# Tracking the Credibility Revolution across Fields<sup>\*</sup>

Paul Goldsmith-Pinkham Yale University and NBER

May 2024

#### Abstract

This paper updates Currie, Kleven, and Zwiers (2020b) by examining the credibility revolution across fields, including finance and macroeconomics, using NBER working papers up to May 2024. While the growth in terms related to identification and research designs have continued, finance and macroeconomics have lagged behind applied micro. Difference-in-differences and regression discontinuity designs have risen since 2002, but the growth in difference-in-difference has been larger, more persistent, and more ubiquitous. In contrast, instrumental variables have stayed flat over this period. Finance and macro, particularly corporate finance, has experienced significant growth in mentions of experimental and quasi-experimental methods and identification over this time period, but a large component of the credibility revolution in finance is due to difference-in-differences. Bartik and shift-share instruments have grown across all fields, with the most pronounced growth in international trade and investment, economic history, and labor studies. Synthetic control has not seen continued growth, and has fallen since 2020.

Goldsmith-Pinkham: paul.goldsmith-pinkham@yale.edu

The credibility revolution in economics has been one of the defining trends of the last two decades (Angrist and Pischke 2010). Leveraging a wealth of new data and a focus on transparent, credible research designs, economists have generated profound insights into an array of pressing questions, from the determinants of economic growth to the impacts of social and educational policies. But to what extent has the credibility revolution permeated different fields of economics? Are the trends identified in the early days of the movement by Angrist and Pischke (2010) still continuing apace? And are different empirical methods being adopted evenly, or are some techniques leading the charge while others languish?

In this paper, I take up these questions by building on the innovative approach of Currie, Kleven, and Zwiers (2020b). Using natural language processing methods, I analyze the text of over 32,000 National Bureau of Economic Research (NBER) working papers to identify the frequency of phrases related to different empirical techniques. By extending the sample period of Currie et al. (2020) to 2024 and including papers from all NBER programs, I assess the latest state of the credibility revolution across fields, including finance and macroeconomics, which were omitted from the original analysis.

The results show that the aggregate trends identified by Currie et al. (2020) are still advancing, with the use of experimental and quasi-experimental methods continuing to rise through 2024. However, there is significant heterogeneity across fields. While applied microeconomics has embraced empirical techniques that emphasize research design, such as difference-in-differences, event studies, and randomized trials, finance and macroeconomics lag behind.

Within finance, corporate finance has seen robust growth in a subset of these tools, particularly difference-in-differences designs, but the use of instrumental variables, regression discontinuity, and experimental methods is a much smaller relative share. The adoption of popular tools like Bartik and shift-share instruments is also highly uneven across fields, with rapid growth in applied micro areas like labor, trade, and economic history, while other tools like synthetic controls appear to have already peaked in their popularity.

These findings provide an important check on the sometimes triumphalist narrative of the credibility revolution rapidly sweeping across economics. They suggest a more nuanced picture, with the frontier of empirical work using credible, transparent research designs still centered in applied microeconomics, and other fields making strides but at an uneven pace. The analysis also highlights how a single method, in this case difference-in-differences, can dominate the rise of empirical work in a field like finance and macroeconomics, when other techniques are not taken up in parallel.

### 1 Data and Methods

To construct measures of the use of empirical methods over time, I follow the approach in Currie, Kleven, and Zwiers (2020b). This involves using the text of papers and looking for sets of keywords using regular expressions that capture the spirit of the credibility revolution (e.g. "threats to identification" or "identification strategy").<sup>1</sup>. I replicate Currie, Kleven, and Zwiers (2020b)'s data collection process for the NBER working paper series, starting from working paper 1000 to 32,436. Unlike Currie, Kleven, and Zwiers (2020b), I do not exclusively focus on papers under the "applied micro" heading, but instead include all papers in the NBER working paper series. After text processing and cleaning, I am left with a sample of 28,397 papers from 1982 to 2024.



(2020b) in "applied micro"

Figure 1: NBER Working Paper Counts over Time. Data for Currie, Kleven, and Zwiers (2020b) is measured in Appendix Figure B.I. in their paper. My sample ends in May 2024.

As discussed in Currie, Kleven, and Zwiers (2020b)'s replication package (Currie, Kleven, and Zwiers 2020a), the data cleaning steps for the PDFs can cause errors, particularly in the PDF-to-text conversion. As a validation exercise, I compare the number of papers in my sample over time in the "applied micro" setting to Currie, Kleven, and Zwiers (2020b) in Figure 1a. My sample has many more gaps in the 1990s, due to data processing errors for PDFs in that time period, but coverage appears

<sup>&</sup>lt;sup>1</sup>See the Appendix for the full set of words. I follow the same method as Currie, Kleven, and Zwiers (2020b).

very close in the early 1980s, and from 1999 onwards. In Figure 2, I compare two headline estimates from Currie, Kleven, and Zwiers (2020b) to my estimates – the rise in the fraction of papers making explicit reference to identification ("identification") and the fraction of papers making reference to randomized controlled trials (RCTs), lab experiments, difference-in-differences, regression discontinuity, event studies, or bunching ("All experimental and quasi-experimental methods"). In both settings, my estimates track reasonably well, except for during the late 1990s period. As a result, in all results going forward, I focus on the period of 2000 onwards for the remainder of the analysis, leaving a sample of 24,702 papers. I plot the sample over time in Figure 1b.



and Zwiers (2020b) in "applied micro"

(a) Comparison of identification measure to Currie, Kleven, (b) Comparison of all experimental and quasi-experimental measure to Currie, Kleven, and Zwiers (2020b) in "applied micro"

Figure 2: Validation of measurement with Currie, Kleven, and Zwiers (2020b). Data for Currie, Kleven, and Zwiers (2020b) is taken from Figure 2 Panel A and B. I plot the raw measure, while the Currie, Kleven, and Zwiers (2020b) measure is a rolling five-year mean.

In the NBER working paper series, papers can be submitted to different programs (there are fourteen in total). A single paper may be submitted to multiple programs, and 55% of papers are submitted to more than one.<sup>2</sup> I report the breakdown by program in Table 1. The most common programs are Economic Fluctuations and Growth (a macroeconomics research program), Public Economics (an "applied micro" research program, as classified by Currie, Kleven, and Zwiers (2020b)) and Labor Studies, (also "applied micro"). Development Economics is smaller in part because it only began as a program in 2012.

In order to provide a simple comparison across programs, I extend Currie, Kleven, and Zwiers (2020b)'s classification of applied micro. I define "finance" as Asset Pricing and Corporate Finance, while "macro" or "macro/other" includes the remainder of programs: Development of the American Economy (the economic history research group),

 $<sup>^{2}45\%</sup>$  have one program, 32% have two programs, 15% have three programs, 5% have four programs, and 2% have five programs.

NBER Program	Field	Number of Papers
Asset Pricing	Finance	2,739
Children	Applied Micro	$1,\!651$
Corporate Finance	Finance	2,502
Development Economics	Applied Micro	1,070
Development of the American Economy	Macro/Others	1,398
Economic Fluctuations and Growth	Macro/Others	$3,\!952$
Economics of Aging	Applied Micro	1,185
Economics of Education	Applied Micro	1,584
Economics of Health	Applied Micro	$2,\!636$
Environment and Energy Economics	Applied Micro	1,143
Industrial Organization	Applied Micro	1,023
International Finance and Macroeconomics	Macro/Others	2,167
International Trade and Investment	Applied Micro	$1,\!179$
Labor Studies	Applied Micro	$3,\!387$
Law and Economics	Macro/Others	995
Monetary Economics	Macro/Others	1,732
Political Economy	Applied Micro	857
Productivity, Innovation, and Entrepreneurship	Macro/Others	2,066
Public Economics	Applied Micro	3,413

Table 1: NBER Working Paper Series counts by program

Economic Fluctuations and Growth, International Finance and Macroeconomics, Law and Economics, Monetary Economics, and Productivity Innovation and Entrepreneurship. These fields are defined in Table 2. Currie, Kleven, and Zwiers (2020b) go one step further and define applied micro as papers that *solely* have applied micro programs listed for them, making applied micro a paper-specific label. To simplify the analysis, I use non-exclusive labels – if a paper is in both finance and applied micro, it is counted in both categories. The amount of overlap is non-trivial, but not extreme. In Table 2, I report the overlap across fields. Roughly 44 percent of papers are excusively applied micro, seven percent in excusively finance, 19 percent in just macro/other, and then a scattering across other pairings. The most common cross field pairings are applied micro and macro/other (19%), and finance and macro/other (6%).

In the results that follow, any field or program-specific results are not mutually exclusive. A paper contributes equally to each program that it is submitted to, and I interpret the results accordingly.

Field	Number of Papers	Share of Papers
Applied Micro	10,654	0.44
Applied Micro, Finance	535	0.02
Applied Micro, Finance, Macro/Others	657	0.03
Applied Micro, Macro/Others	4,521	0.19
Finance	1,633	0.07
Finance, Macro/Others	1,550	0.06
Macro/Others	4,682	0.19

Table 2: Breakdown of papers by field groupings

## 2 Results

#### 2.1 Overall trends

I begin by presenting the updated overall trends over the sample period for all papers. In Figure 3, I present the updated version of Currie, Kleven, and Zwiers (2020b)'s Figure 2.<sup>3</sup> For each graph, the solid line reflects the raw data and the dashed line is the two-year moving average.

Almost all trends are similar to Currie, Kleven, and Zwiers (2020b)'s sample, and continued in the same direction. In Figure 3a, the share of papers that make explicit mention to identification has gone up overall, but has flattened since 2016 at around 40%.<sup>4</sup> In Figure 3b, the share of papers that make reference to any experimental or quasi-experimental method has continued to rise, even after 2016. Growth in administrative data (Figure 3c) and the graphical revolution (Figure 3d, which calculates the share of figure mentions relative to table mentions) have also continued.

### 2.2 Comparison across fields

I next turn to the comparison across fields, using the breakdown defined in Table 2, and replicate Figure 3 split by field in Figure 4.<sup>5</sup> There are a few distinctive patterns that stand out. For mentions of identification, experimental and quasi-experimental methods, and admin data, applied micro is significantly higher than both finance and

<sup>&</sup>lt;sup>3</sup>In Currie, Kleven, and Zwiers (2020b), they use a five year moving average for their results, whereas I present either the raw underlying data, or a two-year moving average, or both.

<sup>&</sup>lt;sup>4</sup>The keywords used are available in the Appendix, as well as the Appendix of Currie, Kleven, and Zwiers (2020b). To give a sense of what this looks for, matches for identification would flag things like "identification assumption" and "causal identification."

<sup>&</sup>lt;sup>5</sup>I report the two-year moving average to simplify the figures.



Figure 3: This figure updates the main Figure 2 from Currie, Kleven, and Zwiers (2020b) using all papers (not just applied micro) and extended until May 2024. Figure (a) reports the share of papers that mention identification strategies or concerns. Figure (b) reports the share of papers that mention any experimental or quasi-experimental method (this includes diff-in-diff, event studies, regression discontinuity, randomized control trials, lab experiments, bunching designs, and instrumental variables). Note that the original Currie, Kleven, and Zwiers (2020b) measure does not include instrumental variables. Figure (c) reports the share of papers that mention administrative data. Figure (d) reports the average number of figure mentions relative to table mentions.

macro/other. In mentions of identification, applied micro has roughly plateaued as of 2017 at 50%, but remains 15% higher than finance and macro/others as of 2024. In share of papers with mentions of methods in Figure 4b, applied micro is at roughly 55% as of 2024, while finance has risen to only 38% and macro/other is at a little over 30%. The graphical revolution in Figure 4d is reversed – macro/other has the highest share of figures relative to tables, followed by finance, and then applied micro.

Since the credibility revolution has grown and permeated the entire economics profession, one useful summary of these results is to examine the state of finance and macro/other *now* relative to applied micro in the past. In terms of mentions of identification, finance and macro/other are roughly where applied micro was between 2008 and 2010. In terms of experimental and quasi-experimental methods, finance and macro/other are roughly where applied micro was between 2012 and 2014. In terms of admin data, finance and macro/other are roughly where applied micro was in 2013.



Figure 4: This figure splits Figure 3 into three overlapping sets of papers: papers submitted to an applied micro group, papers submitted to a finance group, and papers submitted to a macro (or other) group. Figure (a) reports the share of papers that mention identification strategies or concerns. Figure (b) reports the share of papers that mention any experimental or quasi-experimental method (this includes diff-in-diff, event studies, regression discontinuity, randomized control trials, lab experiments, bunching designs, and instruemntal variables). Note that the original Currie, Kleven, and Zwiers (2020b) measure does not include instrumental variables. Figure (c) reports the share of papers that mention administrative data. Figure (d) reports the average number of figure mentions relative to table mentions. See Table 2 for the breakdown of fields, and the Appendix for definitions on keywords.

I next turn to specific identification methods across fields. In Figure 5a, I plot the growth in difference-in-differences over time across the three fields. This includes mentions of both difference-in-differences and event studies. For all three fields, there has been significant growth in difference-in-differences, with applied micro leading the way. However, finance is close behind, in part due to the term "event study," which captures many financial event studies (that are distinct in their design from traditional difference-in-differences).

I next examine the growth in synthetic controls. Notably, in Appendix Figure A.V in Currie, Kleven, and Zwiers (2020b), synthetic control was experiencing rapid growth as of 2018 among applied micro papers. Figure 5b shows that this growth continued until 2020 but appears to have fallen since. Much of this growth was concentrated in applied micro and macro. This suggests that take-up has slowed, and may have even fallen.



Figure 5: Panel (a) reports the share of papers that mention difference-in-differences or event studies. Figure (b) reports the share of papers that mention synthetic controls (this includes both synthetic difference-in-differences and synthetic control methods). See Table 2 for the breakdown of fields, and the Appendix for definitions on keywords.

Next, in a slightly self-indungent fashion (Goldsmith-Pinkham, Sorkin, and Swift 2020), I examine the rise of Bartik and shift-share instruments in Figure 6a. Since 2013, this method has grown rapidly across all fields, but with some fall off in macro/others and finance after 2021. Nonetheless, almost 2-4% of all papers in 2024 mention Bartik or shift-share. To put this in context, I plot the share mentioning instrumental variables at all in Figure 6b. This share has stayed relatively constant over time, with roughly 30% of applied micro papers, 20% of macro/others and 15% of finance papers. Hence, a rough back-of-the-envelope calculation would suggest that, given 2% of finance papers and 4% of applied micro papers mention Bartik, 13% of instrument approaches in finance and applied micro are Bartik or shift-share.



Figure 6: Panel (a) reports the share of papers that mention Bartik or shift-share instruments. Figure (b) reports the share of papers that mention instrumental variables. See Table 2 for the breakdown of fields, and the Appendix for definitions on keywords.

Finally, I examine the use of experiments (randomized control trials) and regression discontinuity designs across fields. In Figure 7a, I plot the share of papers that mention randomized control trials. Here, applied micro is the clear leader, with 20% of papers mentioning RCTs in 2024. For both macro and finance, this share has grown as well, but less. Strikingly, all three fields had a relatively similar base as of 2003.

In Figure 7b, I plot the share of papers that mention regression discontinuity designs. Here, applied micro is roughly 6 percentage points higher than finance and macro/other as of 2024, but for all fields the share flattened in the past 8 years.



Figure 7: Panel (a) reports the share of papers that mention randomized control trials or lab experiments. Figure (b) reports the share of papers that mention regression discontinuity designs. See Table 2 for the breakdown of fields, and the Appendix for definitions on keywords.

One natural question is what types of papers sit in the gap between applied micro and the other fields. Some of this may be pure theory or observational papers. One alternative (already measured in Currie, Kleven, and Zwiers (2020b)) is to look at the share of papers that mention structural estimation (including words like "structural estimation" and "structural model" or "structural general equilibrium model" or "GMM"). In Figure 8a, I plot the share of papers that mention structural estimation. Here, macro/others and finance tend to have a 7.5-10 percent higher share of papers, consistent with the idea that these fields may have more structural models. But, it is worth recalling that applied micro includes Industrial Organization. It is also useful to identify the set of papers that do not mention experimental or quasi-experimental methods and do mention structural estimation. I plot this share in Figure 8b. Here, the gap between applied micro and the other fields is larger, with 20% of finance and macro/other papers used structural estimation as of 2024, and only 10% in applied micro. This suggests that in applied micro papers using structural models, there is more discussion of additional research designs than in finance or macro.



quasi-experimental methods

Figure 8: Panel (a) reports the share of papers that mention structural model estimation. Figure (b) reports the share of papers that mention structural model estimation and do not mention any form of experimental or non-experimental methods. See Table 2 for the breakdown of fields, and the Appendix for definitions on keywords.

### 2.3 Breakdown across programs

What underlying variation drives the trends across fields? As an example, among finance, the types of analyses and approaches for asset pricing and corporate finance are very different, and it is reasonable to assume that these programs may have different levels and trends. This is similarly true for applied micro and macro/other.

In Figure 9, I plot the overall share of papers mentioning identification and experimental and quasi-experimental methods across programs. For each figure, the size of the dot reflects the number of papers, the color reflects the program, and the dots are ordered by their relative share. I plot the vertical weighted average for the overall field in the dotted line, corresponding to the overall average from the previous field graphs. Here, despite heterogeneity within fields, the breakdown across programs is relatively consistent. For example, in Figure 9a, the share of papers mentioning identification in applied micro programs is higher than all finance and macro/other programs, with the exception of Productivity, Innovation, and Entrepreneurship, and Law and Economics. However, there is a large gap between Asset Pricing and Corporate Finance, suggesting that the rise in identification in finance is driven by Corporate Finance. In Figure 9b, the share of papers mentioning experimental and quasi-experimental methods is higher in applied micro programs than all finance and macro/other programs except Law and Economics and Corporate Finance.



Figure 9: This Figure splits out by papers into each of the research programs for which a paper can be submitted. The size of each dot reflects the total number of papers in the program. The vertical dotted lines are the average for each field. Papers can be included in more than one research program. Panel (a) reports the share of papers that mention identification strategies or concerns. Panel (b) reports the share of papers that mention any experimental or quasi-experimental method (this includes diffin-diff, event studies, regression discontinuity, randomized control trials, lab experiments, bunching designs, and instrumental variables). See Table 2 for the breakdown of fields, and the Appendix for definitions on keywords.

How has this changed over time for these groups? In Figure 10, I split the sample into pre-2016 and 2016 and after, and examine the same shares as in Figure 10. On the x-axis is the share of mentions prior to 2016, and the y-axis is the mentions in 2016 to 2024. Each point reflects a program. If there was no change in the share of mentions, the point would lie on the 45 degree line. In Figure 10a, across all fields, there has

been an increase in mentions that is similar across the board. In Figure 10b, some programs have seen much larger changes than others in their mentions of experimental and quasi-experimental methods. Notably, the change for International Finance and Macroeconomics, Economics Fluctuations and Growth, and Asset Pricing have seen less growth than Corporate Finance and Children, for example.



(a) Identification

(b) All experimental and quasi-experimental methods

Figure 10: This figure splits out by papers into each of the research programs for which a paper can be submitted, broken into 2000-2015 (x-axis) and 2016-2024 (y-axis). Papers can be included in more than one research program. Panel (a) reports the share of papers that mention identification strategies or concerns. Figure (b) reports the share of papers that mention any experimental or quasiexperimental method (this includes diff-in-diff, event studies, regression discontinuity, randomized control trials, lab experiments, bunching designs, and instrumental variables). See Table 2 for the breakdown of fields, and the Appendix for definitions on keywords.

What have been the methods that have grown significantly? In Figure 11, I plot the growth in difference-in-differences, instrumental variables, regression discontinuity, and experiments across programs in a similar way to Figure 10. In the vast majority of programs, the growth has been driven by difference-in-differences, as seen in Figure 11a. In Figure 11b, the share of papers mentioning instrumental variables has stayed roughly constant across all programs. In Figure 11c, the share of papers mentioning regression discontinuity has risen slightly across all programs, but the growth has been more muted than difference-in-differences.<sup>6</sup> Finally, in Figure 11d, the share

<sup>&</sup>lt;sup>6</sup>Interestingly, most of the growth and level of RD is concentrated in Public Economics, Economics of Education and Children. Education is perhaps unsurprising given the role of test scores as a

of papers mentioning experiments has risen across all programs, but the growth is concentrated in a few programs (such as Development).

Notably, for finance (and macro), there has been very limited growth in almost all methods *except* difference-in-differences. This suggests that the credibility revolution in finance and macro has been driven by difference-in-differences, and not by other methods.

Lastly, I examine the tremendous recent growth of Bartik and Synthetic controls across programs in Figure 12. In Figure 12a, the share of papers mentioning Bartik and shift-share has grown across all programs, but the growth has been most pronounced in International Trade and Investment, where almost 10% of papers mention shift-share or Bartik instruments, Development of the American Economy, and Labor Studies.<sup>7</sup> In Figure 12b, the share of papers mentioning synthetic controls has grown across all programs, but the growth has been most pronounced in Law and Economics, the Economics of Health, and Children.

How does structural estimation look across groups? In Figure 13a, I plot the overall share of mentions of structural estimation by program. We see a wide range of programs with shares above 30%: Monetary Economics, Industrial Organization, EFG, International Trade and Investment, and Asset Pricing. Hence, even within each field there is tremendous heterogeneity. However, it is quite striking to examine mentions of structural models without explicit mentions of experimental and quasi-experimental methods in Figure 13b. Here, we see large segmentation across programs. Most programs have 10% or less, while some programs have 20% or more. These include Industrial Organization, International Finance and Macroeconomics, Asset Pricing, International Trade, EFG and Monetary Economics. This suggests that in some programs, structural models are used as a primary research approach, while in others they are used as a complement to experimental and quasi-experimental methods.

### 2.4 The dominance of difference-in-differences across fields

In the previous section, I showed that difference-in-differences has grown across all fields. It turns out that this growth in difference-in-difference has significantly increased

canonical RD design.

<sup>&</sup>lt;sup>7</sup>This is likely driven by the use of these instruments in studying the China Shock, popularized by Autor, Dorn, and Hanson (2013), the use of shift-share instruments in studying historical migration popularized by Boustan (2010) in economic history, and the historical use of Bartik instruments in labor studies (Bartik 1991).



Figure 11: This figure splits out by papers into each of the research programs for which a paper can be submitted, broken into 2000-2015 (x-axis) and 2016-2024 (y-axis). Papers can be included in more than one research program. Panel (a) reports the share of papers that mention difference-in-differences or event studies. Panel (b) reports the share of papers that mention instrumental variables. Panel (c) reports the share of papers that mention discontinuity designs. Panel (d) reports the share of papers that mention RCTs or lab experiments. See Table 2 for the breakdown of fields, and the Appendix for definitions on keywords.



Figure 12: This figure splits out by papers into each of the research programs for which a paper can be submitted, broken into 2000-2015 (x-axis) and 2016-2024 (y-axis). Papers can be included in more than one research program. Panel (a) reports the share of papers that mention Bartik or shift-share instruments. Panel (b) reports the share of papers that mention synthetic control methods. See Table 2 for the breakdown of fields, and the Appendix for definitions on keywords.

the overall growth in experimental and non-experimental methods. In Figure 14, I document this relative impact of including DiD as a measure in the experimental and quasi-experimental term. In Figure 14a, I plot the overall increase in these methods, with and without DiD. As of 2024, methods are roughly 15 percentage points higher (roughly 37.5%) than they would be without DiD. In Figure 14b, I plot this change over time by field. For all fields, this gap exists, but as a percentage it is largest for finance, in part due to a lower overall level without DiD. As of 2024, there is a gap of 15 p.p. for applied micro (30%), and 20 p.p. for finance (80%). Hence, finance has been driven mostly heavily by DiD.

In Figure 14c, I split out by research program the average percentage increase of the methods measure from not including DiD to including DiD, over the full sample. Asset Pricing and Corporate Finance have the largest increases, as do Law and Economics and Development of the American Economy. In Figure 14d, I repeat the exercise but focus on the last eight years. A very similar pattern holds up for finance. In both cases, there are several applied micro fields that have high levels of mentions of experimental and quasi-experimental methods (such as development and education) that have not



(a) Stuctural estimation

(b) Structural estimation without mention of experimental and quasi-experimental methods

Figure 13: This figure splits out by papers into each of the research programs for which a paper can be submitted. The size of each dot reflects the total number of papers in the program. The vertical dotted lines are the average for each field. Papers can be included in more than one research program. Panel (a) reports the share of papers that mention structural estimation. Panel (b) reports the share of papers that mention structural estimation without any mention of experimental or quasi-experimental methods (this includes diff-in-diff, event studies, regression discontinuity, randomized control trials, lab experiments, bunching designs, and instrumental variables). See Table 2 for the breakdown of fields, and the Appendix for definitions on keywords.



#### been affected much by difference-in-difference.

(c) Percent increase from including DiD, full sample

(d) Percent increase from including DiD, 2016-2024

Figure 14: This figure compares the level of mentions of experimental and quasi-experimental methods when excluding difference-in-difference methods. Panel (a) looks overall, where the solid line is all methods, as before, and the dashed line excludes any mention of DiD. Panel (b) repeats the exercise, split across fields. Panel (c) compares the percent increase in our measure of experimental and quasi-experimental mentions from including DiD, relative to not inluding the measure, over the full sample. Panel (d) repeats Panel(c), but only in the 2016-2024 period. See Table 2 for the breakdown of fields, and the Appendix for definitions on keywords.

## 3 Conclusion

The credibility revolution has continued through economics over the last two decades, but there remains significant heterogeneity across fields. Applied microeconomics continues to lead the way in adopting empirical methods focused on research design and identification, with finance and macroeconomics lagging behind but still experiencing growth since the early 2000s. Notably, the growth in methods in finance and macro has been driven primarily by the adoption of difference-in-differences designs, while other quasi-experimental approaches like regression discontinuity, RCTs, and instrumental variables have seen less growth.

Looking across programs, corporate finance has seen more adoption of credibility revolution methods compared to asset pricing, explaining much of the overall growth in finance. There is also significant variation within the "macro/other" fields. Nonetheless, papers with no mention of credible empirical methods but that do mention structural estimation are more common in macro, finance, and certain applied micro fields like industrial organization, highlighting the continued importance of economic theory and structural models in many parts of the discipline.

The growing interest in and impact of difference-in-differences research across economics highlights how a single empirical technique, when widely adopted, can meaningfully shift the trajectory of an entire academic field. However, given some of the recent econometrics work flagging sensitivities and weakness in difference-in-differences, there may be value in researchers attempting to more broadly diversify their research methods portfolio (Roth 2022; Roth and Sant'Anna 2023; Rambachan and Roth 2023; Callaway, Goodman-Bacon, and Sant'Anna 2024; De Chaisemartin and d'Haultfoeuille 2020; Chaisemartin et al. 2022). It is also quite striking that given the popularity of difference-in-difference that synthetic control methods have not grown further, as these methods have very similar properties.

### References

- Angrist, Joshua D and Jörn-Steffen Pischke (2010). "The credibility revolution in empirical economics: How better research design is taking the con out of econometrics".
  In: Journal of economic perspectives 24.2, pp. 3–30.
- Autor, David H, David Dorn, and Gordon H Hanson (2013). "The China syndrome: Local labor market effects of import competition in the United States". In: American economic review 103.6, pp. 2121–2168.
- Bartik, Timothy J (1991). "Who benefits from state and local economic development policies?" In.
- Boustan, Leah Platt (2010). "Was postwar suburbanization "white flight"? Evidence from the black migration". In: *The Quarterly Journal of Economics* 125.1, pp. 417–443.
- Callaway, Brantly, Andrew Goodman-Bacon, and Pedro HC Sant'Anna (2024). *Differencein-differences with a continuous treatment*. Tech. rep. National Bureau of Economic Research.
- Chaisemartin, Clément de, Xavier d'Haultfoeuille, Félix Pasquier, and Gonzalo Vazquez-Bare (2022). "Difference-in-differences estimators for treatments continuously distributed at every period". In: arXiv preprint arXiv:2201.06898.
- Currie, Janet, Henrik Kleven, and Esmée Zwiers (2020a). Data and Code for Technology and Big Data Are Changing Economics: Mining Text to Track Methods. Distributor: Inter-university Consortium for Political and Social Research, Ann Arbor, MI. Nashville, TN. DOI: 10.3886/E120827V1. URL: https://doi.org/10.3886/ E120827V1.
- (2020b). "Technology and big data are changing economics: Mining text to track methods". In: AEA Papers and Proceedings. Vol. 110. American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203, pp. 42–48.
- De Chaisemartin, Clément and Xavier d'Haultfoeuille (2020). "Two-way fixed effects estimators with heterogeneous treatment effects". In: *American economic review* 110.9, pp. 2964–2996.
- Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift (2020). "Bartik instruments: What, when, why, and how". In: *American Economic Review* 110.8, pp. 2586–2624.
- Rambachan, Ashesh and Jonathan Roth (2023). "A more credible approach to parallel trends". In: *Review of Economic Studies* 90.5, pp. 2555–2591.

- Roth, Jonathan (2022). "Pretest with caution: Event-study estimates after testing for parallel trends". In: American Economic Review: Insights 4.3, pp. 305–322.
- Roth, Jonathan and Pedro HC Sant'Anna (2023). "When is parallel trends sensitive to functional form?" In: *Econometrica* 91.2, pp. 737–747.

Category	Trigger Phrases	Outcome	Case Sensi- tive	Wildcard at end	Cond. on 'data'
Administrative Data	'administrative data', 'admin data', 'administrative-data', 'admin-data', 'adminis- trative record', 'admin record', administrative regist', 'admin regist', 'register data', 'registry data'	Fraction of pa- pers with at least 1 phrase	No	Yes	Yes
Big Data	'big data', 'big-data'	Fraction of pa- pers with at least 1 phrase	No	Yes	Yes
Binscatter	'binscatter', 'bin scatter', 'binned scatter'	Fraction of pa- pers with at least 1 phrase	No	Yes	No
Bunching	'bunching'	Fraction of pa- pers with at least 1 phrase	No	Yes	No
Clustering	'cluster'	Fraction of pa- pers with at least 1 phrase	No	Yes	Yes
Confidence Interval	'confidence interval'	Fraction of pa- pers with at least 1 phrase	No	Yes	Yes
Data	'data'	Fraction of pa- pers with at least 1 phrase	No	Yes	No
Difference-in- Differences	'Difference in Diff', 'Difference in diff', 'differ- ence in diff', 'Difference-in-Diff', 'Difference-in- diff', 'difference-in-diff', 'Differences in Diff', 'Dif- ferences in diff', 'differences in diff', 'Differences-in- Diff', 'Differences-in-diff', 'differences-in-diff', 'diff- in-diff', 'd-in-d', 'DiD'	Fraction of pa- pers with at least 1 phrase	Yes	Yes	No

#### Table 3: Search Categories and Trigger Phrases

Table $3$ – Continued from previous page					
Category	Trigger Phrases	Outcome	Case Sensi- tive	Wildcard at end	Cond. on 'data'
Event Study	'event stud' ' event-stud'	Fraction of pa- pers with at least 1 phrase	No	Yes	No
External Validity	'external validity', 'external-validity', 'externally valid', 'externally-valid'	Fraction of pa- pers with at least 1 phrase	No	Yes	No
Figure	'graph', 'figure', 'plot', 'chart'	Average word count per pa- per	No	Yes	No
Fixed Effects	'FE', 'Fixed Effect', 'Fixed effect', 'fixed effect', Fixed Effects', 'Fixed effects', 'fixed effects', 'Fixed- Effect', 'Fixed-effect', 'fixed-effects', 'Fixed-Effects', Fixed-effects', 'fixed-effects'	Fraction of pa- pers with at least 1 phrase	Yes	No	Yes
Functional Forms	'CES', 'constant elasticity of substitution', 'Con- stant Elasticity of Substitution', 'Constant elastic- ity of substitution', 'Cobb-Douglas', 'Cobb Dou- glas', 'Stone Geary', 'Stone-Geary', 'CRRA', 'coef- ficient of relative risk-aversion', 'coefficient of rel- ative risk aversion', 'Coefficient of relative risk- aversion', 'Coefficient of relative risk- aversion', 'Coefficient of relative risk aversion', 'Coefficient of Relative Risk-Aversion', 'Coefficient of Relative Risk Aversion', 'CARA', 'constant absolute risk aversion', 'Constant absolute risk- aversion', 'Constant absolute risk-aversion', 'Con- stant absolute risk-aversion', 'Constant Absolute Risk Aversion', 'Constant Absolute Risk-Aversion', 'translog', 'Translog'	Fraction of pa- pers with at least 1 phrase	Yes	No	No
General Equilib- rium	'general equilibr', 'general-equilibr'	Fraction of pa- pers with at least 1 phrase	No	Yes	No
				Continued o	n next page

Category	Trigger Phrases	Outcome	Case Sensi- tive	Wildcard at end	Cond. on 'data'
Identification	Sentence structure: search for sentences that have the term 'identif' in combination with any of the terms: 'effect', 'response', 'impact', 'elasticit', 'pa- rameter', or 'coefficient' with maximum two words in between. Note that even though the search includes wildcards at the end, we exclude any match with the word 'effective'. Also search for these terms: 'causal identification', 'causally iden- tified', 'identification strategy', 'identification ap- proach', 'identification assumption', 'identifying as- sumption', 'identified', 'over-identified', 'under identified', 'under-identified', 'identification prop- erties', 'identification test', 'identification prob- lem', 'identification test', 'identification prob- lem', 'identification issue', 'problem with identifi- cation', 'problems with identification', 'prob- lem identifying', 'problems identifying', 'issue with identification', 'issues with identification', 'prob- lem identifying', 'problems identifying', 'issue iden- tifying','issues identifying', 'threat to identifica- tion', 'threats to identification', 'over identify- ing', 'over-identifying', 'under identifying', 'under- identifying', 'partial identification', 'partially iden- tified', 'non-parametric identification', 'nonpara- metric identification', 'non parametric identifi- cation', 'non-parametric identification', 'nonpara- metric identification condition', 'identifying condi- tion', 'condition for identification', 'conditions for identification', 'point identification', 'point- identification', 'point-identified',	Fraction of papers with at least 1 phrase	tive No	Yes	No
	identified', 'set identifying', 'set-identifying', 'iden- tification analysis', 'weak identification', 'identifi- cation result', 'identification argument', 'identifi-				
	cation framework', 'identification scheme'				

Table 3 – Continued from previous page

	Table $3$ – Continued from pre	Table $3$ – Continued from previous page						
Category	Trigger Phrases	Outcome	Case Sensi- tive	Wildcard at end	Cond. on 'data'			
Internet Data	'internet data', 'internet-data', 'web data', 'web- data', 'scraped data', 'scraped-data', 'scrape data', 'scraping data', 'search data', 'search-data', 'google data', google-data', 'social media data', 'google trend', 'google-trend', 'google search', 'google search', 'google ngram', 'google n-gram', 'google books ngram', 'google books n-gram'	Fraction of pa- pers with at least 1 phrase	No	Yes	Yes			
Instrumental Vari- ables	'Instrumental Variable', 'Instrumental variable', 'instrumental variable', 'Instrumental-Variable', 'Instrumental-variable', 'instrumental-variable', 'Two Stage Least Squares', 'Two stage least squares', 'two stage least squares', '2SLS', 'TSLS', 'valid instrument', 'exogenous instrument', 'IV Estimat', 'IV estimat', 'IV-estimat', 'IV Spec- ification', 'IV specification', 'IV-specification', 'IV Regression', 'IV regression', 'IV-regression', 'IV Strateg', 'IV strateg', 'IV-strateg', 'we in- strument', 'I instrument', 'paper instruments', 'exclusion restriction', 'weak first stage', 'simulated instrument'	Fraction of pa- pers with at least 1 phrase	Yes	Yes	Yes			
Lab Experiments	'Laboratory Experiment', 'Laboratory experi- ment', 'laboratory experiment', 'Lab Experiment', 'Lab experiment', 'lab experiment', 'Dictator Game', 'Dictator game', 'dictator game', 'Ultima- tum Game', 'Ultimatum game', 'ultimatum game', 'Trust Game', 'Trust game', 'trust game', 'Pub- lic Good Game', 'Public good game', 'public good game', 'Public Goods Game', 'Public goods game', 'public goods game', 'Z-tree', 'zTree', 'ORSEE', 'show-up fee', 'laboratory participant', 'lab partic- ipant'	Fraction of pa- pers with at least 1 phrase	Yes	Yes	No			

TT 1 1 0	a 1	e		
Table 3 –	Continued	from	previous	page

Category	Trigger Phrases	Outcome	Case Sensi- tive	Wildcard at end	Cond. on 'data'
Machine Learning	'machine learning', 'lasso', 'random forest'	Fraction of pa- pers with at least 1 phrase	No	Yes	No
Matching	'propensity score', 'propensity score matching', 'propensity-score matching', 'matching estimat', 'nearest neighbor matching', 'nearest-neighbor matching', 'nearest neighbour matching', 'nearest- neighbour matching', 'caliper matching', 'nearest- neighbour matching', 'caliper matching', 'strat- ification matching', 'caliper matching', 'strat- ification matching', 'exact matching', 'strat- ification matching', 'one-to-one matching', 'inverse- probability matching'	Fraction of pa- pers with at least 1 phrase	No	Yes	Yes
Mechanisms	'mechanism'	Fraction of pa- pers with at least 1 phrase	No	Yes	No
Omitted Variables	'omitted variable'	Fraction of pa- pers with at least 1 phrase	No	Yes	Yes
Preanalysis Plan	'pre-analysis plan', 'pre analysis plan', 'preanalysis plan'	Fraction of pa- pers with at least 1 phrase	No	Yes	No
Precisely Estimated	'precisely estimated', 'precisely-estimated'	Fraction of pa- pers with at least 1 phrase	No	Yes	No
Precisely Estimated Zero	'precisely estimated zero', 'precisely-estimated zero'	Fraction of pa- pers with at least 1 phrase	No	Yes	No
Proprietary Data	'proprietary data', 'confidential data', 'nonpub- lic data', 'non-public data', 'proprietary-data', 'confidential-data', 'nonpublic-data', 'non-public- data'	Fraction of pa- pers with at least 1 phrase	No	Yes	Yes

Table 3 –	Continued	from	previous	page
Table 0	Continucu	110116	preduous	puye

Category	Trigger Phrases	Outcome	Case Sensi- tive	Wildcard at end	Cond. on 'data'
Quasi- and Natural Experiments	'quasi experiment', 'quasi-experiment', 'quasi- experiment', 'natural experiment', 'natural- experiment'	Fraction of pa- pers with at least 1 phrase	No	Yes	No
RCTs	'Randomized Controlled Trial', 'Randomized con- trolled trial', 'randomized controlled trial', 'Ran- domized Control Trial', 'Randomized control trial', 'randomized control trial', 'Randomized Field Ex- periment', 'Randomized field experiment', 'ran- domized field experiment', 'Randomized Controlled Experiment', 'Randomized controlled experiment', 'randomized controlled experiment', 'Randomised Controlled Trial', 'Randomised controlled trial', 'randomised controlled trial', 'Randomised Control Trial', 'Randomised control trial', 'randomised con- trol trial', 'Randomised Field Experiment', 'Ran- domised field experiment', 'randomised field ex- periment', 'Randomised Controlled Experiment', 'Randomised controlled experiment', 'randomised controlled experiment', 'randomised field ex- periment', 'Randomised Controlled Experiment', 'Randomised controlled experiment', 'randomised controlled experiment', 'Social Experiment', 'Social experiment', 'social experiment', 'RCT'	Fraction of pa- pers with at least 1 phrase	Yes	Yes	No
Regression Disconti- nuity	'Regression Discontinuit', 'Regression discon- tinuit', 'regression discontinuit', 'Regression- discontinuity', 'regression-discontinuity', 'Regres- sion Kink', 'Regression kink', 'regression kink', 'RD Design', 'RD design', RD-design', 'RD Es- timat', 'RD estimat', 'RD-estimat', 'RD Model', 'RD model', 'RD-model', 'RD Regression', 'RD regression', 'RD-regression', 'RD Coefficient', 'RD coefficient', 'RD-coefficient', 'RK Design', 'RK design', 'RK-Design', 'RK-design', 'RKD', 'RDD'	Fraction of pa- pers with at least 1 phrase	Yes	Yes	No

Table 3 – Continued from previous page

	Table $3$ – Continued from previous page					
Category	Trigger Phrases	Outcome	Case Sensi- tive	Wildcard at end	Cond. on 'data'	
Reverse Causation	'reverse causa', 'reverse-causa'	Fraction of pa- pers with at least 1 phrase	No	Yes	Yes	
Selection	'selection'	Fraction of pa- pers with at least 1 phrase	No	Yes	Yes	
Simultaneity	'simultaneity'	Fraction of pa- pers with at least 1 phrase	No	Yes	Yes	
Structural Model	Sentence structure: we search for instances where, within two full stops, the term 'struc- tural' is mentioned in combination with either 'model', 'specification', 'estimate', or 'parameter'. Also search for these terms: 'Structural Model', 'Structural model', 'structural model', 'Method of Moments', 'Method of moments', 'Method of moments', 'Method-of-Moments', 'Method-of- moments', 'method-of-Moments', 'Berry, Levin- sohn, Pakes', 'Berry, Levinsohn and Pakes', 'Berry, Levinsohn, and Pakes', 'BLP', 'Structural General Equilibrium Model', 'Structural general equilibrium model', 'structural general equilib- rium model', 'GMM', 'Maximum Likelihood Es- timat', 'Maximum likelihood estimat', 'maximum likelihood estimat', 'Maximum-Likelihood Esti- mat', 'Maximum-Likelihood estimat', 'maximum likelihood estimat', 'MLE'	Fraction of pa- pers with at least 1 phrase	Yes	Yes	No	
Survey Data	Sentence structure: we search for instances where the term 'survey' and 'data' are mentioned within two full stops.	Fraction of pa- pers with at least 1 phrase	No	Yes	Yes	
				Continued o	n next page	

Category	Trigger Phrases	Outcome	Case	Wildcard	Cond.
			Sensi-	at end	on 'data'
			tive		
Synthetic Control	'synthetic control'	Fraction of pa-	No	Yes	Yes
		pers with at			
		least 1 phrase			
Table	'table'	Average word	No	Yes	No
		count per pa-			
		per			
Text Analysis	'natural language processing', 'text analys', 'com-	Fraction of pa-	No	Yes	No
	putational linguistics', 'speech processing', 'n-	pers with at			
	gram', 'ngram', 'n gram', 'textual analys', 'lan-	least 1 phrase			
	guage processing', 'language analys', 'text data',				
	'text mining', 'mining text', 'text regression', 'tok-				
	eniz'				

Table 3 – Continued from previous page
--