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MACROECONOMIC RESEARCH, PRESENT AND PAST

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ABSTRACT

How is macroeconomic research conducted and what is it trying to accomplish? We explore these questions using information gleaned from 1,894 articles published in ten leading journals. We find that over the past 40 years there has been a growing emphasis on increasingly sophisticated quantitative theory, such as DSGE modeling, and papers employing these methods now account for the majority of articles in macro journals. The shift towards quantitative theory is mirrored by a decline in the use of econometric methods to test economic hypotheses. Econometric techniques borrowed from applied microeconomics have to a large extent displaced time series methods, and empirical papers increasingly rely on micro and proprietary data sources. Market imperfections are pervasive, and the amount of research involving financial frictions has increased significantly in the past ten years. The frequency with which non-macro JEL codes appear in macro articles indicates a great deal of overlap between macroeconomics and other fields.

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1 Introduction

What is macroeconomics trying to accomplish? What kinds of analytical tools and data sources are brought to bear? And how has the discipline evolved over the past four decades? In this paper, we investigate these questions using information gleaned by hand from nearly two thousand articles published in five leading macroeconomics and the five top general interest journals from 1980 through 2018.[1]

To characterize the nature of the knowledge being pursued in macroeconomic research, we defined eight categories of research objectives, and assigned each of the papers in our inventory to one of the categories. Is the purpose to test a hypothesis? Is it to provide quantitative estimates of the effects of a change in policy? Or is it simply to make a theoretical point? Related to the research objective is the quantitative methodology (if any) used in the analysis: specifically, whether it is based primarily on conventional econometric techniques, as opposed to those used to fit theoretical models to the data. Section 2 describes these categories in detail and presents tabulations of the attributes' prevalence over time and across journals.

We also compiled information on the theoretical methods, empirical techniques and data sources used in macroeconomic research. The theoretical framework is classified according to whether the model is partial or general equilibrium, for example; and whether it qualifies as a Dynamic Stochastic General Equilibrium (DSGE) model. We catalog different styles of DSGE models ("DSGEs" for short), such as Real Business Cycle (RBC) and New Keynesian (NK) models; and different types of imperfections, including financial frictions and nominal rigidities. Papers involving econometrics are distinguished according to whether they use time series or cross-sectional methods, and by the structure of the data employed. Section 3 presents our findings regarding the use of different techniques across journals and over time.

To complement the taxonomic attributes gleaned from our reading of the articles, we collected data on the articles' JEL codes and used this information to assess the amount of overlap between macro and other fields. We report these results in section 4. Finally, in section 5 we use case studies of ten seminal papers to explore the propagation of ideas and methods.

Three features distinguish our investigation from other efforts to assess (and often critique) the state of macroeconomics.[2] First, by compiling the attributes of *all* the papers published in the

[1]The field journals are: the *Journal of Monetary Economics*, the *Journal of Economic Dynamics and Control*, the *Journal of Money, Credit and Banking*, the *American Economic Journal: Macroeconomics*, and the *Review of Economic Dynamics*. The general interest journals are: the *American Economic Review*, *Econometrica*, the *Journal of Political Economy*, the *Quarterly Journal of Economics*, and the *Review of Economic Studies*.

[2]A non-exhaustive list includes: "The Scientific Illusion in Empirical Macroeconomics," (Summers, 1991), "The State of Macro" (Blanchard, 2009), and "The Trouble with Macroeconomics" (Romer, 2016); not to mention the 21 essays recently published in the *Oxford Review of Economic Policy* as part of the "Rebuilding macroeconomic theory"

most influential journals, we provide an unbiased and holistic picture of the field in its entirety, as opposed to a narrow assessment of a particular style of research (e.g. NK models).[3] Second, our taxonomy allows for a multidimensional characterization that we believe comes close to spanning the space of macroeconomic research. Third, our painstaking hand-collection of data allows us to discern nuances that computational methods, such as natural language processing, would have missed.

The full range of results is difficult to summarize concisely, but we regard the following seven findings as particularly noteworthy.

The first is the degree to which theory has become central to macroeconomic research. Formal models, virtually all of which incorporate microfoundations, feature prominently in 70 percent of all articles published in 2016–18. Papers lacking a substantial theory section are rare.

A second is that the field has to a large extent discarded the positivist agenda of testing economic hypotheses. Only ten percent of papers published in 2016–18 set out to falsify or corroborate a theory. Since 1990, the field has moved towards alternative approaches that involve fitting theoretically derived models to the data. Much of this type of research seeks to build quantitative models that mimic certain features of the data (typically, to match the moments of interest). There is also a great deal of research that uses model-fitting methods to make theory-based quantitative statements about the effects of macroeconomic policies on economic outcomes or social welfare.

Third, not only has theory become more prevalent, it has also grown more complex and computationally intensive. Partial and general equilibrium models, set in static and deterministic environments, have largely given way to DSGEs. Representative agent models predominated a decade ago, but as of 2016–18 nearly a third of DSGE papers incorporate heterogeneous agents.

Fourth, research using models characterized by frictionless, competitive markets has become increasingly rare. The vast majority of papers published in recent years incorporate some form of friction or market imperfection, most commonly nominal rigidities and market power. And while it is true that interest in financial market imperfections waned between 1980 and 1990, we document that increasing attention to the financial sector began well before the Great Recession. Nearly half of the papers published in 2016–18 model the financial sector or include financial frictions.

Fifth, we find the econometric techniques used in applied microeconomics have steadily been displacing the time series methods that were popular in the 1980s and 1990s. There has been a parallel shift away from the use of aggregate macro time series data towards micro data. Rarely encountered in 1980-vintage papers, the majority of recently published applied macroeconomics

project (Vines and Wills, 2018, 2020).

[3] We concede that our focus on mainstream journals overlooks heterodox approaches, such as Post-Keynesian and Marxian economics.

research use panel data.

Sixth, our tabulation of JEL codes reveals that the overwhelming majority of articles list at least one field outside of macroeconomics, most frequently microeconomics and financial economics; and many articles list two or more non-macro codes. This points to a significant amount of cross-fertilization between macroeconomics and other fields.

Seventh, we find a great deal of variation in the papers' citation trajectories. For some papers, the diffusion patterns suggest a transmission from the top general interest journals to the field journals, but this is not not always the case. The variable and sometimes long lags between publication and citation reveal significant differences in the rates in the dissemination of new ideas.

2 Epistemology and methods

We begin with a big-picture examination of the nature of macroeconomic research. What is it trying to accomplish? How is knowledge in the field "advanced"? What methods are used in the investigation of macroeconomic issues?

2.1 Epistemology

We first consider the relationship between macroeconomic theory and data: how empirical evidence is used to assess the validity of theory, and conversely how theory structures the ways in which macroeconomists think about and use data. We subscribe to Prescott's (1986, p. 44) view that "[t]he feedback between theory and measurement is the way mature, quantitative sciences advance." In macroeconomics, this feedback occurs in a number of different ways. Informed by the literature on the philosophy of science, economists' writings on the discipline's methods (and our reading of 1,894 published papers), we propose an eight-way taxonomy of the different types of relationships between theory and data, which we refer to as the research *epistemology*.

Central to our taxonomy is the concept of an *economic model*. We define this as a framework built on behavioral relationships, characterizing the decisions of firms, households, or institutions. These correspond to the "microfounded" relationships that now dominate macroeconomics; but they also encompass the "structural" equations of models of the 1960s and 1970s, which were viewed at the time as describing agents' behavior.

What qualifies as an economic model has changed over time. For example, Keynes (1936) asserted that the consumption function was a "psychological law," and so an equation featuring the marginal propensity consumption function would have been interpreted at the time as a behavioral macro model. But lacking "microfoundations," the same equation would not pass muster in 2021.

We make no effort to adjudicate which models qualify as "economic," deferring instead to the author(s) view of whether their model describes underlying behavioral relationships.

Our eight epistemological categories are as follows:

Description. The objective of this type of research is to document facts or highlight features of the data, as opposed to testing the predictions from or implications of an economic model. Or, as Heckman and Singer (2017) summarized it: "…uncovering new facts or providing richer descriptions of old facts." Plots, descriptive statistics, reduced-form regressions, and/or narrative accounts are used to characterize patterns in the data. Also included in this category are forecasting exercises and regime switching models. Any hypothesis testing is solely for the purpose of determining whether the statistical model is an accurate description of the data. There is no better example of descriptive macroeconomic analysis than Burns and Mitchell (1947).

Causal effects. Papers in this category set out to detect and/or measure the effect of changes in variable X on variable Y. Causal relationships are uncovered by finding plausibly exogenous sources of variation in X, thus ruling out reverse causality or other sources of non-causal correlation. In this sense, causal effects analysis resembles the instrumental variables techniques used to estimate the behavioral relationships in earlier generations of structural macroeconomic models. The difference is that the causal effects approach seeks to exploit *theory-free* identifying assumptions, with the exogenous variation in the X analogous to what would have arisen in an experimental setting. Angrist and Pischke (2010) argued that the approach, which has become nearly ubiquitous in applied microeconomics, has led to a "credibility revolution" in economics. They observed that the approach is relatively rare in macroeconomics (at least as of 2010), but pointed to the narrative identification strategy of Romer and Romer (1989) as an application of the framework. Event study analysis also comes under the causal effects heading in our taxonomy. And although Angrist and Pischke might object, we also put into this category research based on structural VARs, whose "shocks" have been interpreted as data-based experiments (see e.g. Christiano et al. 1999, p. 143), and whose responses are often claimed to represent causal effects. This type of analysis does not speak to the economic mechanism(s) giving rise to the observed effects, however: finding that interest rate increases "cause" output to decline, for example, is consistent with any number of underlying behavioral relationships.

Falsification/corroboration. The purpose of this type of research is to confront an economic model with data in such a way that potentially would allow the data to refute the theory. The model is rejected if the theory-implied predictions are contradicted by the data; otherwise, the model is corroborated. This approach draws on Karl Popper's philosophy of critical rationalism, which views empirical falsification as essential to the scientific method. Or, as Friedman (1946) put it:

"[T]he ultimate test of the validity of a theory [is] the ability to deduce facts that have not yet been observed, that are capable of being contradicted by observation, and that subsequent observation does not contradict." Importantly, the model being put to the test is *economic*, in the sense of representing a structural or behavioral relationship. Merely performing a test of whether variable X affects variable Y is not sufficient. A classic example of analysis in this mode is Hall's (1978) test of the Permanent Income Hypothesis (PIH).

Abduction. Heckman and Singer (2017) described abduction as "[t]he process of generating and revising models, hypotheses and data analyzed in response to surprising findings," and argue that it is (or at least should be) the predominant objective of economic analysis. It differs from falsification in that abduction "moves descriptions of the world forward, rather than just confirming or falsifying hypotheses." Operationalizing the Heckman-Singer definition, we put into the abduction bin any paper that (a) specifies an explicit benchmark or null model, (b) presents a "surprising finding" that the null model cannot explain, and (c) proposes a modification to the null model that can account for the finding. These are "puzzle solving" exercises, in other words. For example, Campbell and Mankiw (1990) documented a response of consumption spending to current income, contradicting the PIH, and added "rule-of-thumb" consumers to the model to explain the finding.

Model fitting. These are papers whose primary goal is to construct an economic model that mimics one or more features of the data. Although it is not the only type of modeling represented in this category, the approach is most widely associated with DSGEs. As sketched by Korinek (2018), the typical model fitting DSGE paper proceeds by first establishing a set of "stylized facts" about the quantitative interrelationships between macro variables (typically a collection of first and second moments); second, "writing down" an economic model involving the same set of macro variables; and third, choosing the parameters to "fit" the model to the data. The exercise is judged a success if the model does a good job of approximating the targeted moments. The same criterion was used over 60 years ago by Adelman and Adelman (1959) to evaluate, and deem successful, the Klein-Goldberger structural macroeconomic model.[4] Model-fitting studies perform "quantitative experiments" of the kind described by Kydland and Prescott (1996, pp. 71–72) for the purpose of "developing theory," i.e. to determine "whether the predictions of the theory match the observations."

Quantification. This type of research aims to provide precise numerical answers to specific questions. Often, the objective is to assess or predict the quantitative effects of a policy on an eco-

[4]Using an IBM 650 computer at the University of California's Lawrence Radiation Laboratory, the authors performed 100-year-long simulations of the model's responses to shocks to the behavioral equations, and found that it generated fluctuations that quantitatively matched "the duration of the cycle, the relative length of the expansion and contraction phases, and the degree of clustering of peaks and troughs" of the observed NBER-determined business cycles.

nomic outcome and/or its welfare costs (e.g. a tax change that affects saving). Another application might be to estimate a behavioral parameter of interest (e.g. the intertemporal elasticity of substitution). Importantly, quantification analysis as we have defined it is based on an economic model. This is the key distinction between our definition of quantification and a purely forecasting exercise, which predicts macroeconomic outcomes using atheoretical, non-behavioral relationships. Kydland and Prescott (1996, pp. 71–72) characterized this type of study as "using theory," as opposed to the "developing theory" exercises performed for the purpose of model fitting.

Non-quantitative theory. These papers use mathematical deduction to formally derive conclusions from a set of assumptions.[5] Plausible parameter values may be assigned for illustrative purposes, and numerical methods may be used to solve the model; but parameter values are not chosen to make the model fit the data. Some non-quantitative theory papers have no empirical implications (e.g. proof of the existence of equilibrium). Others *do* make empirically testable predictions; but they remain in the non-quantitative bin so long as those tests are not performed.

Methods. Articles in this category are those that propose new techniques: a novel algorithm or estimator, for example. They may include applications, but primarily for the purpose of illustrating the technique.

Twenty-one papers (1% of our inventory) fall into none of these categories: essays on the philosophy of economics or the history of economic thought, for example. We put these into a ninth bin labeled "other," and exclude them from our tabulations.

2.2 Methods

The second dimension of our high-level taxonomy pertains to the *methods* used to bring data to bear on theory, or vice versa. We identify two broad categories: *theory-centric* and *econometrics-based*.[6]

Papers in our econometrics-based category are those that use statistical methods to estimate parameters, construct confidence intervals, and test hypotheses. The touchstone is whether the methods could be learned from Hamilton (1994) for time series analysis, Wooldridge (2010) for cross-section or panel data applications, and Angrist and Pischke (2009) for causal effects techniques. The computations are readily performed using the built-in capabilities of econometric software such as Stata or RATS; or with R, typically augmented with packages that provide additional econometric capabilities (e.g. the "vars" package for vector autoregressions).

[5]In principle, pure theory need not entail mathematics—Smith and Ricardo expressed their theories in prose, after all—but that has become exceedingly rare.

[6]Neither applies to articles in the "methods" and "other" epistemological categories.

What distinguishes the empirical papers in our theory-centric category from those classified as econometrics-based is the fundamental difference in the relationship between theory and data. Canova (2007, p. 248) succinctly expressed the distinction as follows: "…a theoretical model is a tool to undertake 'computational experiments' rather than a setup to estimate parameters and/or test hypotheses." (*Non*-quantitative theory lacks any such relationship, of course.) We use the ungainly term *quantitative theory-centric modeling* to refer to this type of analysis. The category encompasses a wide range of techniques: predominantly (but not exclusively) DSGE modeling in recent years. A graduate student wishing to learn DSGE methods could read DeJong and Dave (2011); and although some econometrics packages now include DSGE capabilities, the calculations would typically be performed using software such as Dynare, Matlab, or Python.

Papers in this category do sometimes use econometric methods, such as VARs. But these methods are used primarily as a means to establish the "stylized facts" to be explained by the model, or to obtain a parameter for use in a calibration exercise. As DeJong and Dave (2011, p. 138) put it, this approach to research involves the use of "reduced-form models that provide flexible characterizations of the time-series behavior of the …observable variables…[and] summary statistics that frequently serve as targets for estimating the parameters of structural models, and as benchmarks for judging their empirical performance…"

Our methodological classification is not mutually exclusive, unlike our epistemological categorization. A paper may develop a theoretical model to explain the findings from a reduced-form regression, for example; or it may use econometric methods to test the implications of the theory developed in the paper. These papers are tagged as using both methods.

Our two-dimensional classification scheme yields twelve distinct modalities of macroeconomic research, defined by the particular combinations of epistemology and method. Research in all but three of the categories can make use of either econometric or theory-centric methods: e.g. DSGEs and regression analysis can both be used in studies whose objective is abduction. One of the three exceptions is non-quantitative theory, which by its nature does not use data-based methods. The other two are description and causal effects, which we have defined as not incorporating a behavioral economic model.

2.3 Dataset

Our database consists of 1,894 articles published during the 38-year period from 1980 through 2018. It includes 1,428 articles from the leading macro field journals: the *Journal of Monetary Economics* (*JME*), the *Journal of Money, Credit and Banking* (*JMCB*), *American Economic Journal: Macroeconomics* (*AEJ*), the *Journal of Economic Dynamics and Control* (*JEDC*), and the

Review of Economic Dynamics (*RED*).[7] Using information from *EconLit*, we also included in our inventory 466 articles from the top five general interest journals: the *American Economic Review* (*AER*), *Econometrica*, the *Journal of Political Economy* (*JPE*), the *Quarterly Journal of Economics* (*QJE*), and the *Review of Economic Studies* (*ReStud*) corresponding to JEL code "E" ("Macroeconomics and Monetary Economics").[8] It includes data from nine years: 1980, 1990, 2000, 2006, 2008, 2010, 2016, 2017 and 2018. Table 1 gives the breakdown by year and journal: panel A for the five field journals and panel B for the E-designated articles in the five general interest journals, and the totals for both sets combined.

Our tabulations use three overlapping subsets of the inventory. First, to get a sense of the research judged by the editors to be of current interest to macro specialists, we focus on all the articles published in the five field journals in the most recent three years in our inventory, 2016, 2017 and 2018. Our second subset consists of E-designated articles, billed by their authors as covering conventional macro topics. This allowed us to examine the attributes of macro papers published in general interest journals and excludes the non-trivial number of articles in the field journals that cover topics other than those traditionally associated with macroeconomics. Third, to see how macro research has evolved over time, we present tabulations based on E-designated articles in the general interest journals, plus all articles in the *JME* and *JMCB* for all nine years in our inventory. We restricted our attention to the *JME* and *JMCB* for consistency: both have have been published continuously since 1980 (the *RED* and *AEJ* were launched in 1998 and 2009 respectively), and focus primarily on traditional macro topics (unlike the *JEDC*).

The number of publications in macro field journals has increased dramatically in 38 years, from 71 in 1980 to 268 in 2018, partly due to the appearance of new journals. (The discrete jump in 2016 is an artifact of the addition to our inventory of articles from the *AEJ*, *JEDC*, and *RED* in that year.) Interestingly, the number of E-designated articles in the general interest journals fell by more than half in the 30 years from 1980 to 2010; and then more than doubled in the subsequent eight years, from 30 in 2010 to 79 in 2018. Naturally we would like to interpret the recent trend as a resurgence of interest in macroeconomics in the profession at large.

[7]We limit our attention to original research articles. Excluded are editor's notes and introductions, along with other notes, comments, replies, rejoinders, corrections, extensions, book reviews, discussions, and letters. We also exclude special issues, which are often more narrowly focused on specific topics or methods, and hence may not be representative of publishing trends generally.

[8]*EconLit* does not list JEL codes for articles published in 1990 and 1980. For these years, we selected all articles with the subject or title fields containing at least one of the following words: "Aggregate," "Macroeconomic(s)," "Money," "Monetary," or "Inflation." We use the term "E-designated" to refer to articles with the "E" code from *EconLit*, plus those identified using these keywords as as being comparable to those given the "E" code from 2000 onwards.

2.4 Epistemology and methods, present and past

Using the database described in section 2.3, we assigned articles to one of the eight epistemological categories (nine, including "other"), and determined whether its method was theory-centric or econometrics-based.

We performed the coding by hand, without the aid of computational methods such as natural language processing (NLP). The reason for choosing the more painstaking route was that automated methods, which are typically based on keywords (and their proximity to one other) would often have been misleading—especially when it comes to identifying the epistemological objective. For example, a NLP algorithm might classify as "falsification/corroboration" any article containing the phrases "hypothesis test" or "reject the hypothesis." But in many cases, the test in question pertains to a non-economic hypothesis, e.g. for lag length or serial correlation in the regression error term. Conversely, papers that describe their quantitative results as "being inconsistent with" a particular theory are in effect rejecting it, even if no formal statistical hypothesis test is performed, and therefore belong in the "falsification/corroboration" category. Additionally, a careful reading would be required to determine whether the author framed the analysis in terms of a "null model" and proposed a modification that resolved the puzzle, thus making the paper a better fit for our "abduction" category.

Inevitably, a fair number of papers fall into grey areas, with no explicitly stated epistemological objective; or they may have more than one objective. For example, papers using quantitative theory-centric methods to quantify the welfare gains from a particular policy will typically require that the model first be fit to the data. But if the author's ultimate objective were to carefully fit the model in order to maximize the credibility and realism of the estimate of those gains, we would classify it as "quantification" rather than "model fitting." Table A1 gives examples of papers in each of the epistemological and methodological categories.

Table 2 reports the fruits of our taxonomic labors for 997 papers published in 2016–18: 786 in the five field journals, plus 211 E-designated articles in the general interest journals. The first column reports the shares of each epistemological approach. Model fitting, non-quantitative theory, and quantification predominate, collectively accounting for two-thirds of all publications. Description, causal effects, falsification, and abduction are all in the single digits. Only 7% of papers are aimed at falsifying or corroborating an economic hypothesis.

The last line of the table shows that theory-centric methods are most common, accounting for 59% of the total. Only 29% use only econometric methods, while 11% use both. This implies that over 70% of the papers contain a formal theoretical model.

The choice of methodology is not independent of epistemology. By definition, causal effects and description are atheoretical; and while some may offer stylized facts by way of motivation or perform illustrative calculations, non-quantitative theory-centric papers do not use econometrics. Sixty-five percent of falsification papers use only econometric methods, while another 32% develop an economic model and employ econometric methods to test its implications. Theory-centric methods dominate model fitting, quantification and abduction; but only 3% of papers in this methodological category are engaged in falsification or corroboration.

Table 3 reveals wide variation in epistemological approaches across journals. As shown in panel A, in the set of 786 articles published in the five field journals, the *JMCB* and *AEJ* have relatively more falsification/corroboration papers, while only 3% of papers at the *JEDC* fall into this category. The *RED* has the largest share of papers that engage in quantification, while the non-quantitative theory share is highest at the *JEDC*. Methodological contributions are also far more common at the *JEDC* than at any of the other field journals.

There are also noteworthy differences in the distribution of epistemological approaches across field and general interest journals. The first two columns in panel B of table 3 report the breakdown for only the E-designated articles in the two sets of of journals. (Since they publish a large number of articles with JEL codes other than E, limiting the tabulation to field journals' E-designated articles prevents the results from being skewed by differences between fields' epistemological approaches.) Model fitting, quantification and non-quantitative theory predominate in both sets of journals. Model fitting is relatively more common in field journals by a margin of nine percentage points, while non-quantitative theory is more widespread in the general interest journals by six percentage points. Although still relatively rare, papers approaching macroeconomic questions from a causal effects perspective are more common in general interest compared with field journals, with a difference of six percentage points.

We also see a great deal of variation in epistemological approaches between the general interest journals. *Econometrica* and *ReStud* are heavy on the non-quantitative theory, with 41% and 43% respectively; neither contains any descriptive papers. The *QJE* looks very different: the shares of description (19%), causal effects (16%) and falsification (16%) are considerably higher than in the other four journals, and the share of non-quantitative theory (13%) is the smallest of the five. The breakdowns for the *JPE* and *AER* are more balanced, but the *AER* tends to favor description and causal effects and the JPE publishes quantification articles more frequently than its peers.

The epistemological makeup of published macroeconomic articles has changed dramatically over the years. Figure 1 plots the shares in each of the epistemological categories for all the articles in the *JME* and the *JMCB*, plus the E-designated articles in the top five general interest journals, from 1980 through 2018. The figure shows that in 1980, falsification and non-quantitative theory approaches were most prevalent, together comprising about three-quarters of the articles in these journals. Falsification reached its high-water mark in 1990, when 32% of published macro papers took this approach. The falsification and non-quantitative theory shares have both been on a steady downward trend since then, and as of 2016–18 the two categories together account for less than a third of the papers in the seven journals.

Displacing these types of research are papers whose objectives are more amenable to quantitative theory-centric methods: model fitting and quantification. The net effect, shown in figure 2, is a 12 percentage point increase in the combined share of theory-centric and "both" publications. (As documented in section 3.1.1 below, these are predominantly DSGE models.) And since 2010, perhaps not coincidentally the year of Angrist and Pischke's (2010) manifesto in the *Journal of Economic Perspectives*, causal effects-based econometric analysis has been growing, largely at the expense of research aimed at falsifying or corroborating economic models.

3 Models and techniques

We turn now to the more specific characteristics of the analysis used in macro research. Paralleling the methodological distinction outlined in section 2, this section has two parts. Section 3.1 catalogs the attributes of the theory-centric articles in our inventory. Section 3.2 does the same for research based primarily on conventional econometric methods.

3.1 Theory-centric research

We categorize theory-centric research according to equilibrium scope, types of frictions, and genre of DSGE analysis. We also identify a number of unconventional features that appear in macro research, and highlight some general trends in the techniques used to solve and/or fit models.

3.1.1 Equilibrium scope

First, we classify papers according to whether the theoretical framework is partial equilibrium (PE), deterministic general equilibrium (GE), or dynamic stochastic general equilibrium (DSGE).[9] The article is categorized as DSGE if, in addition to being a general equilibrium model, stochastic shocks generate fluctuations in the endogenous variables. We include in this category all equilibrium business cycle models, not just those of the New Keynesian variety. Table A2 provides a number of examples.

[9]Most of the deterministic GE models in our inventory are static.

As shown in panel A of table 4, the majority of theory-centric papers published in field journals in 2016–18 are either GE or DSGE: 63% for the two categories combined, versus 36% for PE. DSGEs are most prevalent, with a 42% share. DSGEs' preeminence is even more apparent among E-designated papers: 61%, with the remaining 39% split roughly equally between static GE and PE. There is also considerable variation across field journals in terms of equilibrium scope. The *JME* and *JMCB* publish relatively more DSGE papers, for example, while the *JEDC* and *RED* publish fewer.

General interest journals publish fewer DSGE-based papers than field journals. As shown in panel B of table 4, the share for E-designated articles in the five general interest journals is 46%, compared with 61% for the comparable E-designated subset of field journal articles. With 33% and 36% shares respectively, DSGE articles are even less common at the *QJE* and *ReStud*; PE models actually appear more frequently than DSGEs in those two journals.

The shares of articles in the three categories have changed dramatically over the past 38 years. As shown in figure 3, there were *no* DSGE-based papers in 1980, as the framework had not yet been developed. PE models accounted for 80%, and static GE models comprised 20%. Since then, the DSGE share has grown monotonically, reaching nearly 50% as of 2016–18. With GE's share holding steady in the neighborhood of 20% over the period, growth in DSGE analysis has mostly been at the expense of PE models.

3.1.2 Frictions

Do the models used in macroeconomics possess classical market clearing properties? Or do they incorporate market imperfections and/or frictions that prevent the competitive equilibrium from reaching the central planner's welfare-maximizing outcome? To understand some of the ways in which "sand has been thrown in the gears" of macroeconomic models, we tag papers according to whether they feature one (or more) of the following (non-mutually exclusive) imperfections or frictions:

- *Financial market imperfections*: there are financial frictions, such as collateral constraints, costly default, and monitoring or agency costs. Analysis involving a financial intermediary also qualifies, on the grounds that intermediaries exist to overcome frictions or imperfections in financial markets (e.g. to perform a monitoring function).
- *Nominal rigidities*: there are frictions (e.g. contracts, menu costs, or staggered price setting) that prevent the instantaneous adjustment of wages and/or prices.
- *Market power*: at least one agent is not a price taker. This encompasses models with monopoly, monopolistic competition, oligopoly, monopsony, or any type of bargaining.

- Search or information frictions: the model includes imperfect or asymmetric information, or search costs. In our inventory, these are found primarily in monetary and labor search models. (There is some overlap with the financial market imperfections attribute, to the extent that asymmetric information impairs the market's functioning.)

Table A3 gives examples of papers that incorporate each of these four features.

The prevalence of financial market imperfections has waned and waxed over the years. The dark grey area in figure 4 represents the number of articles with financial market imperfections published in the *JME* and *JMCB*, as a share of articles in the two journals plus the E-designated articles in the five general interest journals. The light grey area depicts the same information for the E-designated articles in the general interest journals. In 1980, 26% of articles in the two sets of journals fit this description. The share fell by nine percentage points over the next decade, symptomatic of declining interest in financial market imperfections in the two field journals. The number of articles in this category rebounded in 2000, however, driven by an increase in the general interest journals. Not surprisingly, the share of articles with financial market imperfections rose sharply after the financial crisis: in 2016–18, 42% of all published papers feature a financial market imperfection, friction, or intermediary.

Table 5 reports the share of articles containing one or more of the other three kinds of frictions, again relative to the set of papers consisting of the *JME* and the *JMCB*, plus the E-designated articles from the five general interest journals. The second column shows that after a nine percentage point decline from 1980 to 1990, the share of models with nominal rigidities increased markedly after 2000 as New Keynesian models caught on. As of 2016–18, 42% of all theory-centric macro models incorporate some form of nominal rigidity.

Market power is also quite common, and is present in 57% of the theory-centric macroeconomics papers published in 2016–18. Much of its rise over the past two decades is attributable to the growing popularity of New Keynesian models, which generally assume monopolistic competition in the product market. Although they are less prevalent than the other types, search/information frictions have become increasingly common, and they are found in nearly one-third of published macroeconomic research as of 2016–18.

Taken as a whole, the tabulations reveal a pronounced movement away from frictionless classical frameworks, towards ones with frictions and distortions that create inefficiencies and deviations from full employment. As shown in the last column of table 5, as of 2016–18, 82% of the papers in our longitudinal inventory feature at least one type of friction, reflecting upward trends in each of the three categories.

3.1.3 DSGE genres

All DSGE models share a common set of characteristics (e.g. optimizing firms and households, an aggregate resource constraint, etc.), but their specific features vary widely. We identify the following seven distinct "genres" of DSGEs:

- *Real Business Cycle* (*RBC*) models include capital as a state variable. Markets clear. The focus is on deviations from a stationary steady state. Technology shocks are the primary source of fluctuations.
- *Monetary models* include the money supply in such a way as to make it non-neutral in the short run. Modeling strategies include cash-in-advance constraints, shopping costs, and money in the utility function.
- *New Keynesian* (*NK*) models include price and/or wage stickiness, typically (but not exclusively) based on the Calvo (1983) specification. Monetary policy is framed in terms of an interest rate rather than the money supply.
- *Search and matching* models incorporate frictions other than wage stickiness (e.g. search costs), to generate unemployment. Shocks may originate from a number of different sources, including productivity, monetary policy and government purchases.
- *Overlapping Generations* (*OLG*) and *life-cycle* models are those in which agents' saving behavior is determined by age, cohort or generation.
- *Stochastic growth* models are similar to RBCs in their emphasis on market clearing and capital accumulation, but focus on steady states rather than fluctuations.
- *Trade-based DSGEs* include transactions in product or factor markets between two or more countries. They typically share features, such as comparative advantage, with conventional trade models. Shocks may originate from a number of different sources, including productivity, monetary policy and government purchases. Open-economy models with NK features (sticky prices, interest rate rules) are classified as New Keynesian, rather than trade.

Papers with models that do not fit into any of these categories are put into an "other" bin. Table A4 gives examples papers in each of the seven categories.

By a wide margin, NK models have been the most common variety of DSGE in recent years. As shown in table 6, NK models comprise in 40% of all DSGE-based articles published in field journals in 2016–18, and 44% of all E-designated articles in field and general journals collectively. NK models do not have a corner on the DSGE market, however. RBC models account for 17% of published papers in macro field journals, and 19% of all E-designated articles—ten-plus percentage points below their 2000 peak of 29%, but still a substantial share. The figures for the other genres are all mostly in the single digits, but collectively they account for over one-third of all DSGE-based articles.

NK analysis predominates to varying degrees in four of the five field journals. The outlier is *RED*, with only 19% of articles falling into the NK bin. Search and matching models are much more common in the *RED*, on the other hand: 17%, compared with the average of 6% across all field journals. There is also considerable variation among E-designated articles in the general interest journals; but since only the *AER* publishes an appreciable number of DSGE papers, the statistics for the other journals are not particularly informative. Still, it is noteworthy that of none of the eight DSGE articles appearing in the *JPE* are classified as New Keynesian.

3.1.4 Unconventional features of DSGEs

The typical DSGE model economy is populated with infinitely-lived representative agents with rational expectations and Von Neumann-Morgenstern utility functions. The models are formulated in discrete time, and the equilibria are unique. Not all DSGEs fit into this mold, however. This section documents the extent to which the models used in DSGE-based research display more exotic features. We tagged as "unconventional" models with one or more of the following five characteristics:[10]

- *Heterogeneous-agent* models in which households or individuals vary along one or more dimensions, such as age, skills, wealth, income, or preferences.
- *Finite horizon* models with non-infinitely lived households, corresponding to the OLG/life-cycle genre of DSGE flagged in section 3.1.3.
- Models with *non-rational expectations* in which agents use adaptive expectations, rules of thumb, or incorporate learning; and/or with *non-standard preferences*, such as hyperbolic discounting and recursive (e.g. Epstein-Zin) preferences.
- Models with *indeterminacy, sunspot equilibria* or *multiple equilibria*.
- Models formulated in *continuous time*, with stochastic elements described by Brownian motion processes.

Table A5 lists examples of papers that display each of the five unconventional features listed above.

The results reported in table 7 reveal two striking trends. First, heterogenous agent models have become much more widespread since 2000, and appear in 29% of all DSGE papers published in 2016–18. Second, the number of finite-horizon models has fallen off sharply since its peak of 38% in 1990, and this characteristic is found in only 4% of the papers in our inventory.

[10]We also looked for agent-based models, but found only 12 in our inventory, 11 of which were published in 2016 and 2017 in the *JEDC*.

The other three features' popularity has waxed and waned over the decades. For example, the share of papers with non-rational expectations and/or non-standard preferences peaked at 30% in 1990, fell off over the next two decades, and has recovered some ground since 2010. We see similar patterns for both continuous time analysis and papers with indeterminacy: interest peaking in 1990, a decline over the subsequent two decades, and a minor renaissance in the last three years of our inventory.

3.1.5 Solution and fitting techniques

We conclude this section with a broad-brush look at the techniques used to solve and/or fit theory-centric models. We find that there has been a clear trend towards more sophisticated computational methods, reflecting the increasingly quantitative orientation of macro research.

One indicator of this trend is the share of articles that use any kind of numerical method, for either solving or fitting the model. In addition to quantitative analysis, this also includes non-quantitative theory papers that use numerical methods to obtain their results, in lieu of (or in addition to) analytical solutions. As shown in the second column of table 8, the share has increased dramatically over time: from 9% in 1980 to 81% in 2016–18.

The trend is also evident in the increasing sophistication of the techniques used to fit quantitative models to the data. The less computationally intensive method to fit this type of model is to "calibrate" it using off-the-shelf parameters from other sources, some of which may have been obtained from conventional econometric methods, leaving a relatively small subset of parameters to adjust in order to match the target set of moments.[11] More computationally intensive approaches involve formal statistical methods, such as maximum likelihood or Bayesian techniques, to "optimize" the model's fit in a space encompassing most or all of the parameters.[12]

As reported in the third column of table 8, 89% of articles published in 2000 used calibration methods to fit the model to the data.[13] The number has steadily declined over time, however, and as of 2016–18, only 63% used calibration. The fourth column of the table documents the increasing use of optimization, which is now used in 37% of the articles.[14]

An increasing share of DSGE model fitting is performed using Bayesian methods, compared with conventional techniques such as maximum likelihood. In the decade since the method was

[11] Chapters 11 and 12 of DeJong and Dave (2011) are a good reference on this method.

[12] These methods are described in chapters 13 and 14 of DeJong and Dave (2011). The term "estimation" is often used in this context, but we use the term "optimized" to distinguish the procedure from conventional econometric methods.

[13] Although the foundation for RBCs was laid in the 1980s by Kydland and Prescott (1982) and King, Plosser and Rebelo (1988), none of the articles in our inventory for 1990 made a serious attempt to fit those models to the data.

[14] We see similar trends when we look at all quantitative theory-centric papers, not just DSGEs.

popularized by Smets and Wouters (2007), the number of DSGE papers using Bayesian methods has increased rapidly, and accounts for 23% of those using a statistical optimization procedure.

3.2 Econometric methods and data

We now shift our attention to the papers classified in Section 2 as using conventional econometric methods, as opposed to (or in addition to) quantitative theory-centric analysis.

3.2.1 Econometric methods and data types

We classify econometric methods on two dimensions. The first is between *time series* analysis and what we refer to as *applied microeconomic* methods.

The definition of time series analysis is straightforward. The variables are indexed by time, naturally. But the distinguishing feature of models in this category is that they include dynamics of some sort: lagged variables, serially correlated errors, etc. In other words, these are models in which the correct temporal ordering of the observations is essential. Panel time series models, in which T is large relative to N, also fall into this category. Commonly used techniques include vector autoregression (VAR), error-correction and regime-switching models.[15]

Our applied micro category encompasses any econometric model that is not clearly time series analysis. Specifications with only a cross-sectional dimension fall into this category, of course; as do classical "large-N, small-T" panel data models. Commonly used techniques include standard error clustering, fixed effects estimators and difference-in-difference specifications. Large-N dynamic panel data models, like those in which the Arellano-Bond (1991) estimator is applicable, are also in this category.[16]

To complement our cataloging of the methods, we compiled information on three attributes of the data used in the econometric analysis:

- *Microdata*: the unit of observation corresponds to an individual decision maker (a person, household, establishment, subsidiary, or firm), or to an individual asset or product. This excludes papers based on geographical or political unit (e.g. countries, states, MSAs). The designation only applies to papers using cross-sectional or panel data and employing applied micro methods.
- *Data structure*: cross-sectional ("indexed by i"), time series ("indexed by t") or panel ("indexed by i *and* t") data.

[15] A reliable criterion would be to classify as time series any paper whose analysis is based on the methods in Hamilton (1994).

[16] Wooldridge (2010) and Angrist and Pischke (2009) are standard references for these methods.

- *Proprietary*: using data that are not freely available. This includes data purchased from commercial providers (e.g. Compustat), those with restricted access (e.g. Census microdata), data used by special permission (e.g. regulatory or internal firm data), or collected by the researcher (e.g. field experiments, lab experiments or surveys).

Table A6 gives examples of papers using the different kinds of methods and datasets.

A striking finding is the prevalence in macroeconomic research of the techniques associated with applied microeconomics. The top two rows of panel A of table 9 show that nearly 60% of the papers using econometric methods papers published in field journals in 2016–18 used applied micro techniques, compared with 40% for time series methods. Four of the five have shares greater than or equal to 60%. The statistics in panel B of the table indicate that applied micro-style empirical work is even more prevalent in the five general interest journals, with 71% of E-designated articles using applied micro methods, compared with 52% for the corresponding subset of field journal articles. The shares for the *AER* and *JPE* are nearly 80%.

The statistics in the third rows of panels A and B show that the widespread application of applied micro methods goes hand-in-hand with the use of microdata, unsurprisingly. (The only papers in the micro methods category that do not use micro data are those with datasets whose cross-sectional units are geographical or political entities.) Similarly, the fourth rows in the two panels indicate that there is an almost one-to-one mapping between time series data and methods. (The exceptions are studies using panel time series models, and those using data indexed by t but without any form of dynamics.)

The tabulation of data structure in the fourth through sixth lines of both panels of table 9 tell a similar story. Corresponding to the small share of papers using time series analysis, only 39% of articles in field journals use time series data; the share for E-designated articles in general interest journals is even smaller, only 26%. Cross-sectional data is used relatively infrequently: its share is only 11% in the field journals, and 9% for the E-designated general interest journals. Panel data is by a wide margin the most common data structure in macro research: as of 2016–18 it was used in 50% of all articles in field journals, and in 65% of E-designated articles in general interest journals.

The use of applied micro methods has become much more widespread over the past four decades. Table 10 shows that time series analysis dominated in 1980 with a 75% share, compared with 25% for applied micro methods. There has been a steady movement away from time series methods, which now account for only 35% of the articles in our inventory; the remaining 65% use applied micro methods.

The trends in econometric methods are reflected in the characteristics of the datasets employed. As shown in table 10, the share of papers using microdata doubled in less than two decades, from 28% in 2000 to 56% in 2016–18 (relative to the number of articles in the *JME*, *JMCB*, and E-designated articles in the general interest journals). The share for the same set of papers using time series data has been steadily shrinking, from 89% in 1980 to only 34% in 2016–18. The number of papers using panel datasets rose spectacularly over the same period, from 3% to 57%. The share of papers using cross-sectional datasets has remained relatively flat, in the neighborhood of 10%.

Another remarkable aspect of recent empirical macro research is the extent to which it relies on proprietary data sources. Panel A of table 9 shows that of the articles in macro field journals published in 2016–2018, 43% use data that are not publicly available. The share for E-designated articles in general interest journals is 58%, and it exceeds 60% for three of the five journals. Table 10 documents the steady rise over the years in the use of proprietary data, from 13% in 1980 to 52% in 2016–18.

4 Interactions between macro and other fields

To what extent is macroeconomics a self-contained field? How porous are the borders between it and other branches of economics? To get a sense of the extent of interaction between fields, we used *EconLit* to obtain the JEL codes for every article in our 2016–18 inventory and tabulated the frequencies of JEL codes other than E that were listed.

Panel A of table 11 shows that the research published in the five leading macro field journals spans a wide range of other fields. Prominent subfields are Financial Economics (JEL code G), appearing in 41% of papers, and Microeconomics (JEL code D), appearing in 38% of papers. Remarkably, only 61% of papers published in macroeconomics journals list JEL code E, implying a 39% share with non-macro topics. This is perhaps to be expected for the *RED* and *JEDC*, which are not as macro-focused as the other field journals (the shares of articles with the E designation in those two journals are only 46% and 55% respectively).

More surprising are the relatively low shares of E-designated articles in the macro-oriented journals. Indeed, only 67% of the articles in the *AEJ* are classified as E, compared with 40% for Microeconomics (D). Also worth noting is the fact that only only 8% of the articles list JEL code F (International Economics), a smaller cross-field intersection than any of the other fields. This suggests that the vast majority of macro research consists of closed-economy analysis.

The range of JEL codes represented in macro journals is not just the result of the five macro field journals publishing non-macro papers, although that is true to some extent. Table 12 presents a tabulation similar to the one in table 11, but for the set of E-designated articles in the five field and five general interest journals. The vast majority cover one or more topics other than macro and monetary economics: 82% for field journals, 97% for general interest journals, and 87% overall. Of these, Financial Economics (G) and Microeconomics (D) are the most common areas of overlap. Papers with both E and G codes are relatively more common at the *JMCB* and *AER*, both with 40% shares. Nearly half of all E-designated general interest journal articles list Microeconomics as an additional code, compared with one-third for the field journals. With a 61% share, *ReStud* has an especially large share of articles with a microeconomic angle. International Economics (F) remains the least-common non-E code among field journals, listed in only 9% articles; it is in second-to-last place at general interest journals, where it appears in 15% of papers.

5 The life cycle and diffusion of ideas

How do seminal articles in macroeconomics become influential? How rapidly do they catch on, and what is the typical shelf life? In this section, we examine the speed with which groundbreaking papers accumulate citations, the durability of their influence, and the diffusion patterns between general interest and field journals.

We adopt a case study approach to these questions. First, we selected ten seminal papers that cover a variety of different approaches and methods.[17] The average citation count for the group is approximately 1,500; Taylor (1993) is in first place with over 3,000. Four are so so well known that the authors' names have become shorthand for the papers' salient contribution (e.g. the "Taylor Rule").

In order of publication date, these are:

1. Calvo (1983) proposed the staggered price setting mechanism that has come to be known as "Calvo pricing," and commonly used in New Keynesian DSGE modeling. Classified as non-quantitative theory.

2. Blanchard and Quah (1989) developed an econometric technique (the "Blanchard-Quah decomposition") for identifying aggregate supply and demand shocks. Classified as quantification, based on time series econometrics.

3. King, Plosser and Rebelo (1988) played a major role in launching research on Real Business Cycles (RBCs). Classified as non-quantitative theory-centric, although it laid out the road map used in countless model-fitting papers.

4. Romer and Romer (1989) used transcripts from the Fed's FOMC meetings in an effort to identify exogenous shifts in monetary policy. The "Romer Dates" are widely used in other contexts to gauge the impact of monetary policy. The paper was mentioned by Angrist and Pischke (2010) as an example of the causal effects framework.

[17] None of the ten are included in the inventory of papers we used in the previous sections' tabulations.

5. Bernanke and Gertler (1989) is one of the first dynamic macro models with financial frictions, in the form of agency costs, laying the foundation for subsequent research on the credit channel of monetary policy transmission. Classified as non-quantitative theory with financial market imperfections.

6. Taylor (1993) is the source of the eponymous "Taylor Rule." The paper shifted the conceptualization of monetary policy from the discretionary setting of the money supply to an interest rate rule. Classified as descriptive time series analysis.

7. Rotemberg and Woodford (1997) is credited with being the first NK DSGE model with microfoundations, i.e. based on explicit intertemporal optimization by both firms and households; and using the response to monetary policy shocks as the criterion for evaluating the model's fit. Classified as calibrated model fitting, with nominal rigidities.

8. Kiyotaki and Moore (1997) advanced the analysis of financial frictions by jointly modeling collateral constraints and asset price fluctuations. Classified as non-quantitative theory with financial market imperfections.

9. Christiano, Eichenbaum and Evans (2005) popularized the use of the "Calvo pricing" mechanism, which has become nearly ubiquitous in the DSGE literature. Classified as calibrated model fitting with nominal rigidities.

10. Smets and Wouters (2007) pioneered the use of Bayesian methods for fitting DSGE models. Classified as optimized model fitting, using Bayesian methods, and with nominal rigidities.

Google Scholar is the source of our citation data. For each of the ten papers, we tabulated by hand every citation appearing in eight of the ten journals used in the previous analysis, from the year of publication to 2019. (*RED* and *AEJ* are excluded, as they are relatively new, and hence less informative about time variation in citations.) We used these data to construct a time-varying index of citation frequency, what we refer to as the *cumulative citation count ratio*, or *CCR*. To do this, we first constructed a time series of citations for each paper, broken down by the journal in which the citation appeared. Next, for each article/journal pair, we calculated the cumulative number of citations since publication. Finally, for each article/journal pair, we calculated the ratio of cumulative citations to the cumulative total number of articles published in the journal for the field journals; or for the general interest journals, the total number of articles with JEL code E. It can be written as

$$CCR_{i,j,t} = \frac{\sum_{s=t_0}^{t} c_{i,j,s}}{\sum_{s=t_0}^{t} a_{j,s}} \tag{1}$$

in which $c_{i,j,s}$ is the number of citations to article i in journal j in year s and publication year t_0 ; and $a_{j,s}$ is the number of articles published in journal j in year s.

For example, three papers published in the *AER* in 2004 cited Romer and Romer (1989) ("*RR*"), so $c_{RR,AER,1989} = 3$. The cumulative number of citations as of 2004 was eight, making

$\sum_{s=1989}^{2004} c_{RR,AER,s} = 8$. As of 2004, the total number of E-designated articles published in the *AER* was $\sum_{s=1989}^{2004} a_{AER,s} = 398$, making the $CCR_{RR,AER,2004} = 8/398 = 0.02$.

To get a sense of the typical life cycle of an influential macro article, we also calculated a journal-specific composite cumulative citation count ratio, for the eight articles published prior to 2000 collectively. This was obtained by collapsing the sample by journal and years since publication to sum the cumulative number of citations and articles published in each journal, $CCR_{j,t}$. We also calculated an analogous aggregate CCR_t, collapsing the journal-specific cumulative count ratios into a single index.

Figure 5 shows the aggregate citation count ratio for three of the five field journals individually, and the general interest journals, for the 30 years following publication.[18] The aggregate count shows that the number of citations tends to increase rapidly for roughly ten years as the article catches on. This is typically followed by a period of slower growth; and eventually, the count plateaus, indicating that the number of citations as a share of total articles is remaining roughly constant.

The rise-then-plateau pattern is similar for the individual field journals and the general interest journals, but there are some differences. One is that citations in the general interest journals show a distinct head start, with a ratio greater than 0.02 in the year of publication, presumably due to citations to working paper versions of the articles. This could be interpreted as a tendency for general interest journals to lead the way in terms of the diffusion of ideas into the literature.

The aggregate time paths displayed in figure 5 conceal a great deal of variation across articles in life cycles and diffusion patterns. To explore this variation, we show in figure 6 the cumulative citation count ratio time series for each of the ten articles individually, from the publication date to 2019. Each plot has five lines: three for the field journals, one for the general interest journals collectively, and one for the aggregate across all journals, calculated analogously to the procedure used for the overall aggregate *CCR*.

Differences in the absolute levels of the lines reflect differences in the articles' popularity across the journals, attributable to such causes as the editors' tastes, the journal's niche, or the tendency of authors to submit papers to journals in which similar articles had appeared previously. For example, citations to King, Plosser and Rebelo (1988) were very common in the *JME*, especially in the early 1990s, perhaps not coincidentally a period in which one of the authors served as the journal's editor. They were rare at the *JMCB*, on the other hand; and, until 2004, there were no cites to Romer and Romer (1989) in the *JEDC*. There is much less dispersion in the *CCR* for Calvo (1983), whose citation count is relatively consistent across journals. A similar pattern holds for

[18] Christiano, Eichenbaum and Evans (2005) and Smets and Wouters (2007) are not included, as they have only 12 and 14 years of citation data.

Smets and Wouters (2007).

Six of the ten display the growth-then-plateau pattern evident in figure 5, Christiano, Eichenbaum and Evans (2005) perhaps most closely. But there is also a great deal of heterogeneity across both articles and journals.

The lag from publication to "takeoff" is variable and sometimes long. On one hand, Calvo (1983) was rarely cited for the first 17 years after its publication, but the *CCR* increased rapidly in the early 2000s. Similarly, we see a seven-year lag for Taylor (1993), which also garnered relatively few citations until the early 2000s. The growth in these two articles' popularity likely reflects the displacement of the prevailing RBC framework by New Keynesian models, and is consistent with the concurrent decline in citations to King, Plosser and Rebelo (1988).

Citations to two of the articles—Kiyotaki and Moore (1997) and Bernanke and Gertler (1989)—have been steadily rising since their publication (markedly so for the former), and show no signs of a plateau, even after 20 or 30 years. Their staying power is consistent with the increasing emphasis on financial market imperfections, documented earlier in section 3.1.2. Although it has decelerated somewhat in recent years, the *CCR* for Smets and Wouters (2007) continues to increase 12 years after publication. Its growth parallels that of Bayesian methods in fitting DSGE models, documented in section 3.1.5.

In three cases, we see a high initial level of citations in the year of the article's publication (again, likely citations to the working paper version), followed by increases in other journals: King, Plosser and Rebelo (1988), Kiyotaki and Moore (1997), and Christiano, Eichenbaum and Evans (2005). This is suggestive of diffusion from general interest to field journals. In our set of ten articles, there is no clear example of diffusion in the other direction.

6 Discussion and concluding remarks

Our goal in this paper has been to describe the nature of macroeconomic research today and how it has evolved over the past four decades. Having compiled and categorized a variety of attributes of 1,894 published papers, we cannot disagree with Reis's (2018) characterization of macro as "varied," "vibrant," and "more than mindless DSGE modelling." But at a more fundamental level, there has been a remarkable convergence over the past 40 years towards a common underlying approach to applied research.

One hallmark of this approach is a heavy reliance on theory. Formal models, virtually all of which incorporate microfoundations, are integral in 70 percent of all articles published in 2016–18.

Papers lacking a substantial theory section are rare.[19] And unlike the primarily non-quantitative theory-centric papers from 30 years ago, most contemporary research involves building models that can be taken to the data. Moreover, quantitative theory-centric research has increasingly utilized computationally intensive methods, made possible by breathtaking gains in computing power (Sergi, 2017) and the development of powerful, easy-to-use software, such as Dynare.

The quantitative theory-centric approach is most conspicuously exemplified in the DSGE models that have become the standard modeling framework in the field. DSGEs have not completely taken over, however. Partial equilibrium models and conventional econometric methods continue to be used, albeit much less frequently than in years past. In Blanchard's (2009) view, there will always be a place for non-DSGE research:

> "[p]artial equilibrium modeling and estimation are essential to understanding the particular mechanisms of relevance to macroeconomics. Only when they are well understood does it become essential to understand their general equilibrium effects."

Closely intertwined with the adoption of quantitative theory-centric methods is a movement away from research aimed at either refuting or corroborating economic hypotheses, and towards exercises involving fitting theory-derived models to the data. This represents a profound change from the approach prevailing in 1980. Then in the vanguard of the "Keynesian counterrevolution," Lucas and Sargent (1979) advocated a research agenda focused on testing:

> "This research line being pursued by a number of us involves the attempt to discover a particular, *econometrically testable* equilibrium theory of the business cycle, one that can serve as the foundation for quantitative analysis of macroeconomic policy." (Italics added.)

As late as 1990, falsification was by a wide margin the most common mode of applied research. But the tide began to turn in the early 1990s, with the advent of RBC models; and now, thirty years later, falsification exercises account for less than ten percent of published papers. Heckman and Singer (2017) notwithstanding, abduction is also relatively rare in macroeconomics. Instead, most quantitative theory-centric research seeks either to explain patterns in the data, or to quantitatively assess the impacts of policies or shocks. In his description of this style of research, Sims (1996) had clearly abandoned the positivist Lucas-Sargent philosophy:

> "It was once common for economists to think of the scientific enterprise as formulating testable hypotheses and confronting them with data. True hypotheses would survive the tests, while false ones would be eliminated. The science-as-data-compression view

[19] Interestingly, this runs counter to the trend in applied microeconomics, where recent research has tended to deemphasize formal theoretical modeling (Biddle and Hamermesh, 2017).

> lets us see the limits of this hypothesis testing view. The latter is dependent on the idea that there are true and false theories, when in fact the degree to which theories succeed in reducing data can be a continuum. The theory that planetary orbits are ellipses is only approximate if measurements are made carefully enough. It does not seem helpful to say therefore it is false and should be rejected."

The de-emphasis of falsification is understandable, given the intractable identification problems created by the joint endogeneity of virtually all macroeconomic variables. In current research, behavioral relationships are usually imposed *a priori*, deemed legitimate if they are derived from microeconomic first principles, and judged successful if the model that incorporates them yields a good approximation to the data. But the neglect of hypothesis testing suggests a lack of interest in scrutinizing the underlying microfoundations. This runs counter to Deaton's (2010) recommended "hypothetico-deductive" approach to a "progressive empirical research strategy" in which "mechanisms are proposed, key predictions are derived and tested, and if falsified, the mechanisms are rejected or modified."

Even Adelman and Adelman (1959), whose simulations of the Klein-Goldberger model anticipated by several decades the DSGE model-fitting agenda, cautioned against using their results to draw conclusions about the model's validity:

> "...while we have shown that the shocked Klein-Goldberger model offers excellent agreement with economic fact, we have not proved either that the Klein-Goldberger model itself is a good representation of the basic interactions among the several sectors of our economy or that random shocks are the prime cause of business cycles."

The difficulty of testing macroeconomic theories may explain the skepticism some have voiced regarding the field's status as a science. In calling attention to what he referred to as the "scientific illusion" in empirical macroeconomics, for example, Summers (1991) observed that econometric methods were unable to provide definitive answers to even the most basic macroeconomic questions, such as the long-run neutrality of inflation. Romer (2016) scathingly referred to the use of opaque and untestable microfoundations as a reliance on "facts with unknown truth values," and unobserved shocks as "phlogiston." And Korinek (2018) questioned the scientific rigor of moment-matching exercises, and expressed doubts about the common practice of imposing assumptions and choosing parameter values that are inconsistent with micro-level evidence in order to better fit the macro data.

The inherent limitations of aggregate data in testing macroeconomic theories likely explains the growing use of applied microeconomic methods and microdata, which is clearly evident in our data. Significantly, Nakamura and Steinsson (2018) focused almost exclusively on micro-based identification strategies, rather than macro-based schemes, such as imposing restrictions in structural VARs. Much of the work in this vein is clearly inspired by the Angrist and Pischke (2010) approach of leveraging natural experiments. Prominent examples (not in our dataset) include Mian and Sufi (2009, 2012, 2014), which used microdata to explore a wide range of macro questions, including the impact of subprime lending, house price declines and fiscal policy. However, the increasing use of proprietary microdata does raise concerns about the ability of other researchers to replicate and independently corroborate published results.

Methods are not the only aspect of the field to have undergone profound changes in the past 40 years; macroeconomic doctrine has evolved as well. Arguably the most significant shift is from a frictionless classical view of the economy towards one in which frictions and market failures are pervasive. Nominal rigidities and market power are ubiquitous in recent research. And contrary to some critics' assertions (e.g., De Grawe, 2009; Skidelsky, 2009; and Stiglitz, 2018), a significant amount of macroeconomic research has always incorporated financial market imperfections. Not surprisingly, interest in financial frictions and intermediation has increased dramatically in the aftermath of the financial crisis, and financial economics is now one of the two most commonly listed non-macro JEL classification for papers published in macroeconomics.

What do these findings imply about macroeconomic research going forward? Will a new framework eclipse New Keynesian DSGE modeling? Will the field's theoretical emphasis continue, or will causal effects analysis become ascendant? As memories of the financial crisis fade, what will be the next big issue to attract macroeconomists' attention (and others' criticism for having previously been ignored)? It is tough to make predictions (especially about the future), so we will leave the state of macroeconomics in 2061 as a fruitful topic for future research.

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Table 1: Number of Articles by Year and Journal

A: Macro field journals

	All Field	*JME*	*JMCB*	*AEJ*	*JEDC*	*RED*
2018	268	50	62	32	85	39
2017	252	33	51	32	102	34
2016	266	55	53	29	90	37
2010	116	62	54			
2008	124	68	56			
2006	182	95	87			
2000	80	52	28			
1990	69	40	29			
1980	71	34	37			
Total	1,428	489	457	93	279	110

B: E-designated articles in general interest journals

	All GI	*AER*	*ECMTA*	*JPE*	*QJE*	*ReStud*	**Total**
2018	79	31	8	9	9	22	347
2017	71	26	9	10	15	11	323
2016	61	23	10	8	7	13	327
2010	30	13	2	4	4	7	146
2008	34	13	4	8	4	5	158
2006	34	13	4	3	4	10	216
2000	47	26	5	7	6	3	127
1990	47	11	5	14	13	4	116
1980	63	16	8	18	14	7	134
Total	466	172	55	81	76	82	1,894

Note: The field journal abbreviations are as follows: *AEJ* is *American Economic Association: Macroeconomics*, *JEDC* is *Journal of Economic Dynamics and Control*, *JME* is *Journal of Monetary Economics*, *JMCB* is the *Journal of Money, Credit and Banking*, and *RED* is the *Review of Economic Dynamics*. The general interest journal abbreviations are as follows: *AER* is the *American Economic Review*, *ECMTA* is *Econometrica*, *JPE* is the *Journal of Political Economy*, *QJE* is the *Quarterly Journal of Economics*, and *ReStud* is the *Review of Economic Studies*. See section 2.3 for a description of the dataset used for the tabulations.

Table 2: Epistemology and Methodology

		Methodology Shares of epistemology category		
Epistemology	Share of Total	Theory-centric	Econometric	Both
Description	7	…	97	3
Causal Effects	5	…	89	11
Falsification	7	3	65	32
Model Fitting	27	69	16	15
Abduction	7	79	7	13
Quantification	18	59	27	15
Non-quantitative Theory	21	100	…	…
Methodology	7	38	54	7
Other	< 1	25	75	0
All Approaches	100	59	29	11

Note: The figures in the second column are the number of articles in each epistemological category, expressed as the percentage of articles in the five field journals, plus the E-designated articles in the five general interest journals, published in 2016–18. The figures in the third, fourth and fifth columns are number of articles using the indicated method, expressed as the percentage of articles taking the epistemological approach indicated in each row. (The shares may not sum to 100 due to rounding.) By definition, description and causal effects papers are not theory-centric; and non-quantitative theory papers do not use econometrics. See section 2 for the definitions of the epistemological approaches and analytical methods.

Table 3: Epistemological Approaches by Journal

A: All articles in field journals

	All Field	*JME*	*JMCB*	*AEJ*	*JEDC*	*RED*
Shares, %						
Description	7	9	16	5	4	2
Causal Effects	3	4	8	3	1	0
Falsification	7	7	15	11	3	4
Model Fitting	28	28	20	30	25	46
Abduction	7	6	5	8	9	5
Quantification	19	25	16	25	13	26
Non-quantative Theory	21	15	17	15	30	14
Methodology	7	4	2	3	15	3
Other	0	0	1	0	1	0
Number of articles	786	138	166	93	279	110

B: E-classified articles in field and general interest journals

	All Field	All GI	*AER*	*ECMTA*	*JPE*	*QJE*	*ReStud*
Shares, %							
Description	7	6	8	0	0	19	0
Causal Effects	3	9	10	4	7	16	9
Falsification	8	8	5	4	11	16	7
Model Fitting	32	23	26	11	37	26	15
Abduction	6	7	14	0	0	0	9
Quantification	20	17	19	15	30	10	13
Non-quantitative Theory	18	24	15	41	15	13	43
Methodology	6	5	1	26	0	0	4
Other	0	1	3	0	0	0	0
Number of articles	427	211	80	27	27	31	46

Note: The shares are calculated relative to the total number of articles published in 2016–18, reported in the bottom row, classified according to the criteria described in section 2. (The shares may not sum to 100 due to rounding.) The journal abbreviations are given in the note to Table 1.

Table 4: Scope of Equilibrium

A: Articles in macro field journals

	All Field	*JME*	*JMCB*	*AEJ*	*JEDC*	*RED*
Shares,%						
DSGE	42	51	55	38	33	47
General	21	18	10	39	19	26
Partial	36	31	35	23	48	28
Number of articles	529	99	69	66	197	98

B: E-classified articles in field and general interest journals

	All Field	All GI	*AER*	*ECMTA*	*JPE*	*QJE*	*ReStud*
Shares, %							
DSGE	61	46	60	47	40	31	36
General	18	20	15	18	25	31	23
Partial	21	33	25	35	35	38	41
Number of articles	283	142	53	17	20	13	39

Note: The shares are calculated relative to the number of theory-centric articles from 2016–2018, reported in the bottom row, classified according to the criteria described in section 3.1.1. (The shares may not sum to 100 due to rounding.) The journal abbreviations are given in the note to Table 1.

Table 5: Frictions

Year	Nominal Rigidities	Market Power	Search/Info. Friction	At least one Friction
1980	36	9	18	55
1990	17	20	17	50
2000	17	32	15	68
2006–10	37	49	25	79
2016–18	42	57	32	82

Note: The figures are percentages of articles with general equilibrium or DSGE models in the *JME* and *JMCB*, plus the E-designated articles in the five general-interest journals. The frictions are defined in section 3.1.2. The 2006–10 figures use data from 2006, 2008 and 2010; and the 2016–18 figures use data from 2016, 2017 and 2018.

Table 6: DSGE Genres

A: Articles in field journals

	All Field	*JME*	*JMCB*	*AEJ*	*JEDC*	*RED*
Shares, %						
New Keynesian	40	34	61	42	44	19
Real business cycle	17	12	12	25	19	21
Asset pricing	5	12	0	8	3	2
Growth	9	10	2	13	6	15
Monetary	5	8	5	4	3	4
OLG/life cycle	7	10	2	8	9	6
Search/matching	6	8	0	0	1	17
Trade	4	2	7	0	4	4
Other	8	4	10	0	11	11
Number of articles	232	50	41	24	70	47

B: E-classified articles in field and general interest journals

	All Field	All General	*AER*	*ECMTA*	*JPE*	*QJE*	*ReStud*
Shares, %							
New Keynesian	46	44	60	33	0	50	43
Real business cycle	19	10	7	11	13	50	7
Asset pricing	3	11	7	22	25	0	7
Growth	6	8	3	11	13	0	14
Monetary	6	2	0	0	0	0	7
OLG/life cycle	6	6	3	0	13	0	14
Search/matching	5	8	10	11	13	0	0
Trade	4	6	7	0	25	0	0
Other	6	5	3	11	0	0	7
Number of articles	178	63	30	9	8	2	14

Note: The shares are calculated relative to the number of theory-centric articles from 2016–2018, reported in the bottom row, classified according to the criteria described in section 3.1.3. (The shares may not sum to 100 due to rounding.) The journal abbreviations are given in the note to Table 1.

Table 7: Unconventional DSGE Features

Year	Heterogeneous agents	Finite horizon	Unconventional expectations / preferences	Indeterminacy	Continuous Time
1980	0		18	0	
1990	10	38	30	10	13
2000	10	10	27	0	5
2006–10	15	6	19	6	3
2016–18	29	4	25	9	9

Note: The figures are percentages of all articles in the *JME* and *JMCB*, plus the E-designated articles in the five general interest journals. The 2006–10 figures use data from 2006, 2008 and 2010; and the 2016–18 figures use data from 2016, 2017 and 2018.

Table 8: Solution and Fitting Techniques in Theory-Centric Research

Year	All articles: numerical methods	Of DSGE: Calibration	Of DSGE: Optimization	Of optimized DSGE: Bayesian methods
1980	9	0	0	0
1990	33	0	0	0
2000	71	89	11	0
2006–10	78	73	27	15
2016–18	81	63	37	23

Note: The second column reports the share of theory-based articles that use numerical methods to solve or fit the model. The third and fourth columns report the shares of articles with quantitative DSGE models using calibration versus optimization to fit the model. The fifth column reports the share of DSGEs with optimized fit that use Bayesian methods. See section 3.1.5 for details. The calculations are based on articles in the *JME* and *JMCB*, plus the E-designated articles in the five general interest journals. The 2006–10 figures use data from 2006, 2008 and 2010; and the 2016–18 figures use data from 2016, 2017 and 2018.

Table 9: Empirical Methods

A: Articles in field journals

	All Field	*JME*	*JMCB*	*AEJ*	*JEDC*	*RED*
Shares, %						
Methods						
Applied micro	59	66	60	71	40	73
Time series	41	34	40	29	60	27
Data						
Microdata	50	53	49	55	40	68
Time series	39	32	42	26	55	23
Cross section	10	17	7	13	10	9
Panel	50	51	51	61	34	68
Proprietary	43	51	47	47	33	27
Number of articles	268	47	103	38	58	22

B: E-classified articles in field and general interest journals

	All Field	All GI	*AER*	*ECMTA*	*JPE*	*QJE*	*ReStud*
Shares, %							
Methods							
Applied micro	52	70	78	50	79	67	55
Time series	48	30	22	50	21	33	45
Data							
Microdata	43	66	75	50	71	50	73
Time series	45	26	22	33	21	29	36
Cross section	9	9	8	0	21	0	18
Panel	46	65	69	67	57	71	45
Proprietary	38	58	64	33	64	67	27
Number of articles	165	98	36	6	14	24	11

Note: The figures represent the number of econometrics-based articles from 2016–18 using the methods or data indicated in each row, expressed as shares of the totals reported in the last row of the table. (The shares may not sum to 100 due to rounding.) Section 3.2 describes the criteria used for the classifications. The journal abbreviations are given in the note to Table 1.

Table 10: Econometric Methods and Data Types Over Time

	Methods		Data				
Year Year	Time series	Applied micro	Micro data	Time series	Cross section	Panel	Proprietary
1980	75	25	22	89	8	3	13
1990	62	38	28	70	14	16	32
2000	58	42	28	54	8	38	30
2006–10	46	54	41	42	13	45	41
2016–18	35	65	56	34	10	56	52

Note: The figures are the shares, expressed as percentages, of econometrics-based articles articles in the *JME* and *JMCB*, plus the E-designated articles in the five general-interest journals. The method and data attributes are defined in section 3.2. The 2006–10 figures use data from 2006, 2008 and 2010; and the 2016–18 figures use data from 2016, 2017 and 2018.

Table 11: Topics Represented in Field Journals

	All	*JME*	*JMCB*	*AEJ*	*JEDC*	*RED*
Shares, %						
Macro and Monetary (E)	61	67	79	67	46	55
Financial (G)	41	38	51	25	46	27
Microeconomics (D)	38	31	39	40	36	49
Mathematical Methods (C)	14	4	14	5	25	5
International Economics (F)	8	6	11	12	7	7
Development (O)	13	13	7	27	10	18
Labor Economics (J)	18	24	5	33	10	35
Public Economics (H)	14	20	11	15	11	19
Industrial Organization (L)	14	7	14	24	14	17
All other JEL codes	19	12	22	32	16	21
Articles with JEL codes	785	138	166	93	278	110
Average # codes per article	2.4	2.2	2.6	2.8	2.2	2.5

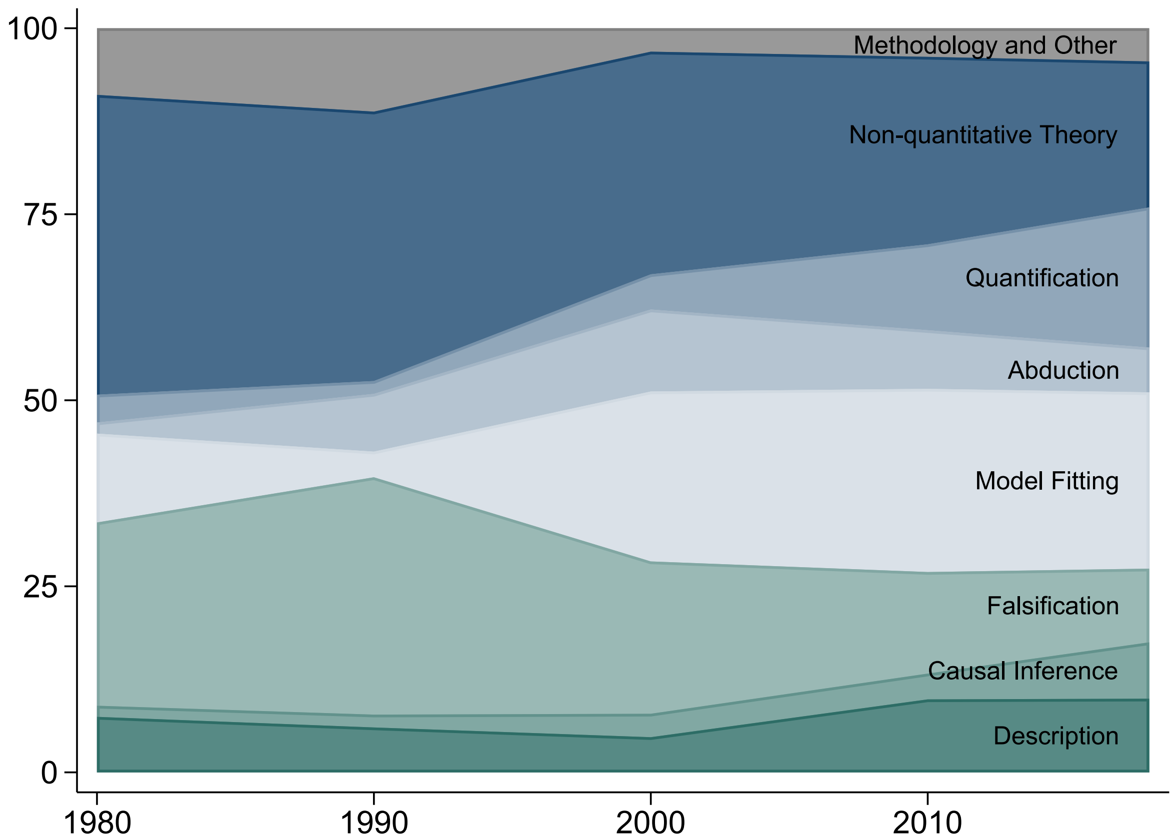
Note: JEL codes are obtained from *EconLit* and shares are calculated relative to all field journal articles in our sample published in 2016–2018.

Table 12: Topics Represented in E-designated Articles

	Overall	*JME*	*JMCB*	*AEJ*	*JEDC*	*RED*	All Field
Shares, %							
Any JEL code other than E	87	80	83	90	78	87	82
Financial (G)	33	30	40	26	30	28	32
Microeconomics (D)	38	25	37	35	31	41	33
Mathematical Methods (C)	12	3	15	6	21	5	12
Labor Economics (J)	15	22	5	18	10	25	14
Development Economics (O)	12	15	6	21	9	15	12
International Economics (F)	10	2	9	18	9	8	9
		AER	*ECMTA*	*JPE*	*QJE*	*ReStud*	All GI
Shares, %							
Any JEL code other than E		98	100	100	90	95	97
Financial (G)		40	33	33	38	21	34
Microeconomics (D)		44	52	41	52	61	49
Mathematical Methods (C)		5	33	0	3	18	10
Labor Economics (J)		21	19	19	7	16	17
Development Economics (O)		13	15	7	14	8	11
International Economics (F)		19	11	26	14	3	15

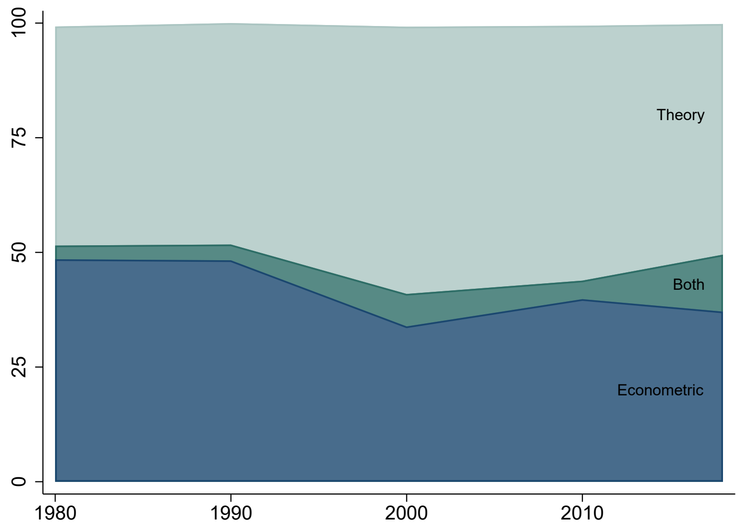
Note: JEL codes are obtained from Econlit and shares are calculated relative to all articles in our sample *with JEL code E* published in 2016–18.

Figure 1: Evolution of Epistemological Approaches



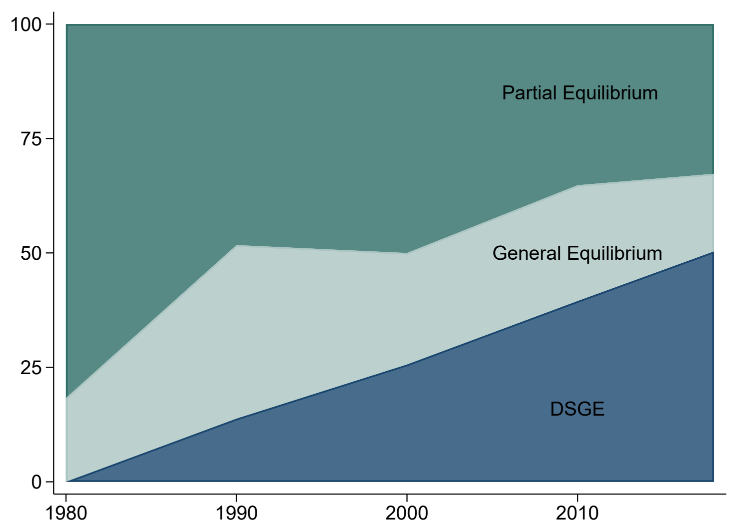
Note: The areas represent the shares of articles published in the *JME* and *JMCB*, plus the E-designated articles in *AER*, *QJE*, *JPE*, *ReStud*, and *Econometrica*, corresponding to the epistemology categories defined in section 2. The 2010 data points are averages for 2006, 2008, and 2010; and the 2018 data points are averages for 2016, 2017, and 2018. The data points for the individual years are reported in Appendix B (online).

Figure 2: Evolution of Methodology



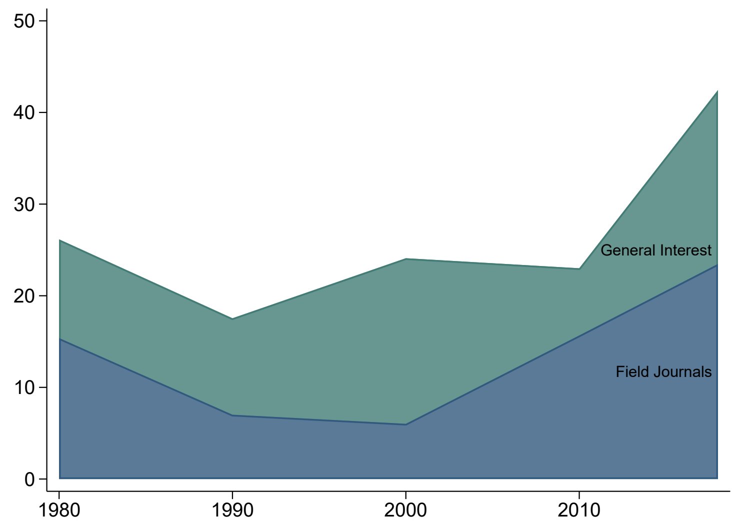
Note: The areas represent the shares of articles published in the *JME* and *JMCB*, plus the E-designated articles in *AER*, *QJE*, *JPE*, *ReStud*, and *Econometrica*, categorized as theory-centric, econometric, or both, as defined in section 2. See also note to figure 1.

Figure 3: Scope of Equilibrium Over Time



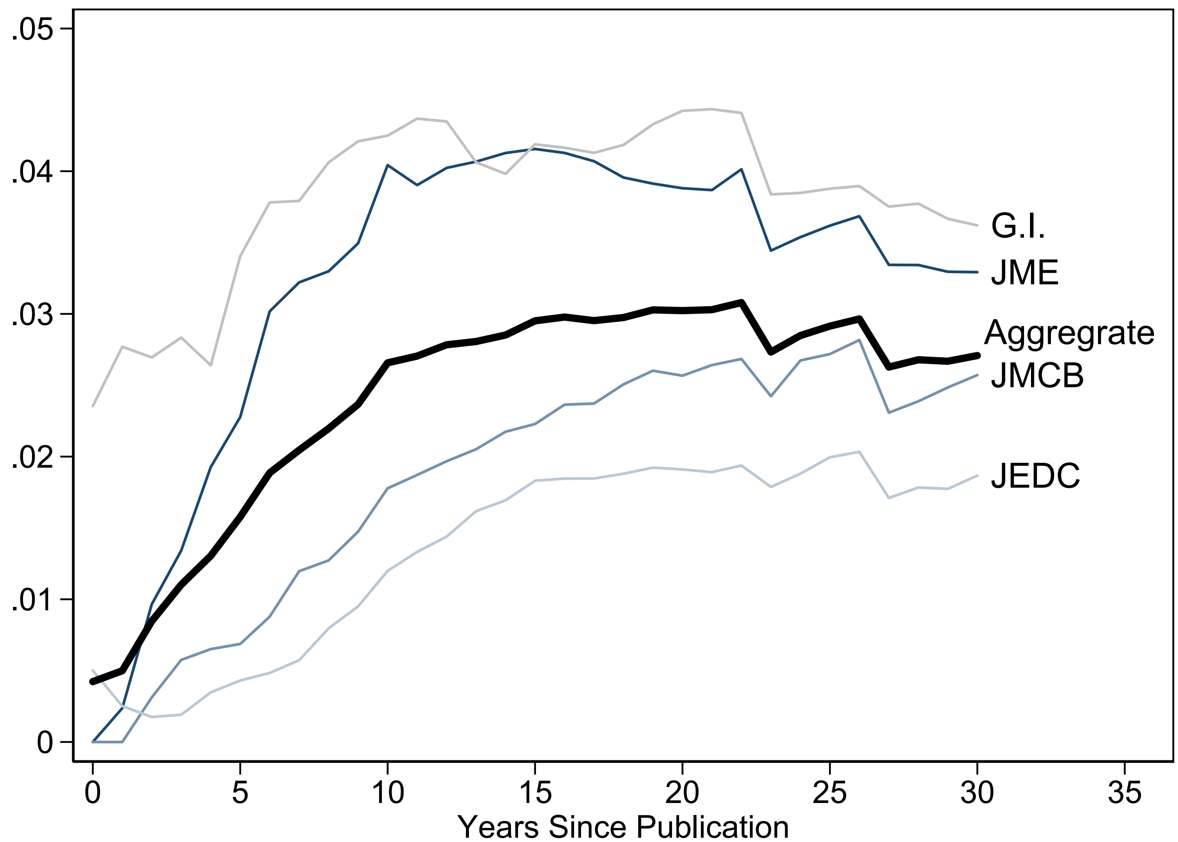
Note: The areas represent the shares of theory-centric articles published in the *JME* and *JMCB*, plus the E-designated articles in *AER*, *QJE*, *JPE*, *ReStud*, and *Econometrica*, classified as partial equilibrium (PE), general equilibrium (GE) and dynamic stochastic general equilibrium (DSGE), as defined in section 3.1.1. See also note to figure 1.

Figure 4: Financial Market Imperfections Over Time



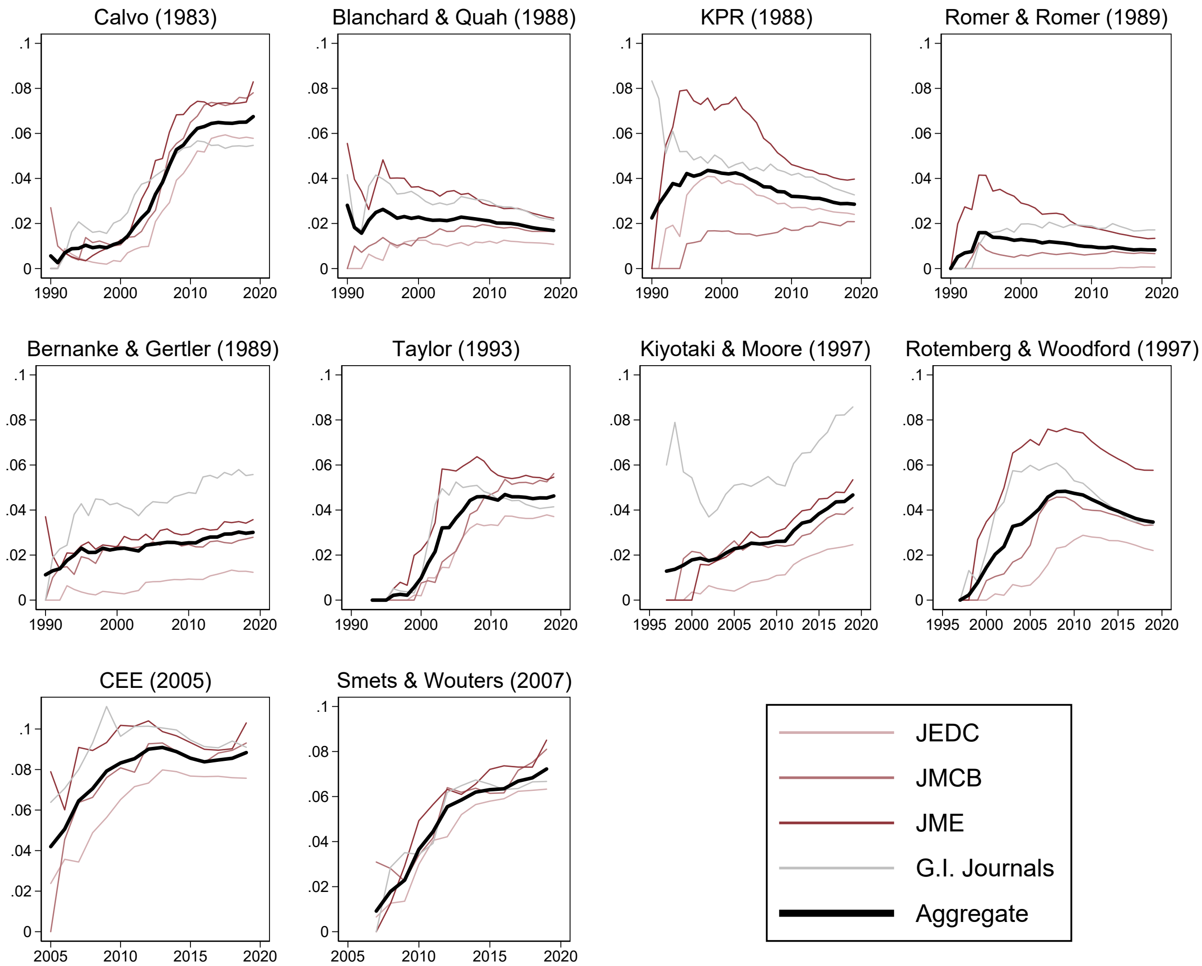
Note: The areas represent the shares of theory-centric articles published in the *JME* and *JMCB*, plus the E-designated articles in *AER*, *QJE*, *JPE*, *ReStud*, and *Econometrica*, that include various forms of financial frictions and/or intermediaries, as defined in section 3.1.2. See also note to figure 1.

Figure 5: Aggregate Citation Patterns



Note: The vertical axis is the Cumulative Citation Count Ratio (CCR) for the following eight articles: Calvo (1983), Blanchard and Quah (1989), King, Plosser and Rebelo (1988), Romer and Romer (1989), Bernanke and Gertler (1989), Taylor (1993), Rotemberg and Woodford (1997) and Kiyotaki and Moore (1997). See section 5 for details.

Figure 6: Citation Patterns for Individual Articles



Note: The vertical axis in each panel is the Cumulative Citation Count Ratio (CCR) for the cited in the heading. See section 5 for details.