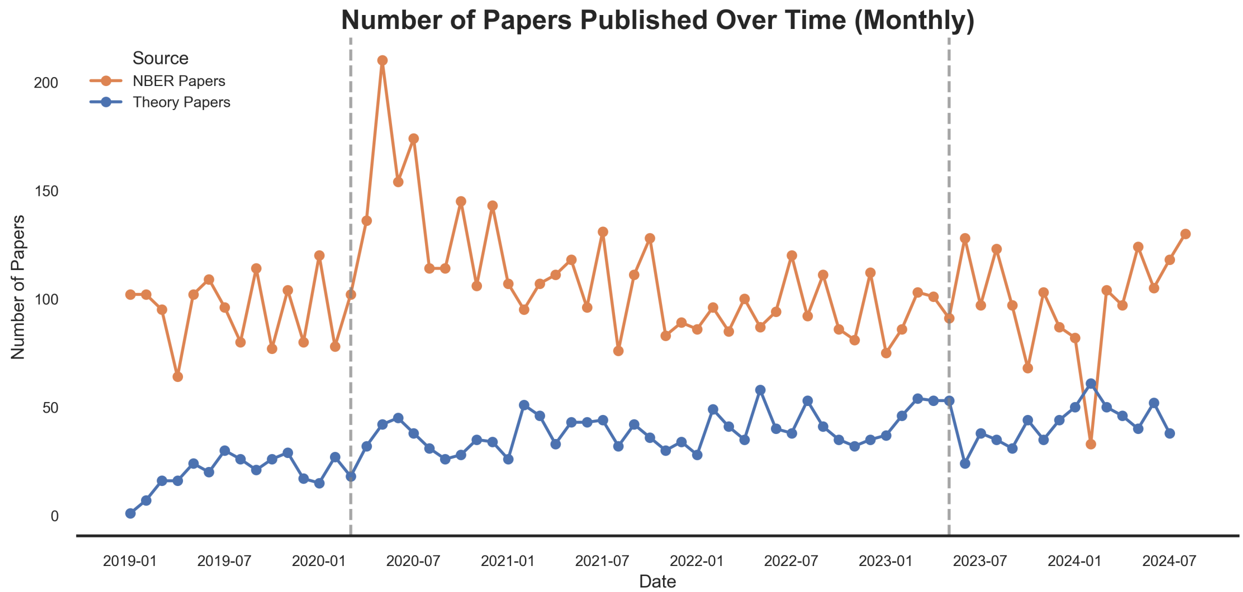


Figure A.1: Monthly counts of empirical papers (from NBER) and theoretical papers (from arXiv). The gray lines mark the WHO's declaration of COVID-19 as a pandemic and the WHO's declaration of the end of the emergency. This figure shows how applied/empirical output (NBER working papers) and theoretical work (arXiv submissions) evolved around the pandemic period. It documents the sharp COVID-era surge in empirical economics output relative to theory.

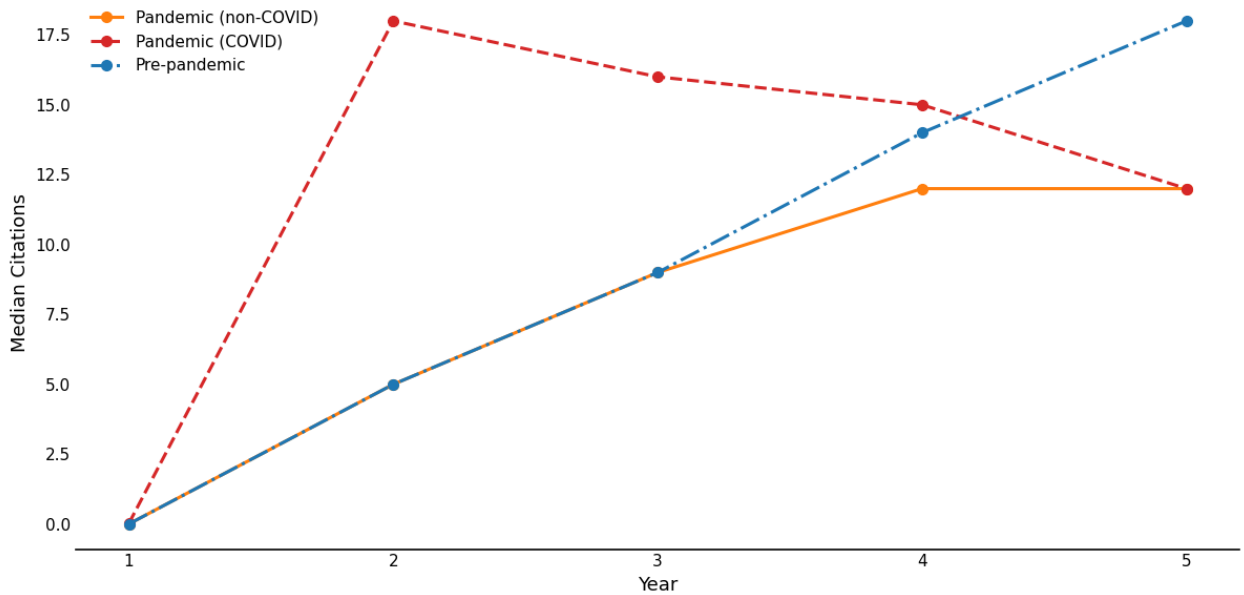


Figure A.2: Median citation trajectories over five years for the top quartile of NBER working papers by year, split by timing and topic: pre-pandemic (blue), pandemic non-COVID (orange), and pandemic COVID (red). COVID papers exhibit front-loaded trajectories with steep initial rises, early peaks, and subsequent declines. Non-COVID work follows slower but more sustained growth. This highlights that pandemic-era attention was intense but decayed quickly.

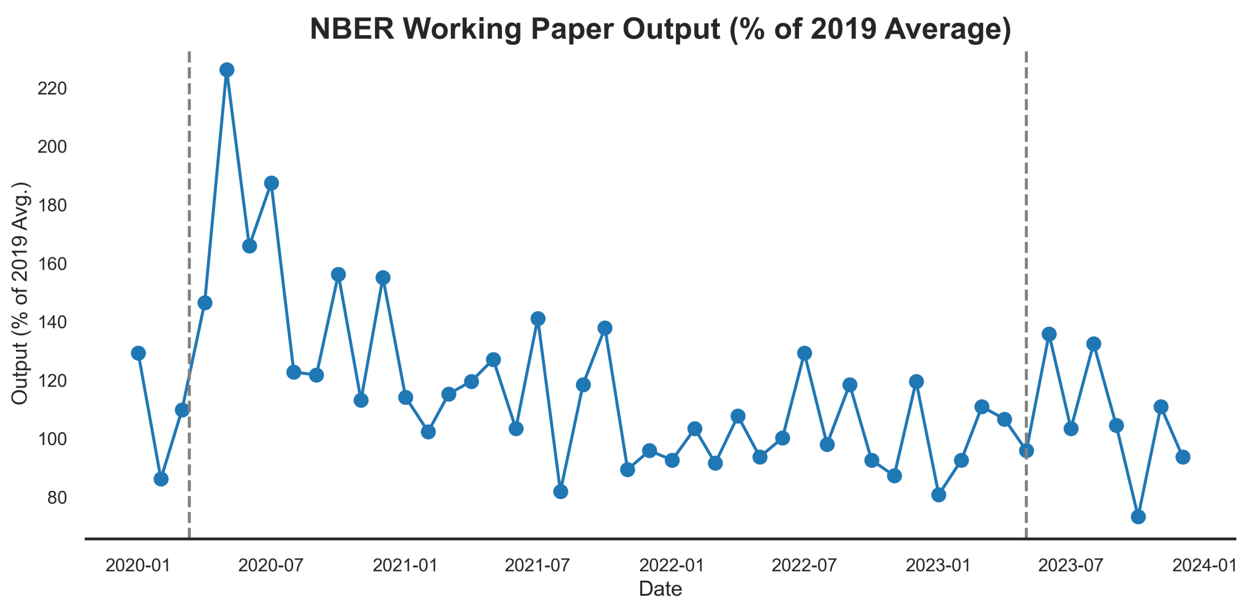


Figure A.3: NBER working paper output expressed as a percent of the 2019 average. Output spiked in early 2020 and remained elevated through 2021. The figure normalizes each month's publication count by the 2019 average, showing the level shift in total output during the pandemic.

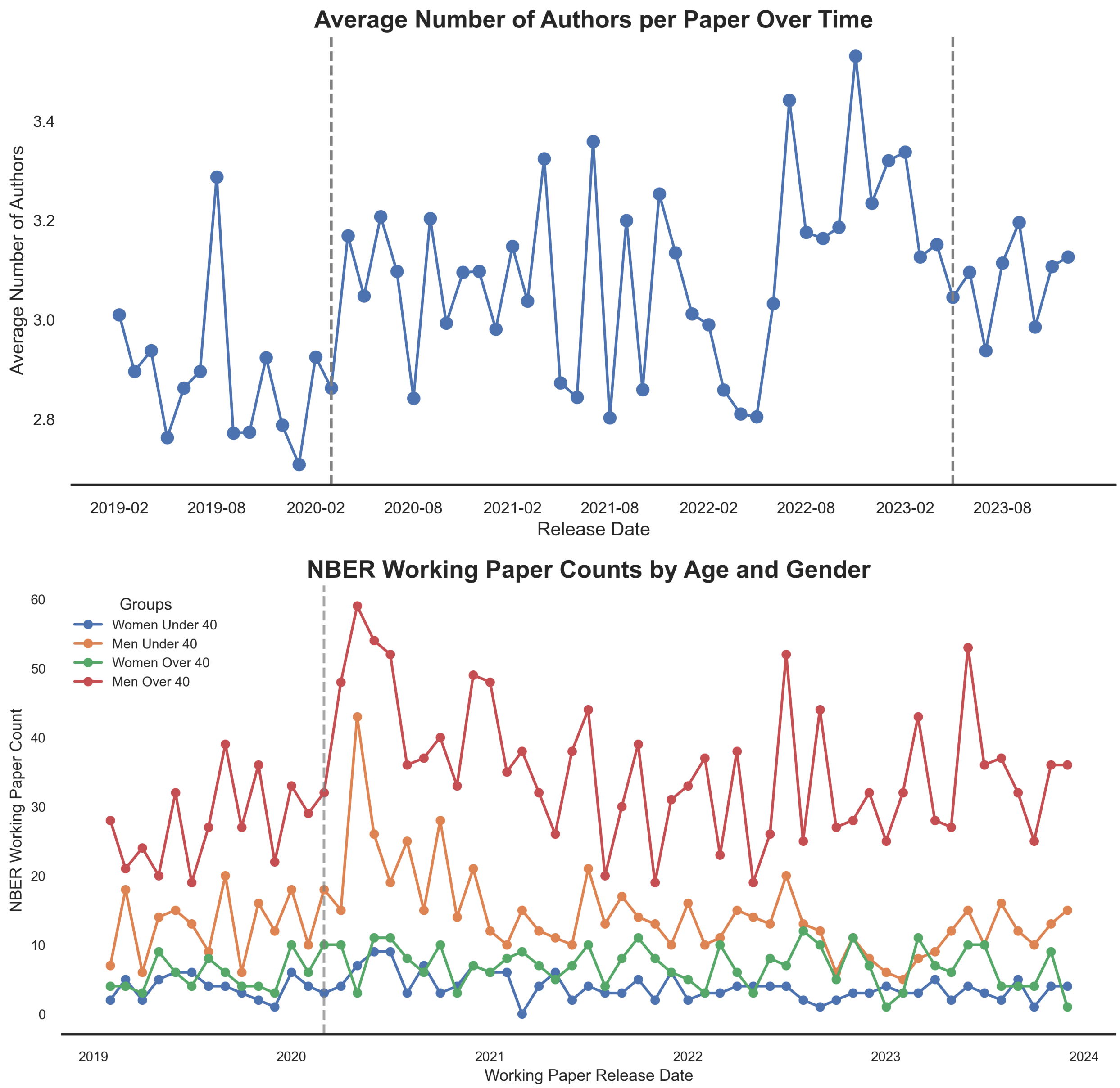


Figure A.4: Collaboration and author composition over time. Top: average number of authors per paper. Bottom: output by author gender and age. Vertical gray lines mark the WHO pandemic declaration (March 2020) and official end (May 2023). The top panel shows that team size increased slightly during the pandemic, indicating greater collaboration intensity. The bottom panel shows that most of the surge in COVID-related output came from senior (often male) researchers.

B Model Robustness

B.1 Citation Count Distribution and Overdispersion

Table B.1: Descriptive Statistics and Dispersion Diagnostics of Citation Counts

Statistic	Value
Citations Minimum	0
Citations Maximum	5,849
Citations Mean	54.77
Citations Variance	27,551.92
Citations 95th Percentile	244.00
Citations 99th Percentile	642.90
Citations Variance / Mean Ratio	503.07

Notes: The variance-to-mean ratio exceeds 500, indicating severe overdispersion and a heavy right tail (few extremely high-citation papers). This motivates the use of Negative Binomial models rather than Poisson/log-linearized OLS for citation outcomes in the main text.

B.2 Negative Binomial vs. Quasi-Poisson Diagnostics

Table B.2: Summary of Pearson Residuals (Negative Binomial)

	Mean	Std. Dev.	Min	Max	25%	Median	75%
Value	-0.012	1.017	-0.858	14.400	-0.677	-0.344	0.280

Notes: Pearson residuals from the Negative Binomial regression in the main analysis. The mean near zero and standard deviation ≈ 1 indicate a good fit across most of the support. Large positive residuals in the tail correspond to a small set of extremely highly cited papers.

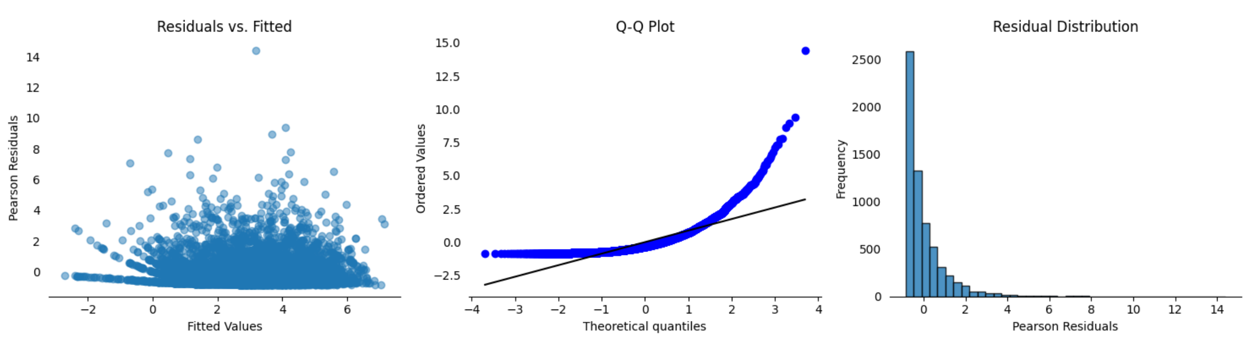


Figure B.5: Diagnostic plots for the Negative Binomial model of citation counts.

Notes: Left: Pearson residuals vs. fitted values show no clear pattern, suggesting no major omitted nonlinearity. Middle: Q–Q plot vs. theoretical quantiles shows modest tail deviation driven by a few superstar papers. Right: histogram shows residuals centered near zero with right skew. Together, these support the Negative Binomial specification.

Table B.3: Summary of Pearson Residuals (Quasi-Poisson with Robust SE)

	Mean	Std. Dev.	Min	Max	25%	Median	75%
Value	0.301	6.996	-29.418	79.287	-3.138	-0.852	1.976

Notes: Pearson residuals from the quasi-Poisson regression with robust standard errors. The very large standard deviation and extreme tails indicate that quasi-Poisson does not fully capture the heavy right tail of citation counts.

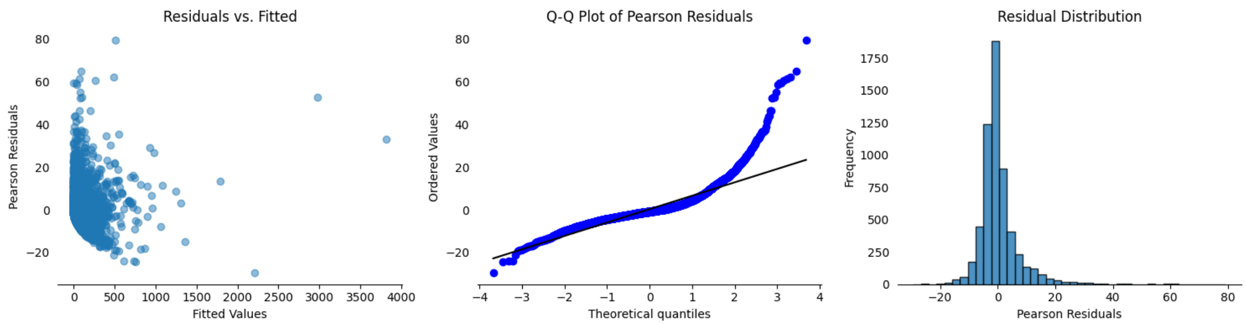


Figure B.6: Diagnostic plots for the Quasi-Poisson model of citation counts.

Notes: Residual variance increases sharply with fitted values (left panel), and the Q–Q comparison shows large positive tail deviations. The quasi-Poisson adjusts variance linearly, which is not flexible enough for this setting. This motivates the choice to report Negative Binomial results in the main text and use quasi-Poisson as robustness.

B.3 Alternative Citation Specifications

Table B.4: Quasi-Poisson Regression Estimates

Variable	Coefficient	Std. Error	p-value
About COVID	0.999***	0.077	0.000
Observations		6,236	

Notes: Quasi-Poisson GLM of citation counts. Covariates include month and year of release, primary discipline, journal group, author fixed effects, team size, an indicator for post–March 11, 2020 release, and an indicator for COVID-focused topic. Robust standard errors. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.5: Negative Binomial Regression Estimates (Excluding Top 1% of Citations)

Variable	Estimate	p-value
Post	0.018	0.921
	(0.186)	
About COVID	0.701***	0.000
	(0.091)	
Observations	6,173	

Notes: Negative Binomial regression of citations after dropping the top 1% most-cited papers. Standard errors (in parentheses) are clustered at the release-date level. The COVID coefficient remains large and highly significant, showing that headline results are not driven solely by superstar outliers. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.6: Negative Binomial Regression Results: Subsample Comparisons

	Excluding Zero Citations	Excluding Citations ≥ 5
Post	0.031	0.008
	(0.119)	(0.813)
About COVID	0.868***	0.753***
	(0.054)	(0.100)
Observations	5,399	4,178

Notes: Negative Binomial regressions across restricted samples. Left: excludes papers with zero citations. Right: keeps only papers with fewer than five citations. Robust standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. The COVID premium is stable across both subsamples.

B.4 Model Fit and Dispersion for Policy / Media Outcomes

Table B.7: Model Fit and Dispersion Summary

Statistic	**Value**
Mean Citations	57.25
Variance Citations	31,402.23
Variance / Mean Ratio	548.55
Poisson AIC	495,157.82
Negative Binomial AIC	33,847.71
Poisson BIC	495,367.28
Negative Binomial BIC	34,063.33
Dispersion (Poisson)	334.87
Estimated α	1.5258
LR Test p-value	0.000000

Notes: Fit and dispersion statistics comparing Poisson and Negative Binomial. The very large variance-to-mean ratio and the likelihood ratio test both reject Poisson equidispersion. Much lower AIC/BIC for the Negative Binomial confirms it is the appropriate baseline model.

B.5 Regression Discontinuity Robustness: Citation Counts

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Bandwidth (months)	1	2	4	3	3	3	3
Cutoff date	Mar 11	Mar 11	Mar 11	Mar 18	Mar 25	Apr 02	Apr 08
Post	0.374	0.494*	0.294	0.373	-0.079	-0.290	-0.327*
	(0.358)	(0.281)	(0.198)	(0.233)	(0.187)	(488918.651)	(0.190)
Discipline FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Release-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	207	435	675	654	637	621	599

Table B.8: Robustness of Enhanced Model to Bandwidth and Cutoff Choices

Notes: Each column reports the coefficient on the post-cutoff indicator (Post) from a separate negative binomial generalized linear model of citation counts. The treatment indicator equals one for papers released on or after the cutoff date shown in the header. Bandwidths denote symmetric windows (in months) around each cutoff. The extreme standard error in column (6) arises because one paper—Dingel and Neiman (2020), released on April 1—received thousands of citations, heavily influencing the likelihood. Re-estimating the same specification using a median (quantile, $\tau = 0.5$) regression yields statistically insignificant results with more reasonable standard errors ($Post$ = –6.703, SE = 9.246). All specifications include a linear running variable in days from the cutoff, an indicator for COVID-related papers, and fixed effects for primary discipline and release month. Standard errors are clustered by release week.

B.6 Regression Discontinuity Robustness: Media Engagement

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Bandwidth (months)	1	2	4	3	3	3	3
Cutoff date	Mar 11	Mar 11	Mar 11	Mar 18	Mar 25	Apr 02	Apr 08
Post	0.628	0.267	-0.316	0.046	-0.648	-0.065	-0.145
	(0.690)	(0.494)	(0.360)	(0.321)	(0.417)	(0.394)	(0.372)
Discipline FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Release-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	126	271	579	425	429	438	443

Table B.9: Robustness of Media Engagement RD to Bandwidth and Cutoff Choices

Notes: Each column reports the coefficient on the post-cutoff indicator (Post) from a separate negative binomial generalized linear model of media engagement. The treatment indicator equals one for papers released on or after the cutoff date shown in the header. Bandwidths denote symmetric windows (in months) around each cutoff. All specifications include a linear running variable in days from the cutoff, an indicator for COVID-related papers, and fixed effects for primary discipline and release month. Standard errors are clustered by release week.

B.7 Regression Discontinuity Robustness: Policy Mentions

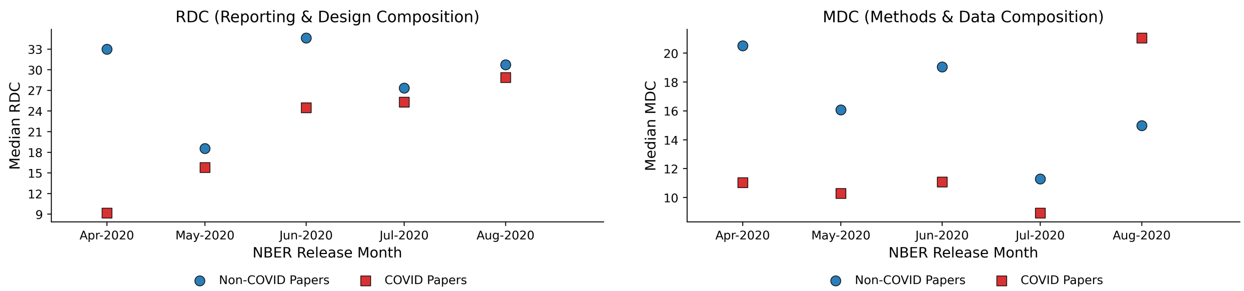
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Bandwidth (months)	1	2	4	3	3	3	3
Cutoff date	Mar 11	Mar 11	Mar 11	Mar 18	Mar 25	Apr 02	Apr 08
Post	0.508	0.240	-0.344	0.039	-0.650	-0.048	-0.167
	(0.697)	(0.488)	(0.367)	(0.322)	(0.424)	(0.395)	(0.369)
Discipline FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Release-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	126	271	579	425	429	438	443

Table B.10: Robustness of Policy Mentions RD to Bandwidth and Cutoff Choices (Negative Binomial GLM, $\alpha = 5.0$)

Notes: Each column reports the coefficient on the post-cutoff indicator (Post) from a separate negative binomial generalized linear model of policy mentions. The treatment indicator equals one for papers released on or after the cutoff date shown in the header. Bandwidths denote symmetric windows (in months) around each cutoff. All specifications include a linear running variable in days from the cutoff, an indicator for COVID-related papers, and fixed effects for primary discipline and release month. Standard errors are clustered by release week.

C Paper Indices

C.1 Index Trajectories (RDC and MDC)



(a) Reporting & Design Composition (RDC)

(b) Methods & Data Composition (MDC)

Figure C.7: Monthly binned scatter of index scores by topic, Apr–Aug 2020. Blue: non-COVID papers. Red: COVID papers.

Notes: RDC summarizes reporting/identification transparency; MDC summarizes methodological and data-construction investment. COVID papers start lower on both measures early in the pandemic, then converge toward non-COVID levels by mid-summer 2020 as revision cycles lengthen.

C.2 Journal Rankings Used in Analysis

Table C.11: Economics Journals by Rank

Rank	Journal name	Rank	Journal name
1	Quarterly Journal of Economics	31	IMF Economic Review
2	American Economic Review	32	J. Assoc. Environ. and Resource Economists
3	Econometrica	33	Games and Economic Behavior
4	Review of Economic Studies	34	European Economic Review
5	Journal of Political Economy	35	Econometrics Journal
6	American Economic Journal–Macroeconomics	36	Economic Theory
7	American Economic Journal–Applied Economics	37	Journal of Money, Credit and Banking
8	Journal of the European Economic Association	38	Journal of Industrial Economics
9	American Economic Journal–Economic Policy	39	Journal of Urban Economics
10	Journal of Labor Economics	40	Journal of Law & Economics
11	Theoretical Economics	41	Journal of Risk and Uncertainty
12	Review of Economics and Statistics	42	Journal of Health Economics
13	Journal of Monetary Economics	43	Economic Development and Cultural Change
14	American Economic Journal–Microeconomics	44	Scandinavian Journal of Economics
15	Journal of Human Resources	45	Economica
16	Quantitative Economics	46	Journal of Financial Econometrics
17	Journal of Economic Growth	47	Journal of Policy Analysis and Management
18	Economic Journal	48	Journal of Economic History
19	RAND Journal of Economics	49	J. Environ. Economics and Management
20	Review of Economic Dynamics	50	Econometric Reviews
21	Journal of Business & Economic Statistics	51	World Bank Economic Review
22	Journal of International Economics	52	Int. Journal of Industrial Organization
23	International Economic Review	53	Journal of Economic Behavior & Organization
24	Journal of Economic Theory	54	Journal of Law, Economics & Organization
25	Journal of Public Economics	55	Labour Economics
26	Journal of Econometrics	56	Journal of Population Economics
27	Experimental Economics	57	Quantitative Marketing and Economics
28	Econometric Theory	58	Economic Inquiry
29	Journal of Development Economics	59	Journal of Economic Dynamics & Control
30	Journal of Applied Econometrics	60	Education Finance and Policy

Table C.12: Economics Journals by Rank (continued)

Rank	Journal name
61	Canadian Journal of Economics
62	Explorations in Economic History
63	Oxford Bulletin of Economics and Statistics
64	Journal of Economics & Management Strategy
65	Journal of Economic Surveys
66	Journal of Mathematical Economics
67	American Law and Economics Review
68	International Journal of Game Theory
69	Economics of Education Review
70	National Tax Journal
71	Social Choice and Welfare
72	Regional Science and Urban Economics
73	Theory and Decision
74	Journal of Human Capital
75	Macroeconomic Dynamics
76	Review of Economic Design
77	Geneva Risk and Insurance Review
78	Journal of Demographic Economics
79	International Tax and Public Finance
80	Oxford Economic Papers
81	Journal of Economic Inequality
82	Review of Income and Wealth
83	American Journal of Health Economics
84	Journal of Economic Psychology
85	Economic History Review
86	Journal of Regional Science
87	Economics Letters
88	Health Economics
89	Journal of Public Economic Theory
90	European Review of Economic History

Rank	Journal name
91	Mathematical Social Sciences
92	Public Choice
93	Economics and Philosophy
94	Journal of Comparative Economics
95	Southern Economic Journal
96	Review of World Economics
97	B. E. Journal of Economic Analysis & Policy
98	Review of Network Economics
99	Economics & Politics
100	Fiscal Studies

Table C.13: This list defines journal "rank groups" used in the publication regressions (Section 4.2) and to benchmark correlations between the constructed indices and outlet selectivity. Ranks 61–100 continue the journal list in Table C.11. These journals enter the "Top 50 / Top 100" and "high-impact" groupings used in Section 4.2 when testing publication outcomes and time-to-publication.

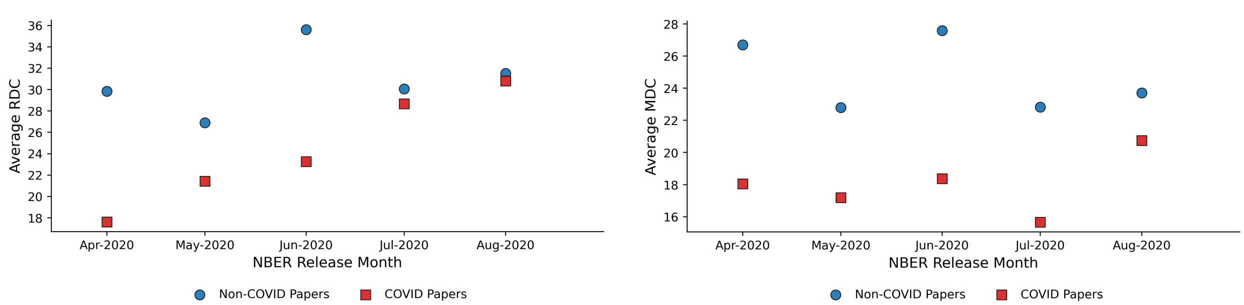
C.3 Equal-Weighted Index Regressions

Table C.14: Effects on Research Indices: Author and Journal Specifications

	Author Reg			Journal Reg		
	(1) RDC	(2) MDC	(3) DIC	(4) RDC	(5) MDC	(6) DIC
Post (β)	-0.637	-0.761	0.070	-0.796	-1.838***	0.390
	(0.969)	(0.605)	(0.643)	(0.719)	(0.448)	(0.470)
About COVID (β)	-3.756***	-3.648***	-0.495	-5.012***	-4.723***	-0.661
	(1.102)	(0.688)	(0.731)	(0.832)	(0.518)	(0.544)
Author FE	✓	✓	✓			
Discipline FE	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Journal FE				✓	✓	✓
N	6,857	6,857	6,857	6,369	6,369	6,369
Pre-COVID mean	28.493	24.205	54.056	28.493	24.205	54.056

Notes: OLS regressions predicting composite research indices. Columns (1)–(3) include author fixed effects; columns (4)–(6) include journal fixed effects. RDC measures reporting/identification transparency; MDC measures methods/data investment; DIC measures differentiation and positioning within the literature. All indices here are the *equal-weighted* versions. All models include discipline, month, and year controls. Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

C.4 Equal-Weighted Index Trajectories



(a) Reporting & Design Composition (RDC) (b) Methods & Data Composition (MDC)

Figure C.8: Monthly binned scatter of equal-weighted RDC and MDC indices by topic, Apr–Aug 2020. COVID papers again start lower and converge toward non-COVID papers within a few months.