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THE INTELLECTUAL IDEAS INSIDE CENTRAL BANKS: WHAT'S CHANGED (OR NOT) SINCE THE CRISIS?

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Abstract. I explore how the intellectual ideas inside central banks have shifted over the first two decades of the new century. To do this I collect every research paper published by advanced economy central banks and examine them using tools from computational linguistics. The analysis points to a shift in the intellectual focus, from a relatively macroeconomic perspective towards a less aggregated view. In part, these changes seem to reflect lessons from the 2008 financial crisis – for example, that macroeconomic models can only get you so far and that microeconomic data are useful for teasing out the causes of aggregate fluctuations. There has been an increase in the amount of research dedicated to the banking and household sectors and a reduction in the amount of intellectual effort invested in modelling the macroeconomy – though some of these shifts had already begun before the crisis. Consistent with this, the similarity of central banking research to that published in top macroeconomic journals has been widening since the crisis.

Keywords. Communication; Machine learning; Monetary policy

1. Introduction

It is now over 10 years since the 2008 financial crisis. As the dust has settled, central bankers have had the chance to reflect on what they thought they knew about monetary economics and to re-think their modelling frameworks.

Indeed, a lot of intellectual capital has been invested in looking back at the 2008 financial crisis. There has been an extensive search for 'lessons for central bankers' (Braude *et al*., 2012) and a lot of academic work dedicated to addressing shortcomings in modelling frameworks used to inform monetary policymaking (Beyer *et al*., 2017).

Two of the most prominent among these lessons are:

1. *models only get you so far* (Potter, 2019); and
2. *microdata are useful* (Mian and Sufi, 2010).

Kohn and Sack (2018) argue that research prior to the crisis had become too narrowly focused on developing sophisticated models of the economy and policymakers had placed too much emphasis on the predictions of these models. Potter (2019) notes that the crisis was an exercise in humility for central bankers, who had to face up to their failure to foresee the crisis, despite some of the early warning

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indicators that were available before 2008. He argues that central bankers had excessive self-confidence in the ability of their macroeconomic models to make precise predictions. Consistent with this, Fligstein *et al*. (2014) argue that the Federal Reserve's empirical framework for making sense of the economy – macroeconomic theory – made it hard for them to connect the dots between the disparate events that ultimately led to the crisis.

The second of these 'lessons' is to pay more attention to microdata. Mian and Sufi (2010) argue that the usefulness of microdata – in particular household-level data – in teasing out the underlying causes of macroeconomic fluctuations was under-appreciated prior to the crisis. As noted in Simon (2019) '*the crisis also highlighted that microeconomic issues do not wash out in aggregate and can have massive macroeconomic consequences*'.

Against this background, the aim of this paper is to see if the rhetoric regarding these two 'lessons' matches the reality. More broadly, I shed light on shifts in the intellectual ideas occurring within central banks over the past 20 years by examining the research papers they publish.

In particular, techniques from computational linguistics are applied to examine every research paper published by inflation-targeting central banks, covering 10 years before and 10 years after the crisis.

The goal is to try and focus on what has changed intellectually inside central banks, rather than what has changed on the policy front. Glancing at the most commonly used words in central banking research over the past two decades, it is of little surprise that terms such as 'financial', 'bank', 'crisis' and 'shock' have increased in frequency since the crisis (Figure 1).

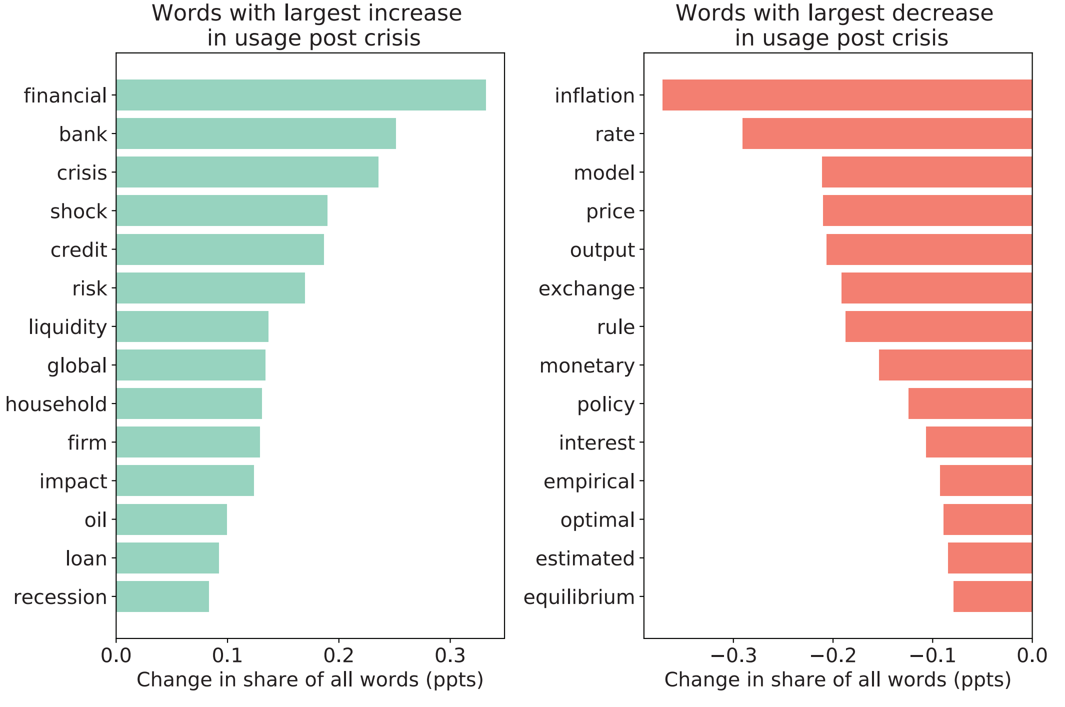

Figure 1. Shifts in the Language of Central Banking Research.
Notes: Advanced economy central banks: 2000–2019; word count calculated after tokenizing, removing stop words and lemmatizing.
Source: Author's calculations; IDEAS.

To dig deeper and find patterns in the text that are consistent with the intellectual shifts described above, I employ two empirical techniques:

1. First, topic models are used – latent Dirichlet allocation (LDA) (Blei *et al.*, 2003) and dynamic topic models (Blei and Lafferty, 2006) – to examine if there has been a shift away from modelling and towards a greater focus on microdata. These models are useful in discovering topics from a large and unstructured collection of documents.
2. Second, I use latent semantic analysis (LSA) to examine if central bank research has moved away from an excessive focus on modelling. In particular, I measure the similarity of central bank research to frontier research dedicated to macroeconomic modelling (the conceptual approach here is similar to Iaria *et al.*, 2018). To characterize frontier research, an index is built comprising almost 10,000 academic papers from some of the highest rated macroeconomics journals.

In doing so, this paper makes a methodological contribution to the economics literature. It is the first paper to apply natural language processing techniques (LDA and LSA) – widely used in other domains – to better understand how the nature of economic inquiry has evolved. A handful of other recent papers have pioneered the use of LDA in economics in other contexts (see, e.g. Hansen *et al.*, 2017; Thorsrud, 2020) and fewer still have used LSA (Iaria *et al.*, 2018).

This paper also contributes to the growing literature on central bank communication. For example, Stekler and Symington (2016) use the Federal Open Market Committee's minutes as data to examine its information set during the 2008 financial crisis; Hansen *et al.* (2019) use the Bank of England's *Inflation Report* to extract signals that drive long-run interest rates; and Picault and Renault (2017) measure the stance of the European Central Bank's monetary policy using the text of its press conferences as data. By contrast, this is the first paper to study central bank communication through the lens of the economic research central bankers publish.

This work has important policy implications. Economic researchers play a critical role within central banks by anchoring policy deliberations to conceptual and empirical foundations and providing input into policy decisions. It is therefore critical to assess if central bank research has *demonstrably* learned the lessons elucidated from the crisis by pivoting away from paradigms that have not proven useful to policymakers and adopting more fruitful lines of inquiry.

While the results in the paper are mostly descriptive and should not be over-interpreted, the weight of the evidence shows that central bank researches have learnt important lessons from the crisis. The results from the topic modelling exercise indicate that there has been a shift towards a greater focus on microdata alongside a reduction in the emphasis on modelling over the past 20 years. Similarly, I find that central bank research has become more 'distanced' from frontier research dedicated to macro modelling since the crisis – as measured by paper similarity scores.

The rest of this paper is organized as follows: Section 2 outlines the web scraping exercise used to collect the research abstracts that are analysed in this paper. Section 3 outlines the topic modelling methodology, describes the identified topic landscape and examines how topics have evolved over time. Similarly, Section 4 reviews the LSA methodology and presents the results from this exercise. Finally, the conclusions are provided in Section 5, along with limitations.

2. Data

2.1 *Collection*

I scrape the IDEAS economic research repository to gather the research abstracts analysed in this paper. IDEAS is the largest bibliographic database dedicated to economics and available freely on the internet.

Table 1. Web Scraping for Research: 2000–2019.

Central bank	Number of abstracts
European Central Bank Working Paper Series	2285
Federal Reserve	1498
Bank of Canada Staff Working Papers	895
Bank of England Working Papers	687
Norges Working Paper	335
Bank of Japan Working Paper Series	281
Sveriges Riksbank Working Paper Series	262
RBA Research Discussion Papers	210
Reserve Bank of New Zealand Discussion Paper Series	184
Total	6637

Academic journals	Number of abstracts
American Economic Journal: Macroeconomics	365
Journal of Monetary Economics	1601
The Journal of Macroeconomics	1400
The B.E. Journal of Macroeconomics	601
Review of Economic Dynamics	994
Journal of International Economics	1801
Journal of Economic Dynamics and Control	2601
Total	9636

Note: The python code used to perform the scraping exercise is on GitHub.
Source: Author's calculations; IDEAS.

In particular, every research abstract published by nine advanced economy inflation-targeting central banks over the period 2000–2019 is collected (Table 1).

Likewise, to compare central bank paper abstracts to academic research abstracts (with similarity evaluated by LSA) I scrape the IDEAS pages of seven of the highest rated macroeconomic journals to collect around 9,600 academic papers. These journals publish significant theoretical and empirical research spanning the entire range of macroeconomics and monetary economics.

I focus only on advanced economy inflation-targeting central banks to control for fundamental factors that shape research agendas. The central banks of emerging market economies tend to focus their research efforts on a very different set of issues. Likewise, lessons from the 2008 financial crisis are arguably more relevant for advanced economies, just as lessons from the Asian financial crisis or the Latin American debt crisis were more relevant for emerging market economies.

A natural question to ask is why I do not focus exclusively on the US Federal Reserve, given the crisis originated in the United States. Other advanced economy central banks are included because lessons learned from the crisis are very relevant for these economies too. This notwithstanding, results are presented separately for the Federal Reserve where relevant.

2.2 *Text Pre-Processing*

After collecting the abstracts, text pre-processing was required before making use of topic models to examine the evolution of topics over time as well as LSA to examine the similarity of research abstracts.

For every abstract, all punctuation and numbers were removed and all characters were made lower case. I then eliminated all stop-words, which are typically ‘function’ words. These words have very little substantive meaning and primarily denote grammatical relationships between ‘content’ words, such as prepositions (of, by, from), conjunctions (and, but, as) and in/definite articles (a, an, the). In addition, I remove ‘domain-specific’ stop words, which do not add any semantic value. Words that appear in most economic articles were removed, such as ‘study’, ‘paper’, ‘find’, ‘effect’, ‘discuss’, ‘suggests’, ‘implies’ and ‘indicates’.

‘Lemmatization’ was then conducted to find the lemma – or dictionary form – of each word in order to further reduce dimensionality (i.e. the total number of words), without losing generality. The lemma of each word is taken rather than its stem because it better preserves both meaning and part-of-speech information. For example, the lemma of the word *productivity* is productivity, whereas its stem is *product* – a semantically very different word. Since the identification of topics relies on the subjective interpretation of word distributions, lemmatization is more appropriate than stemming. In all, pre-processing reduces the number of unique words in the corpus from 15,159 words to 13,251 (Table 2).

Table 2. Text Pre-Processing.

	Raw text	Removing stopwords	Removing domain stopwords	After lemmatizing
Words	923,555	577,729	546,483	546,483
Unique words	15,159	15,039	15,000	13,251

Notes: The raw tokenized text contains 923,555 words, of which 15,159 are unique. After removing (i) standard stopwords, (ii) the domain- specific list of stop words; and (iii) lemmatizing there are 546,483 words, of which 13,251 are unique.
Source: Author’s calculations; IDEAS.

The final pre-processing step is to transform the research abstracts into a $D \times V$ document-term matrix – or a bag-of-words. In a bag-of-words, each document is represented in a vector of an unordered collection of words – for a total of V words in a corpus, each abstract becomes a V-dimensional vector.

For the LSA, the individual word counts in the $D \times V$ matrix are reweighted by their term frequency inverse document frequency (tf-idf) using Equation (1) below. Here, if the frequency of term i in document j is high then the weight of that term will be high; however, if the term appears in a lot of documents, the weight will decline. This transformation essentially decreases the relative importance of words that carry little information, but appear in many documents.

$$\text{weight}_{i,j} = \text{frequency}_{i,j} \times \log_2 \frac{\text{Number of documents}}{\text{document freq}_i} \tag{1}$$

3. Topic Models

To examine the themes in central banking research, I use the very popular LDA algorithm developed by Blei *et al*. (2003). This allows us to compare the weight of various topics found in central banking research and how the relative importance of these topics has changed over time. A dynamic topic model is also used, which respects the dates the research papers were published (Blei and Lafferty, 2006). This allows us to look within topics over time and examine how the topic itself has evolved.

3.1 *The LDA Model in Concept*

In concept, the LDA topic model is most easily described by the imaginary random process by which the model assumes documents are created:

1. First, authors begin by choosing a distribution over topics for their paper.
2. Second, before writing a word, authors choose what topic it belongs to.
3. Finally, authors look up the distribution over terms associated with that topic, draw a word from the topic and commit that word to paper.

To generate a complete document, this process is repeated for every word. A new document is then created, with words chosen in the same way. Importantly, the topics stay the same from document to document, but how each document exhibits those topics changes.

This is the essence of the LDA model, which is formally a mixed membership model. That is, each document is coming from a mixture model, where the mixture proportions change from document to document, but the mixture components are fixed across the whole collection.

The machine learning and algorithmic challenge is that we do not get to observe the above imaginary generative process. Instead, to infer all of the values associated with this latent generative process, posterior inference is used – that is, the *conditional distribution* of the hidden variables given the observed variables. The observed variables are the words of the documents. The hidden variables are the per-document topic proportions, the per-topic word distributions and the per-word topic assignment (for more details see Appendix A).

3.2 *The LDA Model in Practice*

In practice, to implement LDA, we begin by passing the algorithm two inputs. The first is the pre-processed corpus of all central bank research abstracts published since 2000. The second is the fixed number of topics that do not change and are used to represent each research paper abstract. Topics are subjectively labelled with reference to their fixed distribution over words. For example, one would expect the topic labelled *macro modelling* to assign a high probability to the word *forecast*. A 10-topic model is chosen, which ensures that the identified topics are easily interpretable.[1] However, this comes at the cost of model precision, with a larger number of topics improving the performance of the model (see Chang *et al*. (2009) for a summary of this trade-off).

Upon completion of LDA inference, there are two outputs. The first is a $D \times K$ per-document topic proportion matrix θ. The dimension of this matrix is around 6600×10. The second is a $V \times K$ per-topic word distribution matrix Φ, with a dimension of around 13500×10. An example of these outputs is provided in Table 3.

Under the assumptions of the simple LDA model, the temporal order of documents does not matter (i.e. the documents are exchangeable). This assumption may be unrealistic when analysing long-running collections that span several decades, such as the collection of central bank research abstracts. As a result, I also employ a *dynamic topic model*, where the distribution of words that define a topic evolves over time (e.g. over the past 20 years or so the *macro modelling* topic would have evolved to capture new modelling frameworks that were previously unheard of and this evolution is captured in these models). This approach lets us look at the change *within* topics and track how it has changed.

To do this, the corpus is divided into 20 yearly time slices, with the assumption that within each slice documents are exchangeable. The topic distributions over words are then allowed to evolve from slice to slice. The intuitive idea is given by Equation (2).

$$\beta_{t,k} | \beta_{t-1,k} \sim \mathcal{N}\left(\beta_{t-1,k}, \sigma^2 I\right) \tag{2}$$

Table 3. LDA Output Examples.

Output 1: Per-document topic proportions (θ_d)						Output 2: Per-topic word distributions (ϕ_k)				
	T_1	T_2	…	T_K	Sum		T_1	T_2	…	T_K
$Abstract_1$	0.2	0.5	…	0.1	1	$word_1$	0.01	0.02	…	0.02
$Abstract_2$	0.5	0.2	…	0.1	1	$word_2$	0.02	0.02	…	0.01
…	…	…	…	…	1	…	…	…	…	…
$Abstract_D$	0.9	0.0	…	0.0	1	$word_V$	0.04	0.01	…	0.01
						Sum	1	1	1	1

Here, $\beta_{t,k}$ denotes the kth topic at time t, given that same topic in the previous year. This is distributed as a normal, whose mean is the topic in the previous year along with a covariance σ^2, which represents how much the topic can move from year to year (see Appendix A).

Equation (2) is then mapped to a probability distribution over words. The hyper-parameter σ^2 is important as it governs how fast or slow topics evolve over time. If σ^2 is too large then the model will be able to 'explain' new topics by completely changing the set of words over which that topic is defined. In practice, σ^2 is set to the default value of 0.005 as suggested by Blei and Lafferty (2006).

3.3 *The Identified Topic Landscape*

The extracted and labelled 10 topics from central banking research are presented as word-clouds in Figure 2. As indicated by the colour scheme, the topics neatly resemble the way central banks typically organize their work so as to produce information that is relevant for setting policy, namely:

- modelling topics (yellow): *policy transmission*, *inflation modelling*, *macro modelling*;
- economic analysis topics (blue): *banking sector*, *household sector*, *corporate sector*;
- financial markets topics (red): *financial markets*, *external finance and trade*;
- the payments system (purple); and
- financial stability (purple).

The topics also neatly cluster into intuitive groups. Figure 3 shows that the modelling topics (*inflation modelling*, *macro modelling* and *policy transmission*) are closely related to each other. Likewise, topics focusing on individual sectors of the economy (*households*, *corporates* and *banks*) cluster into a neighbourhood. Unsurprisingly, the topic *financial stability risks* is also tightly connected to the *banking sector* topic.

To get a sense of the importance of each topic, Table 4 sorts topics according to their proportions in the whole collection of abstracts (i.e. by taking the average of each topic in the topic proportion matrix θ). The number of abstracts in which each topic has the highest proportion is also provided, together with the six most frequent words for a given topic. Appendix B plots the word count and importance of keywords for each topic.

Over the period 2000–2019, the *banking sector* has had the highest weight in central banking research. This is due to a significant increase in the post-crisis period, as explained in the next section. Unsurprisingly, papers dedicated to *policy transmission*, *inflation modelling* and *macro modelling* have also historically been important themes in central banking research. Receiving less attention have been topics related to the individual sectors of the economy (i.e. *households* and *corporates*).

Figure 2. **Topics Covering Central Banking Research.**
Source: Author's calculations; IDEAS.

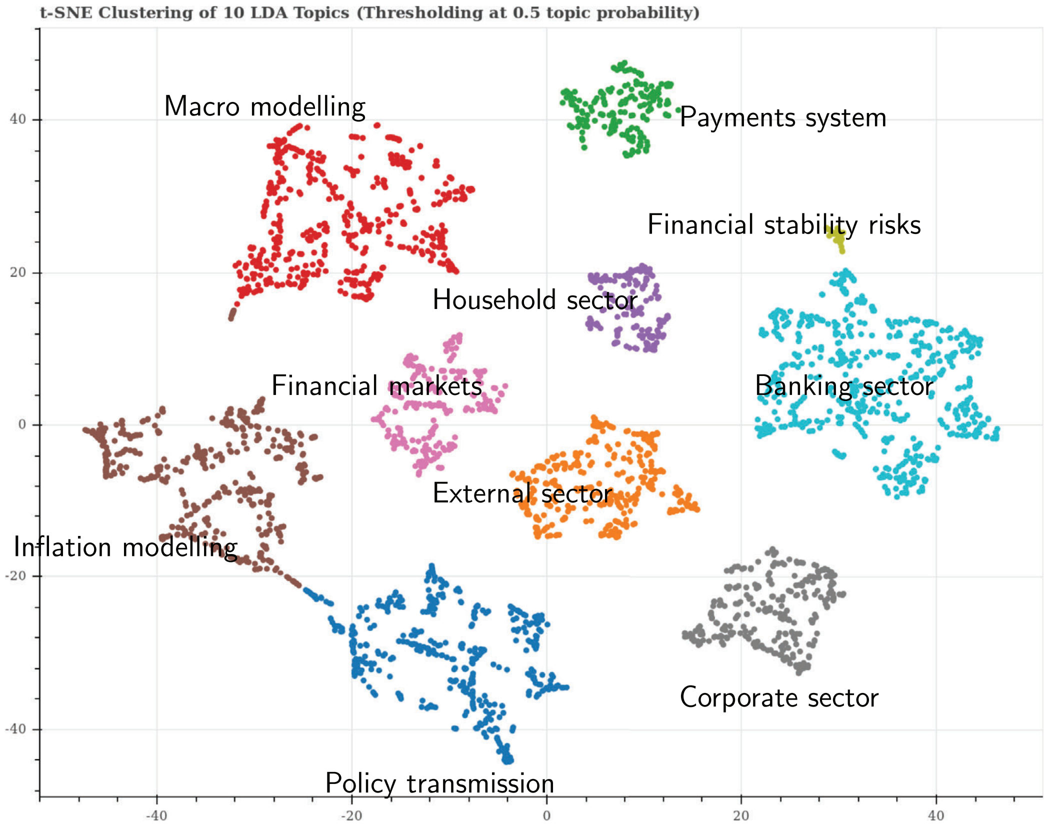

Figure 3. The Clustered Topics of Central Bank Research.
Notes: This figure uses the *t*-distributed stochastic neighbour embedding (t-SNE; van der Maaten and Hinton, 2008) – a popular dimensionality reduction algorithm – to reduce the topic proportions for each abstract into a two-dimensional space, with each dot representing a central bank research abstract.
Source: Author's calculations; IDEAS.

3.4 *LDA Topic Trends: How Fixed Topics Have Evolved Over Time*

Using the identified topic landscape, I now examine how the intellectual ideas within central banks have evolved over time. In particular, I see if the topics have shifted in a way that is broadly consistent with the two so-called 'lessons learned' since the crisis, namely: (1) that *models only get you so far;* and (ii) that *microdata are useful*.

To examine topic trends over time using the simple LDA model, the topic-proportion matrix (θ) is collapsed by taking the mean of the topic proportions for all abstracts by year. This approach to examining the changing weight of fixed topics over time has been popular in the literature (see, for example, Lee and Kang, 2018).

Table 4. Topics of Central Banking Research: 2000–2019.

Top 6 topic words	Number of abstracts	Proportion (%)	Topic label
bank financial credit crisis loan firm	1183	0.139	Banking sector
model shock price output inflation real	895	0.136	Inflation modelling
model forecast data time method approach	864	0.117	Macro modelling
policy monetary inflation rate central bank	814	0.116	Monetary policy transmission
country price exchange rate euro economy	764	0.107	International finance and trade
firm wage growth market level productivity	590	0.084	Corporate sector
rate interest term market bond yield	577	0.081	Financial markets
market liquidity payment transaction price reserve	412	0.054	Payments system
household income housing tax wealth consumption	428	0.052	Household sector
risk asset default portfolio capital credit	110	0.024	Financial stability risks

Notes: The column 'Number of abstracts' indicates the number of times a given topic had the highest weight in a central bank research abstract; the column 'Proportion' indicates the mean topic proportion across all abstracts.
Source: Author's calculations; IDEAS.

The time-varying topic proportions are then regressed on a linear time trend to identify those topics with significantly increasing or decreasing topic weights over the 20-year period. Topics whose regression slopes are positive (negative) at a significance level of 1% are plotted in Figure 4.

Research dedicated to the *banking sector* has significantly increased since the 2000s, especially so since the crisis. Research on the *household sector* topic has also increased, though the impact of the crisis is difficult to discern. The topic proportion exhibits a significant increase both before and after the crisis. On the other hand, research output falling under the broad umbrella of modelling (*policy transmission*, *inflation modelling* and *macro modelling*) has significantly declined.

At face value, these trends are consistent with central banks looking beyond their macro models and instead adopting a less aggregated perspective. Again, however, it is difficult to identify a noticeable impact of the financial crisis on these trends.

Overall, these trends are likely to reflect lessons from the crisis as well as a number of other mutually reinforcing factors. For example, there has been an increasing ability to create, access and analyse much larger data sets over the 20-year sample period. As more researchers have seen the potential in these datasets, there has been a rise in associated research output.

The fall in research dedicated to *monetary policy transmission* and *inflation modelling* could also be a sign of learning. Simon (2019) suggests that as questions about the monetary policy framework have been adequately answered there are less questions to be asked and so less research produced.

To examine changes in the mean topic weight for each topic over the pre- and post-crisis periods, Equation (3) below is estimated for all central banks and for the US Fed in isolation:

$$T_{i,a,t} = \sum_{t=1}^{T=2} \sum_{i=1}^{I=10} \lambda_{i,t} D_{i,t} + \varepsilon_{i,a,t} \tag{3}$$

Here, $T_{i,a,t}$ denotes topic $i's$ proportion in abstract a in time period t (pre- or post-crisis), D_{it} is a dummy variable for topic i in time period t and the coefficient on λ_{it} captures the mean topic proportion for topic i in the pre- and post-crisis period. With this simple regression, for each topic, we can examine if the mean topic proportion shifted significantly in the post-crisis period.

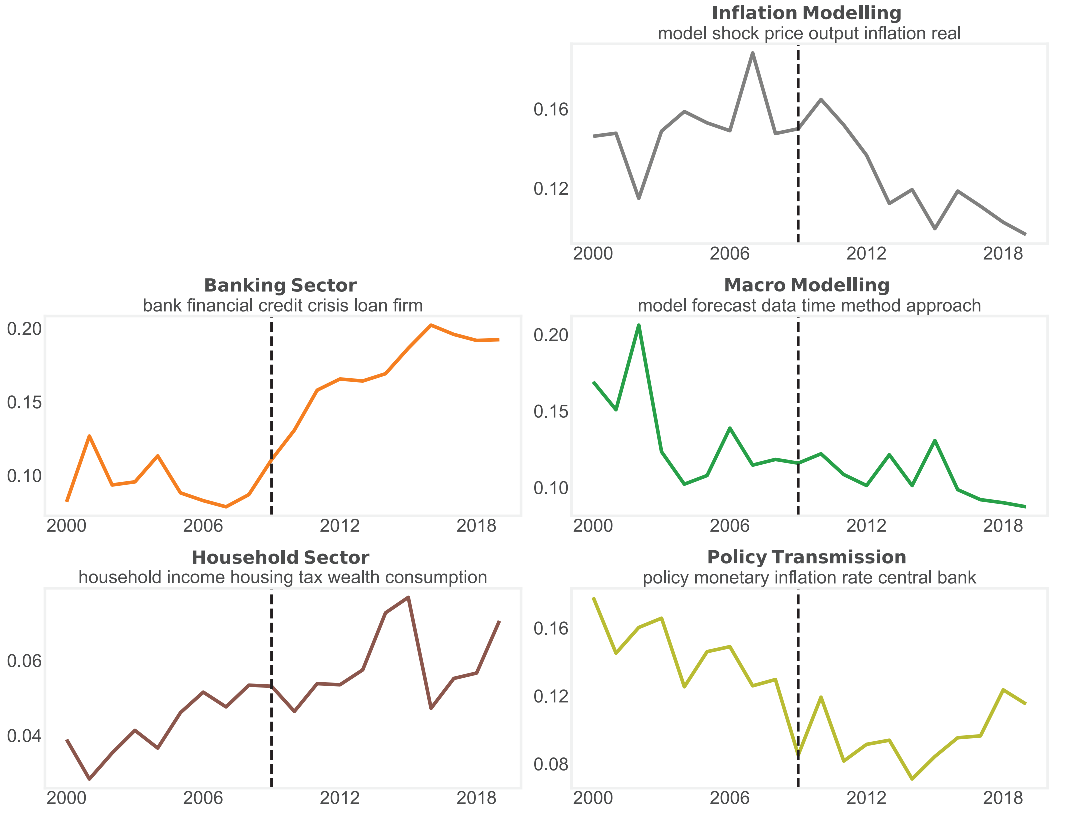

Figure 4. Hot and Cold Topics in Central Bank Research.
Notes: For significant time trends at the 1% level; for each topic, the subtitle lists the top six words (by weight) that define the topic.
Source: Author's calculations; IDEAS.

For all central banks, there has been a significant decline in *inflation modelling*, *macro modelling* and *monetary policy transmission* since the crisis (Table 5). On the other hand, topics related to the *banking sector* and the *household sector* have increased significantly, while the focus on the *corporate sector* has remained unchanged.

Post-crisis shifts in the intellectual ideas within central banks are less evident when looking at the US Fed in isolation. There is no evidence of a significant change in the weight given to either *macro* or *inflation modelling*. Moreover, while there has been a significant decline in the topic weight on *monetary policy transmission*, the fall is less pronounced relative to other central banks. Of the individual sectors, only the banking sector has increased in weight in the post-crisis period. However, relative to other central banks, the Fed's pre-crisis research was less heavily weighted towards modelling topics to begin with. Instead, it had placed more emphasis on research about the individual sectors of the economy. This is neatly illustrated in Appendix C, which plots the relative topic strength for each central bank.

The methods employed above do not precisely distinguish between longer-term changes in the intellectual ideas within central banks versus something more directly attributable to the financial crisis. A regression setting similar to regression discontinuity design can be used to go some way towards making

Table 5. Pre- and Post-Crisis Topic Proportions.

	All central banks	US Fed
Pre-crisis topic proportion		
Inflation modelling	0.15***	0.11***
Macro modelling	0.13***	0.11***
Policy transmission	0.14***	0.11***
Financial mkts	0.08***	0.12***
External finance	0.11***	0.03***
Banking sector	0.09***	0.12***
Household sector	0.04***	0.10***
Corporate sector	0.09***	0.13***
Payments system	0.05***	0.06***
Financial stability	0.02***	0.03***
Change in topic proportion		
Post-crisis × Inflation modelling	−0.03***	0.00
Post-crisis × Macro modelling	−0.02***	−0.01
Post-crisis × Policy transmission	−0.05***	−0.02**
Post-crisis × Financial mkts	0.00	−0.02*
Post-crisis × External finance	−0.01**	0.01
Post-crisis × Banking sector	0.08***	0.06***
Post-crisis × Household sector	0.02***	0.00
Post-crisis × Corporate sector	−0.00	−0.03***
Post-crisis × Payments system	0.01***	0.01*
Post-crisis × Financial stability	0.01***	0.00
Observations	66,370	14,980

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ using HAC robust standard errors; the number of observations is equal to the number of abstracts times the number of topics (6637 × 10).
Source: Author's calculations; IDEAS.

this distinction. The results presented in Appendix D suggest that the crisis itself reduced the amount of research dedicated to the topics *monetary policy transmission* and *inflation modelling* and meaningfully increased the amount of research dedicated to the *banking sector*.

3.5 *Dynamic Topic Trends: How Topics Have Evolved Over Time*

To dig deeper and examine how topics themselves have evolved from year to year, I now turn to the results from the dynamic topic model. Here, I focus on the *household sector* and *macro modelling* topics.

Figure 5 illustrates the top five words from the topic model before (2000), immediately after (2009) and following the crisis (2018). It also shows estimated word importances as a function of each year for three words from each topic that describe important changes in the topic definition over time. Appendix E shows the top 30 words for each topic and selected time slice (2000, 2009, 2018) along with the associated word importances.

Interestingly, trends in word usage for the *household sector* reveal that the topic has evolved over time to incorporate a more micro perspective. The words *survey*, *data*, *micro*, *distribution* and *inequality* have become more important in defining the *household sector* topic over time. In addition, looking at the five

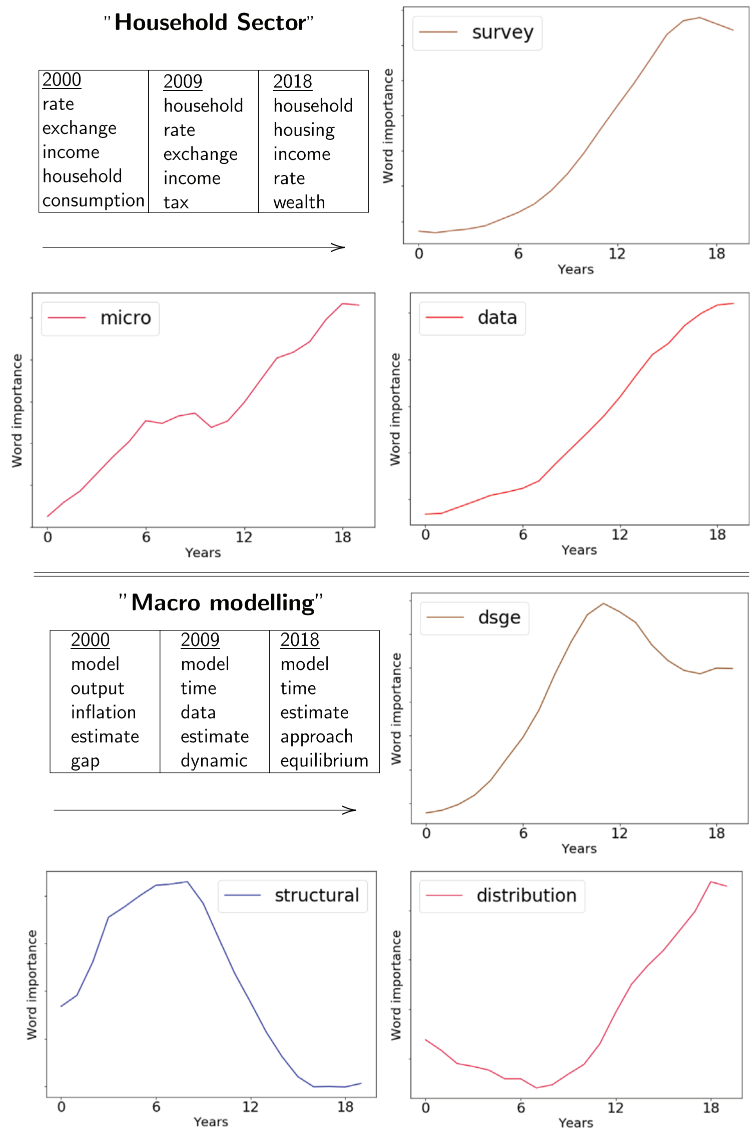

Figure 5. Dynamic Topic Evolution.

Notes: This figure shows how the top five words for the *household sector* and *macro modelling* topic changed for three time slices: 2000 (before the crisis), 2009 (just after the crisis) and 2018 (following the crisis). It also shows estimated word importances for each year for three words from each topic that describe important changes in the topic definition over time.

Source: Author's calculations; IDEAS.

words with the highest weight in the topic definition, it appears that the topic has evolved from a focus on the impact of external-sector shocks to a focus on the effect of domestic factors. For example, the words *exchange* and *currency* have declined noticeably since 2000 and instead words like *mortgage*, *debt* and *housing* have increased in importance.

Trends in the word usage for the *macro modelling* topic seem to indicate an evolution away from large-scale structural modelling. For example, since the crisis, the term *DSGE* (the acronym for Dynamic Stochastic General Equilibrium models) has played a declining role in defining the topic. Likewise, the term *structural* has declined in importance over time. By contrast, terms such as *distribution*, *micro*, *sector*, *financial* and *friction* have increased. These trends speak to a shift from a relatively macroeconomic perspective towards incorporating financial frictions and micro-foundations into macro modelling and theory.

4. Latent Semantic Analysis

To complement the topic modelling analysis, I now examine how the similarity of central bank research to frontier research in macroeconomics has evolved over time. The prior is that if central bank researchers have indeed shifted away from an excessive focus on macro modelling over time, then the 'distance' of central bank research to frontier academic research dedicated to macroeconomics should have increased.[2] The methodology used here closely follows Iaria *et al*. (2018), who used LSA to examine the similarity of academic research between opposing camps involved in World War 1.

LSA is a machine learning technique that uncovers semantic connections between words. It was developed by Deerwester *et al*. (1990) for the task of automatically retrieving information from search queries. LSA improved search results by taking into account the relationships and potential multiple meanings of words. In this context, using this algorithm means that research abstracts with completely different words can still be classified as similar if the words are regularly used in similar contexts. A neat example is provided by Landauer (2007). Using LSA, the passages *a circle's diameter* and the *radius of spheres* have similar meaning, despite having no word in common. By contrast, the text *music of the spheres* is measured as dissimilar by LSA. This property makes LSA much more preferable than using raw word frequencies to make comparisons.

LSA learns the hidden semantic connection between words and documents by using truncated singular value decomposition (TSVD) – the same transformation used in principal component analysis. TSVD reduces the dimensionality of the pre-processed document-term matrix ($D \times V$) to a document-component matrix ($D \times C$). The number of components is user chosen. Including both central bank research abstracts and academic abstracts, the document-term matrix has dimension of around 16000×16000, which reduces to a document component matrix of 16000×300.[3] The rows of this latter matrix capture the semantic relationships between documents (for a good overview see Iaria *et al*. (2018)'s technical appendix as well as Schwarz (2017)).

With the document component matrix at our disposal, it is used to measure the 'similarity' of central bank research to frontier macroeconomic research in the following steps:

1. First, I build a 'search index' using only the research from the academic literature dedicated to macroeconomics.[4]
2. Second, for every central bank research abstract two similarity measures to the academic articles in the 'search index' are calculated:
   a. the similarity to the most similar abstract from the academic literature dedicated to macroeconomics; and
   b. the average similarity to the five most similar abstracts.

The similarity of abstracts is calculated using the cosine similarity – often used in machine learning. The cosine similarity of central bank research abstract i to an academic abstract j is given by the following expression:

$$\frac{\sum_{c=1}^{C} \delta_{i,c}\delta_{j,c}}{\sqrt{\sum_c \delta_{i,c}^2}\sqrt{\Sigma_c \delta_{j,c}^2}}$$

where $\delta_{i,c}$ and $\delta_{j,c}$ are the elements inside the document-component matrix for documents i and j.

The similarity score is 1 for abstracts that are identical and 0 for abstracts that are completely different. The similarity measures are standardized to have zero mean and unit variance. An example of a randomly chosen central bank research abstract and its most 'similar' academic counterpart is provided in Appendix F.

4.1 *LSA Results*

By selecting the best macro-journal article match for every central bank abstract (as defined by the cosine similarity) I can examine trends in abstract similarities over time.

After the crisis, the similarity between central bank research and that published in the top macroeconomic journals declined by around 0.3 standard deviations (left panel, Figure 6). Moreover, this result is unchanged if abstract similarity is measured using the five most similar abstracts from the academic literature. The right panel of Figure 6 shows that research similarities within academia remained broadly unchanged before and after the crisis. This confirms that it is shifts in the nature of central bank research driving the increased distance to the macro academia.

To examine if these shifts are significant and which central banks drove the change, it is useful to compare research similarities leading into the crisis (2006–2009) to contemporary research similarities (2016–2019) in an econometric setting. Specifically Equation (4) below is estimated:

$$S_{ij,t} = \sum_{t=1}^{T=2} \sum_{c=1}^{C=9} \lambda_{c,t} D_{c,t} + \varepsilon_{c,t} \tag{4}$$

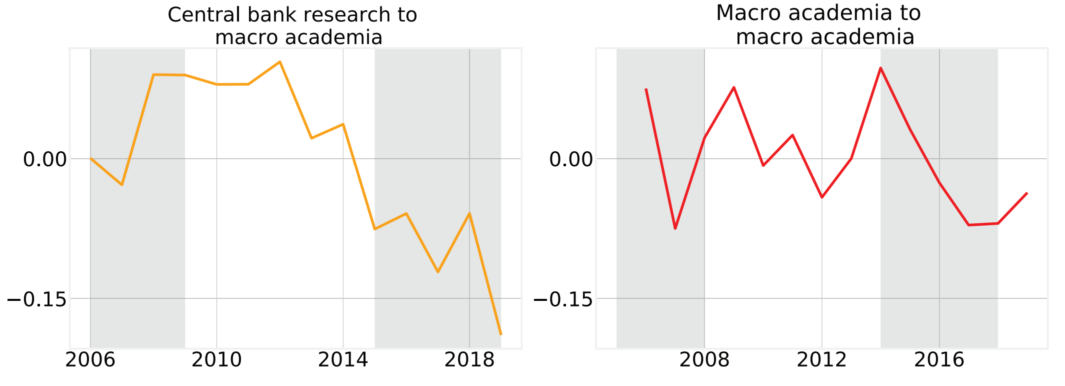

Figure 6. Research Similarities: Standardized Cosine Distances.
Notes: Similarities are standardized to have zero mean and unit variance.
Source: Author's calculations; IDEAS.

Table 6. Pre- and Post-Crisis Research Similarities.

	Cosine similarity
Pre-crisis standardized cosine similarity	
Fed	0.17^{***}
ECB	-0.04
BoE	0.03
BoC	-0.02
BoJ	-0.00
RBA	0.24
RBNZ	-0.15
Norges	0.23^{*}
Riksbank	0.23^{*}
Change in standardized cosine similarity	
Post-crisis × Fed	-0.28^{***}
Post-crisis × ECB	-0.07
Post-crisis × BoE	-0.28^{**}
Post-crisis × BoC	0.04
Post-crisis × BoJ	-0.01
Post-crisis × RBA	-0.29
Post-crisis × RBNZ	0.48^{***}
Post-crisis × Norges	-0.28^{*}
Post-crisis × Riksbank	-0.35^{**}
Observations	2801

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ estimated using HAC standard errors; pre-crisis defined as 2006–2009; post-crisis defined as 2016–2019.
Source: Author's calculations; IDEAS.

Here, $S_{ij,t}$ denotes the similarity of central bank research abstract i to its most similar academic abstract j in time period t (pre- and post-crisis). $D_{c,t}$ is a dummy variable for central bank c in time period t. With this simple regression, I can examine if the cosine similarity shifted significantly in the post-crisis period for each central bank.

The results show that the divergence from frontier research has been driven by the US Federal Reserve, the BoE, the Swedish Riksbank and Norway's Norges Bank. In the pre-crisis period, the Fed, Riksbank and Norges Bank were significantly more similar than other central banks to frontier macroeconomic research, with cosine similarities around 0.15–0.25 standard deviations above the mean (Table 6, top panel). In the post-crisis period the Fed and BoE's similarity to academia declined by around 0.3 standard deviations (Table 6, bottom panel). The decline was even greater at the Riskbank, which had pioneered the use of working DSGE models in regular rounds of monetary policy discussions in the pre-crisis period (Linde, 2018).

4.2 *Controlling for the Counterfactual: Difference-in-Difference (DiD) Estimation*

These results notwithstanding, an important limitation is that no counterfactual is available. That is, how would central bank research have evolved relative to academic research in the absence of the financial crisis?

Table 7. Post-Crisis Similarities to Frontier Macro Research: Difference-in-Difference Estimates.

	Coefficient estimate	Coefficient
$D_i \times \text{Post}_t$	**–0.12****	β_{DD}
Post-crisis	–0.01	β_{Post}
D_i	–0.20***	β_D
Constant	0.30***	β_0
Observations	5,602	

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ estimated using HAC standard errors; the number of observations reflect two similarities per central bank abstract: (1) the highest similarity to other central bank abstracts and (2) the highest similarity to frontier research.
Source: Author's calculations; IDEAS.

To control for this, I estimate a DiD regression. The 'control' group is the similarity of central bank research to other central bank research. The 'treatment group' is the similarity of central bank research to frontier macro research – where I assume 'treatment' is due to the crisis causing a shift in the nature of central bank research *relative to* academic research. We are then interested in *the difference in the change* between the treatment and control group (i.e. the DiD).

The DiD regression is estimated in the following regression:

$$S_{ik,t} = \beta_0 + \beta_D D_i + \beta_{\text{Post}}\text{Post}_t + \beta_{DD}(D_i \times \text{Post}_t) + u_{it} \tag{5}$$

where $S_{ik,t}$ is the similarity of central bank research abstract i to all other abstracts k, where $i \neq k$. D_i is a dummy variable equal to 1 for treated observations (i.e. central bank-to-academic research similarities); $Post_t$ denotes a dummy equal to 1 in the post-crisis period and 0 otherwise. The four parameters can be interpreted as follows:

β_0: mean abstract similarity in control group before the crisis,
β_{Post} : post-crisis change in the mean similarity in the control group,
β_D: difference in mean similarity between treatment and controls before the crisis,
β_{DD}: difference in the mean change between treatment and controls (the DiD).

The results are presented in Table 7. The key DiD estimate (β_{DD}) shows that after the crisis, the similarity of central bank research to frontier research fell by more than the similarity between central bank research and other central bank research. That is, after differencing out other factors that may have affected the similarity of research abstracts, the crisis appears to have led to a decline in the similarity between central bank and frontier macro research. This result is consistent with central bank learning; in particular, placing less emphasis on macro modelling in the aftermath of the crisis.

Turning to the other estimates, unsurprisingly, the estimate on β_D shows that before the crisis, central bank research abstracts were more similar to each other relative to frontier macro research. And the estimate on β_{Post} shows that the similarity between central bank research did not change meaningfully in the post-crisis period.

5. Conclusion

This paper gathered around 6600 research papers written by advanced economy central banks over the past 20 years. The textual data were then used to examine how the intellectual ideas occurring within central banks have evolved, with a focus on the impact of the financial crisis.

Central banks have exhibited a significant degree of intellectual nimbleness over time. Broadly speaking, research has shifted from a relatively macroeconomic perspective to a less aggregated view. This shift appears related to two prominent *ex post* criticisms of central bank research in the lead up to the crisis, namely: (1) that central banks failed to pick up on early-warning indicators prior to the crisis because they relied too heavily on the forecasts from macro models; and (2) that the usefulness of microdata in teasing out the causes of aggregate fluctuations was under-appreciated.

In particular, using popular natural language processing models, significant shifts in a number of fixed research topics over time were identified – as well as changes within topics over time. Notably, there was an increase in research dedicated to better understanding the behaviour of individual sectors of the economy, namely, the banking and household sectors. I also identified a decline in research that focused on modelling (for example, macro modelling and inflation modelling). This notwithstanding, some of these trends were already occurring before the financial crisis.

Techniques from computational linguistics were also used to compare central bank research to around 10,000 academic papers published in top field journals explicitly dedicated to macroeconomics. In the lead up to the crisis it appears that central bank research was closely aligned to the macro academia, which was ultimately to the detriment of the policy recommendations derived from this work. However, in the post-crisis years there is strong evidence of a change in intellectual focus, with the distance between central bank research and frontier research dedicated to macroeconomics widening notably.

Future research could leverage off the findings in this paper in a number of ways. For example, more use could be made of other meta-data associated with the research papers I collected. For example, author-topic models could be used to identify 'super-star' researchers that were ahead of the learning curve and drove changes in the intellectual fashion. In terms of a broader research agenda, another step could be to map the identified intellectual changes into changes in the policy debate. This could be achieved by examining more policy-relevant textual data, such as speeches, minutes and monetary policy statements. This would speak to the 'influence' economic research is having in the policy sphere, which first and foremost is the goal of any central banking research department.

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Data Availability Statement

The data that support the findings of this study are available on my GitHub page. These data were derived from resources that are publicly available (see Table 1).

Notes

1. In a similar context, Hansen *et al*. (2017) use a 15-topic model to examine the effect of central bank communication on both market and real economic variables.

2. By restricting the search index to top-*macroeconomic* journals (instead of top journals across the entire field of economics), I am able to hold the 'topic' of the search index constant. An alternative way to test my hypothesis would have been to scrape all top economics journals and then identify those dedicated to macroeconomics.
3. The results are robust to various component sizes. Following Iaria *et al*. (2018) I settled on 300 components.
4. In scraping *ideas.repec* for the journal articles several did not have good abstract availability prior to 2006. Accordingly, the LSA is restricted to the period 2006–2019 to avoid jumps in the richness of the 'search index' over time. The results are robust to only including journals with comprehensive abstract availability back to 2000.
5. The results presented here are broadly similar if a two-year window (2008–2009) or a one-year window is used (2008).

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Appendix A: LDA

The LDA model can be described more formally with the following notation (for a neat explanation, see Blei, 2012). The topics are $\beta_{1:K}$, where each β_k is a distribution over words. The topic proportions for the dth document are θ_d where $\theta_{d,k}$ is the topic proportion for topic k in document d. The topic assignments for the dth document are z_d, where $z_{d,n}$ is the topic assignment for the nth word in document d. Finally, the observed words for document d are w_d, where $w_{d,n}$ is the nth word in document d, which is an element from the fixed vocabulary.

The generative process for LDA then corresponds to the following joint distribution of the observed and hidden variables:

$$p(\beta_{1:K}, \theta_{1:D}, z_{1:D}, w_{1:D}) = \prod_{i=1}^{K} p(\beta_i) \prod_{d=1}^{D} p(\theta_d) \left(\prod_{n=1}^{N} p\big(z_{d,n}|\theta_d\big) p\big(w_{d,n}|\beta_{1:K}, z_{d,n}\big) \right)$$

This distribution specifies a number of dependencies. For example, the topic assignment $z_{d,n}$ depends on the per-document topic proportions θ_d. As another example, the observed word $w_{d,n}$ depends on the topic assignment $z_{d,n}$ and all of the topics $\beta_{1:K}$.

A.1 Priors and Posterior Computation for LDA

In a Bayesian inference context, the posterior distribution gives the probability of observing certain parameter values after observing the data (the corpus in the LDA case). This is in contrast to the prior distribution, which assigns probabilities before considering the data.

Relating this to LDA, the prior distributions are usually selected to be Dirichlet distributions due to the fact that these distributions lend high probability to a small group of words. This supports the underlying intuition that topics are characterized by frequent occurrences of a small number of words.

Additionally, a Dirichlet allows simpler calculation of the posterior due to its conjugate relationship with the multinomial distribution. This implies that the prior and the posterior are from the same distributional family and we can write down a closed-form expression for the posterior.

These two factors have ensured that a Dirichlet prior has been the standard approach in LDA. Furthermore, symmetrical distributions are usually used to signal that all topics have equal chance of being assigned to a document and all words have equal chance of being assigned to a topic. This results in the most general and flexible formulation of an LDA approach.

Formally stated, using α and ϕ to denote the hyper-parameters for the priors, we take:

$$\theta_d \sim \mathrm{Dir}(\alpha) \qquad \beta_k \sim \mathrm{Dir}(\phi)$$

As mentioned above, we cannot actually observe the imaginary generative process which has been specified and the hidden parameter values must be inferred from posterior analysis. Algebraically, the posterior can be denoted as follows:

$$p(\theta, \mathbf{z}|\mathbf{w}, \alpha, \beta) = \frac{p(\theta, \mathbf{z}, \mathbf{w}|\alpha, \beta)}{p(\mathbf{w}|\alpha, \beta)}$$

That is, we would like to find the distribution of the hidden latent variables θ and z, given the prior distributions and the observed data.

Unfortunately this expression is known to be intractable to compute and must be approximated. One approach is to use *variational inference* where Jensen's inequality is used to repeatedly find a lower bound for the log-likelihood (this approach is used here). Another is to use Gibbs sampling, which constructs a sequence of random variables dependent on the previous (i.e. a *Markov chain*), whose limiting distribution is the posterior.

A.2 Dynamic Topic Models

Dynamic topic models extend the idea of LDA and introduce a time dependency element.

Documents are grouped into time periods and the given topics in each sequential time period are related. That is to say that the topics cannot wildly vary from one year to the next (assuming we were grouping by year).

It is important to note that the overall number of topics in the model remains fixed. To add dynamics to the model, we introduce a probabilistic relationship between the topic distribution in one period and the topic distribution in the other period.

Formally stated:

$$\beta_{t,k}|\beta_{t-1,k} \sim N\left(\beta_{t-1,k}, \sigma^2 I\right)$$

$$\alpha_t|\alpha_{t-1} \sim N\left(\alpha_{t-1}, \delta^2 I\right)$$

where $\beta_{t,k}$ is the word distribution of topic k at time t and α_t is the per-document topic distribution at time t.

Aside from the added dynamics, the LDA formulation and computation operates very similarly within each time period. However, an important difference is that the Dirichlet is not amenable to sequential modelling. Instead, the natural parameters of each topic $\beta_{t,k}$ are chained together in a state space model that evolves with Gaussian noise.

Appendix B: Importance of Topic Keywords

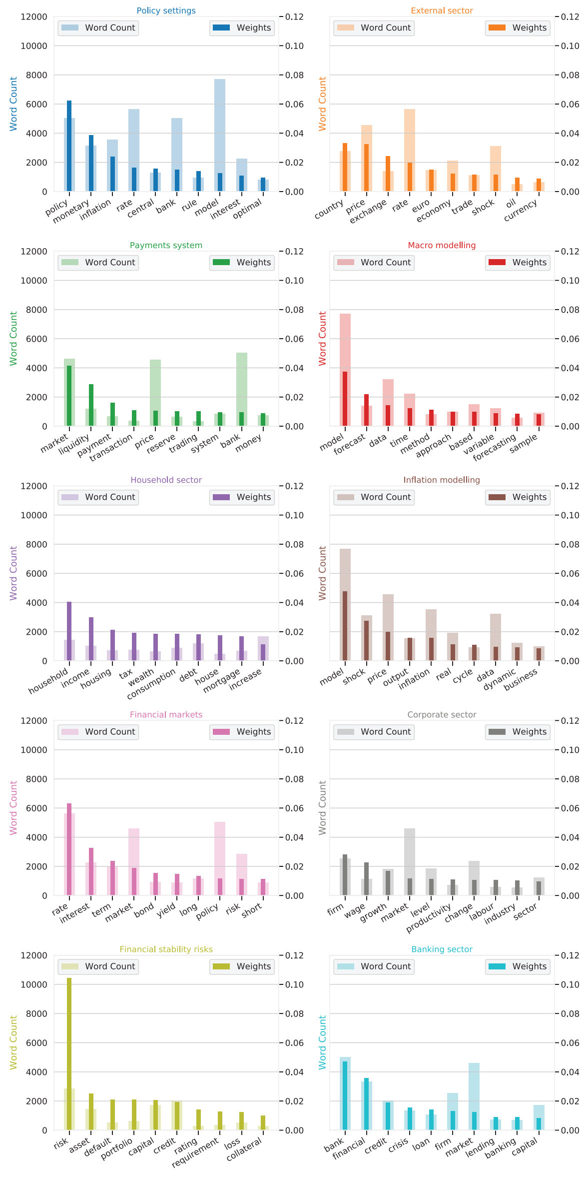

Figure B1. **Word Count and Importance of Topic Keywords.**
Source: Author's calculations; IDEAS.

Appendix C: Relative Topic Weights Between Central Banks

Figure C1 shows a heatmap of the relative topic strength for each central bank. It also shows a dendrogram obtained from hierarchical clustering indicating which central banks are most similar in terms of the relative weight they attach to different research topics. For example, the figure shows that the Bank of England (BoE) has typically placed a large relative weight on "banking sector" research, while the dendrogram on the left of the figure shows that its research focus is most similar to Sweden's Risksbank, the Bank of Canada (BoC) and Norway's Norges Bank.

As noted in the text, the US Federal Reserve is somewhat of an outlier. It places relatively less weight on topics dedicated to *inflation modelling*, *macro modelling* and *monetary policy transmission*. Instead, the Fed has traditionally placed more emphasis on individual sectors of the economy as well as financial stability risks.

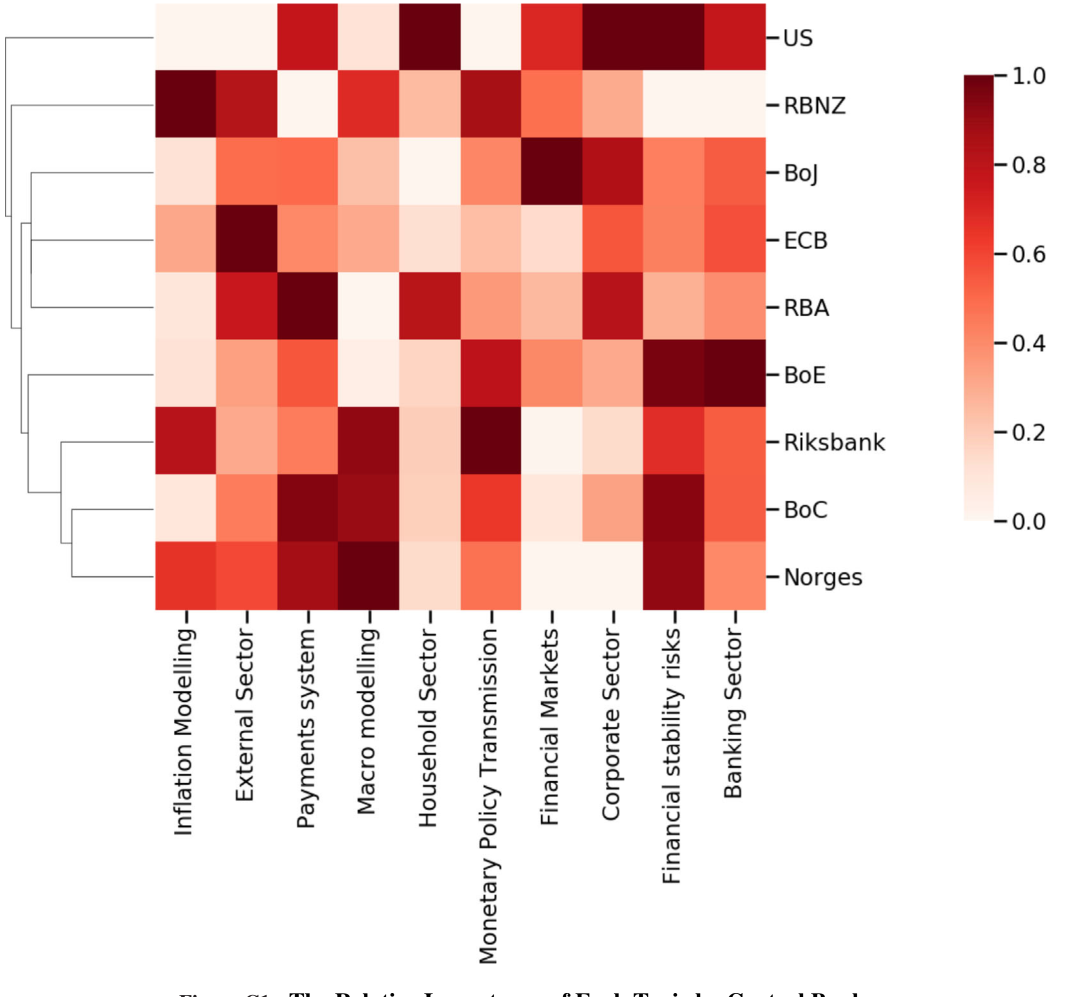

Figure C1. The Relative Importance of Each Topic by Central Bank.
Source: Author's calculations; IDEAS.

Appendix D: Trying to Isolate the Impact of the Crisis

The methods employed in Section 3.4 were not able to precisely distinguish between longer-term changes in the intellectual ideas within central banks versus something directly attributable to the financial crisis. To attempt to make this distinction a regression setting similar to regression discontinuity design can be used.

The idea behind this approach is that research published just before the onset of the crisis and shortly after the crisis should be very similar, except for the impact of the crisis. This can then be exploited for identification. The 'control group' is defined as research published in 2007 and the 'treatment group' as research published in 2011. A three-year 'discontinuity window' is used to capture lags in the learning process as well as publication delays.[5] This approach is quite intuitive: if the only reason why research in 2007 was different to research in 2011 was the effect of the crisis, then the impact of treatment will be the difference in outcomes between observations in 2007 compared to 2011.

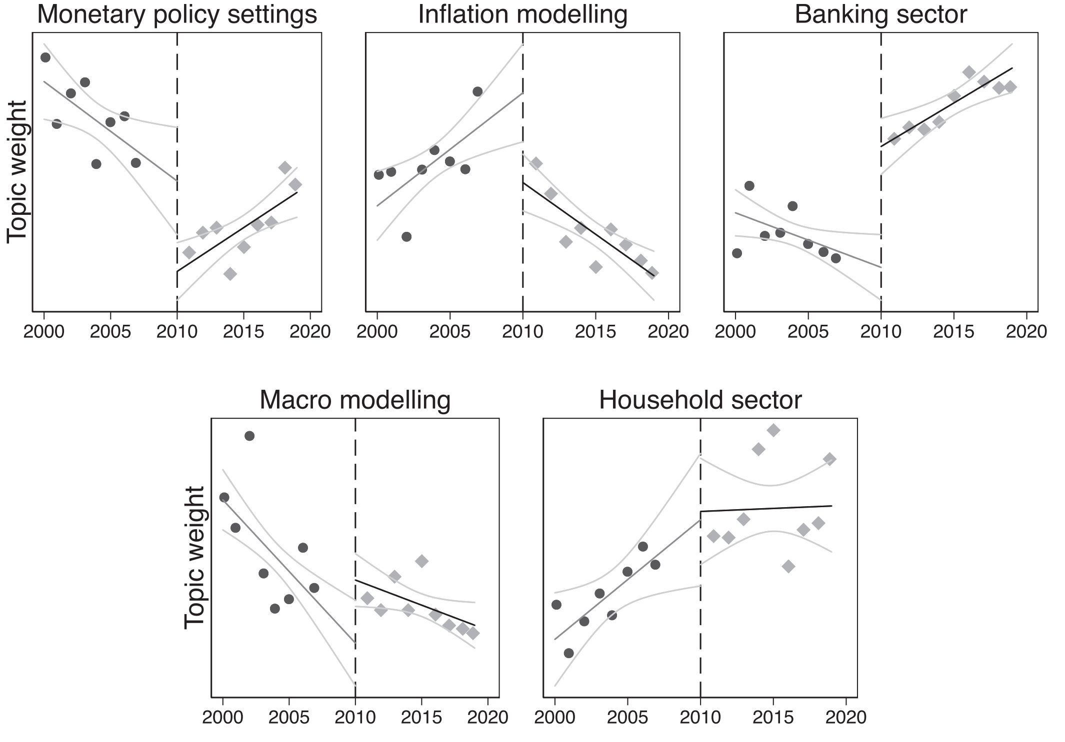

Figure D1. Trying to Identify the Impact of the Crisis using Regression Discontinuity.
Notes: This figure clusters topic proportions by year (with each dot representing all the research produced in that year) and fits a linear trend for the pre-crisis (before 2008) and post-crisis period (after 2010); the years 2008–2010 are excluded to capture lags in the learning process as well as publication delays; the discontinuity used for identification is indicated by the vertical line; the bands indicate a 95% confidence interval.
Source: Author's calculations; IDEAS.

Of course, an important assumption is that other factors that affect research trends – for example, senior staff in the central bank's research department that set research agendas – should show no jumps within the three-year window.

The results (summarised in Figure D1) suggest that the crisis reduced the amount of research dedicated to the topics *monetary policy transmission* and *inflation modelling*. The crisis also meaningfully increased the amount of research dedicated to the *banking sector*.

Appendix E: Dynamic Topics

Table E1. The Evolution of the Household Sector Topic.

2000		2009		2018	
Words	Weights	Words	Weights	Words	Weights
Rate	0.071	Household	0.036	Household	0.047
Exchange	0.054	Rate	0.033	Husing	0.029
Income	0.028	Exchange	0.030	Income	0.028
Household	0.026	Income	0.026	Rate	0.025
Consumption	0.024	Tax	0.023	Wealth	0.020
Tax	0.020	Consumption	0.020	Mortgage	0.019
Currency	0.019	Housing	0.018	Exchange	0.018
Wealth	0.018	Wealth	0.017	Tax	0.017
Housing	0.012	Currency	0.014	Consumption	0.017
Saving	0.011	House	0.014	House	0.012
Dollar	0.010	Mortgage	0.013	Data	0.012
Mortgage	0.009	Individual	0.013	Debt	0.010
Individual	0.008	Data	0.009	Individual	0.010
House	0.008	Estimate	0.009	Currency	0.010
Data	0.008	Debt	0.008	Level	0.009
Estimate	0.007	Import	0.007	Share	0.009
Import	0.007	Level	0.007	Estimate	0.009
Share	0.007	Dollar	0.007	Price	0.007
Level	0.006	Price	0.007	Saving	0.006
Pas	0.006	Share	0.007	Home	0.006
Price	0.006	Percent	0.006	Survey	0.006
Debt	0.005	Saving	0.006	Inequality	0.006
Panel	0.005	Home	0.006	Percent	0.006
Age	0.005	Elasticity	0.006	Dollar	0.005
Account	0.005	Effect	0.005	Effect	0.005
Elasticity	0.005	Spending	0.005	Distribution	0.005
Percent	0.004	Account	0.005	Elasticity	0.005
Ratio	0.004	Value	0.005	Import	0.005
Home	0.004	Distribution	0.005	Value	0.005
Effect	0.004	Emerging	0.005	Across	0.005

Table E2. The Evolution of the Macro Modelling Topic.

2000		2009		2018	
Words	Weights	Words	Weights	Words	Weights
Model	0.051	Model	0.067	Model	0.047
Output	0.014	Time	0.009	Time	0.010
Inflation	0.011	Data	0.009	Estimate	0.009
Estimate	0.010	Estimate	0.009	Approach	0.008
Gap	0.009	Dynamic	0.008	Equilibrium	0.008
Equilibrium	0.009	Equilibrium	0.008	Method	0.008
Data	0.008	Approach	0.007	Data	0.008
Approach	0.008	New	0.007	Based	0.007
Variable	0.007	Method	0.007	Dynamic	0.006
Test	0.007	Based	0.006	New	0.006
Method	0.007	Variable	0.006	Sample	0.006
Optimal	0.007	Inflation	0.006	Variable	0.006
Estimated	0.007	Show	0.006	Parameter	0.005
Dynamic	0.007	Estimated	0.006	Used	0.005
New	0.006	Parameter	0.006	Show	0.005
ased	0.006	Sample	0.005	Distribution	0.005
Time	0.006	Used	0.005	Gap	0.005
Used	0.005	Structural	0.005	Framework	0.004
Curve	0.005	Gap	0.004	Estimation	0.004
Parameter	0.005	DSGE	0.004	Test	0.004
Sample	0.005	Estimation	0.004	Estimated	0.004
Empirical	0.005	Output	0.004	Function	0.004
Show	0.005	Test	0.004	State	0.004
Function	0.004	Optimal	0.004	Inflation	0.004
Estimation	0.004	Well	0.004	Empirical	0.004
Targeting	0.004	Empirical	0.004	Well	0.004
Uncertainty	0.004	General	0.004	Provide	0.004
Structural	0.004	Function	0.004	Different	0.004
Different	0.004	VAR	0.004	Non	0.004
Well	0.004	Keynesian	0.004	DSGE	0.003

Appendix F: Document Similarity Example

Central Bank: **Skaperdas (2017)**, 'How Effective is Monetary Policy at the Zero Lower Bound? Identification Through Industry Heterogeneity', *Federal Reserve System*

US monetary policy was constrained from 2008 to 2015 by the zero lower bound, during which the Federal Reserve would likely have lowered the federal funds rate further if it were able to. This paper uses industry-level data to examine how growth was affected. Despite the zero bound constraint, industries historically more sensitive to interest rates, such as construction, performed relatively well in comparison to industries not typically affected by monetary policy. Further evidence suggests that unconventional policy lowered the effective stance of policy below zero.

Academia: Belongia, M and Ireland P (2017), ‘Circumventing the zero lower bound with monetary policy rules based on money’, *Journal of Macroeconomics*

Discussions of monetary policy rules after the 2007–2009 recession highlight the potential ineffectiveness of a central bank’s actions when the short-term interest rate under its control is limited by the zero lower bound. This perspective assumes, in a manner consistent with the canonical New Keynesian model, that the quantity of money has no role to play in transmitting a central bank’s actions to economic activity. This paper examines the validity of this claim and investigates the properties of alternative monetary policy rules based on control of the monetary base or a monetary aggregate in lieu of the capacity to manipulate a short-term interest rate. The results indicate that rules of this type have the potential to guide monetary policy decisions towards the achievement of a long-run nominal goal without being constrained by the zero lower bound on a nominal interest rate. They suggest, in particular, that by exerting its influence over the monetary base or a broader aggregate, the Federal Reserve could more effectively stabilize nominal income around a long-run target path, even in a low or zero interest-rate environment.