

ECONOMICS IN THE AFTERMATH OF THE GLOBAL  
FINANCIAL CRISIS  
A TEXT MINING APPROACH

**Master Thesis submitted to the Faculty of Economics and Business**

Institute of Economic Research

University of Neuchâtel

For the degree of Master of Science in Economics, Major in Economic Policy

by

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# Economics in the Aftermath of the Global Financial Crisis

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### Abstract

Using several text mining techniques on 28,974 abstracts coming from 16 of the most influential academic journals in economics and the National Bureau of Economic Research (NBER), I explore the state of mainstream economics in the aftermath of the financial and economic 2007-2009 crisis. Exploring the variation in the relative term frequency of the most used economic terms, I find that the core of the economic discipline did not change except for the small but significant increase in focus on finance and risk-related topics. I present evidence showing that secondary changes occurring at the periphery of mainstream economics are visible. Among others : the drop of importance of Japan and Britain, the increased importance of China, the increased focus on energy, oil and climate change topics, and the rise in the usage of new methods like regression discontinuity or Dynamic Stochastic General Equilibrium (DSGE) modeling. Using cluster analysis, I find evidences depicting economics as a monolithic science with a strong paradigmatic cohesion rooted in its methodology. I discuss the absence of major changes in mainstream economics by focusing on its strong reliance on mathematical deductivist methods.

**Keywords** Economics, global financial crisis, great recession, 2008 financial crisis, economic thought, paradigm, content analysis, text mining, clustering, term frequency, methodology, mainstream economics.

**JEL Classification** A10, B20, B41, C89

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<sup>c</sup>This version is the corrected and accepted one. It received a grade of 6.

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*“The ideas which are here expressed so laboriously are extremely simple and should be obvious. The difficulty lies, not in the new ideas, but in escaping from the old ones, which ramify, for those brought up as most of us have been, into every corner of our minds.”*

Keynes (1936, Preface)

## 1 Introduction

The financial crisis of 2007-2008 is a chain of events which started unraveling with the 2006 housing crisis in the United States and whose peak occurred with the bankruptcy filing of Lehman Brothers in September 2008. The economic consequences following the crisis spread at a worldwide level in terms of forgone growth, stagnation, mass unemployment, economic recession and sovereign debt booms.

Directly after the crisis, different scientific narratives emerged in order to explain the process which led the world economy to such turmoil. After an overview of 21 of these major narratives, Lo (2012) concludes “[...]there is still significant disagreement as to what the underlying causes of the crisis were, and even less agreement as to what to do about it (Lo, 2012, p. 173).” This blatant lack of a uniform narrative explaining such a massive economic event as the crisis led him to reconsider whether financial economics can still be seen as a science (p. 173). This very point reveals a conception of science bound to exist only within a dominating paradigm<sup>1</sup> from which dissent, or economics heterodoxy is seen as unscientific. Even though I do not share this rather restricted conception of science, I see Lo’s remark as a good indicator of the bewilderment to mainstream economics caused by the crisis. I expect this confusion to challenge the profession of economics and accelerate its evolution or at least set it in motion.

In opposition to Lo, I welcome these dissentious points and ask with this thesis whether the dissent went further as simply the causes of the crisis, and whether the crisis started a deep transformation of economics itself. I interpret the crisis as what Kuhn names a *novelty*<sup>2</sup>. For him a novelty is an event or a theory challenging the course of “normal science,” which in my thesis is the course of normal mainstream economics. In the Kuhnian framework, fundamental novelties could be fully integrated and lead science to a revolutionary phase and a paradigmatic shift, or they could be suppressed in order to preserve a *status quo*.

*“Normal science, the activity in which most scientists inevitably spend almost all their time, is predicated on the assumption that the scientific community knows what the world is like. Much of the success of the enterprise derives from the community’s willingness to defend that assumption, if necessary at considerable costs. Normal science, for example, often suppresses fundamental novelties because they are necessarily subversive of its basic commitments.” (Kuhn, 1970, p. 5)*

How the novelties of the financial crisis impacted mainstream economics is the very subject of my inquiry. In my thesis I explore with text data coming from mainstream economic journals’ abstracts, what the crisis meant for economics, its paradigms and the place left for conflicting narratives. What changed? Was the economic crisis also a crisis of economics or just one suppressed *anomaly* in an overall consensual science? If this is the case, how did economists succeed to, in Kuhn’s words, “make the anomaly conform” (Kuhn, 1970, p. IX of the preface) and avoid any paradigmatic shift by making it conform to the preexisting paradigm?

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<sup>1</sup>I use the word *paradigm* following the definitions of Kuhn (1970, p. VIII of the preface) as “universally recognized scientific achievements that for a time provide model problems and solutions to a community of practitioners”.

<sup>2</sup>Kuhn seems to use the word *anomaly* and *novelty* interchangeably.

I chose to delve into this topic because of the concrete dramatic real-life impact that changes in economic thought could have, as Economics often represents an interpretative framework for policymakers. One example of this dramatic effect is given in an article by [Hall \(1993\)](#) where he shows the impact that the shift from Keynesianism to Monetarism had on British policy-making. He differentiates 3 orders of changes in the shift of policy, though only the third highest level is considered a paradigmatic shift. For him it came to full effect with the election of Margaret Thatcher in 1979:

*“Monetary policy replaced fiscal policy as the principal macroeconomic instrument, and it was reoriented toward fixed targets for the rate of monetary growth. Many regulatory instruments associated with state intervention, such as incomes policies, exchange controls, and quantitative limits on bank lending, were eliminated. This was a clear case of third order change in policy.”* ([Hall, 1993](#), p. 284)

Hall’s hindsight is helpful not only to understand the steps present in a shift of economics paradigm, but also to see the impact of such a shift on politics and society.

The first results derived from my text-mining methodology showed that the core of mainstream economics did not change. See [figure 13](#) for a compelling graph supporting this claim. Through cluster analysis and a case study of two heterodox concepts, I was able to confirm the ‘monolithic’ state of mainstream economics<sup>3</sup>, in which no place is left for pluralistic methodologies and views. If the core of mainstream did not change, this could not be said for the overall mainstream economics. As seen in [figure 14](#), relative term frequency of many words did vary a lot in the aftermath of the crisis. I find that finance-related terms showed a significant usage increase as well as climate change related terms, among others. I find also that Britain and Japan are less and less the subjects of economic research, and that the opposite is true for China. These secondary findings support the view of a dynamic science.

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<sup>3</sup>On the monolithic state of mainstream economics see [King \(2013\)](#).

## 2 Theoretical Framework

### 2.1 The Global Financial Crisis: Dissent in the Mainstream

Before starting my analysis and presenting the main methods and authors on which I based my work, I found it of interest to show briefly how mainstream economists reflected upon the crisis and the type of dissent which emerges. The points which follow are neither representative nor exhaustive but were all presented in the influential *Journal of Economic Literature* by Lo (2012). They are therefore a good sample of how the novelty of the crisis is phrased, the terms of the debate, and the scope of dissent in mainstream economics.

Some of the main dissentious points concerning the crisis are directly revealed in Lo's review where he concluded that there is no simple explanation of the crisis and that the commonly plausible accepted views about the crisis often do not hold up to some measurable facts. He takes for example the common views that "*Wall Street compensation contracts were too focused on short-term trading profits rather than longer-term incentives.*"(p. 152) and mentions on the same page that this very point is contradicted by the fact that "*CEOs' aggregate stock and option holdings were more than eight times the value of their annual compensation*". Lo calls for a thorough analysis of the complex event of the crisis, and summarizes a few different conflicting narratives explaining the crisis.

He starts by commenting on the view of Shiller (2008), who focuses his analysis on the housing bubble. For Shiller, "*a general contagion of mistaken beliefs about future economic behavior,[...]*" was at the origin of the event which unraveled into a full economic crisis. Lo goes on to describe the account of Gorton (2010), which was one of the first to describe securitization, mortgage-based securities and CDO as a mechanism for reducing transparency. Gorton argues that the increased opaqueness caused the entire structured investment market to collapse as investors struggled to sort out how contaminated by the subprime their products were. This led the repurchasing market to stall, and represented the first stage of a broader liquidity crunch where the interbank short term lending rate went up dramatically as a consequence of banks losing trust in the solvency of their partners. The declining lending standards which enabled more and more risky loans to be emitted and sold was also a decisive factor.

Gorton strongly rejects the "originate to distribute" explanation of the crisis. According to this narrative, the main problem which caused the crisis was the new behavior of financial institutions which contrasted with the older model of "originate to hold". In the "originate to distribute" model, banks contracted loans not to hold them but to repackage them and resell them to other investors. The main problems of this new behavior are the misaligned incentives of the underwriters with an underexposure to the risk of the products they were selling and the failing of the rating agencies to correctly represent risk to investors. This "originate to distribute" explanation is held by Akerlof and Shiller (2010) who see concealment, deception, and willful blindness where Gorton saw opaqueness dictated by the structure of the securities in question (Lo, 2012, p. 159).

Lo then describes what he sees as the most empirically-grounded work: *This Time is Different, Eight centuries of Financial Folly* by Reinhart and Rogoff. The main argument from the authors is that the crisis from 2007-2008 is not especially unique when compared with the historical records of past crises. The authors already stated it in the abstract of the working paper preceding their book: "*We find that serial default is a nearly universal phenomenon as countries struggle to transform themselves from emerging markets to advanced economies. Major default episodes are typically spaced some years (or decades) apart, creating an illusion that "this time is different" among policymakers and investors. A recent example of the "this time is different" syndrome is the false belief that domestic debt is a novel feature of the modern financial landscape*" (Reinhart and Rogoff, 2008).

## 2.2 Main References in Economics and Hypotheses

To the best of my knowledge nobody studied the evolution of mainstream economics after the 2007-2008 crisis with a text mining methodology. Some authors (Rochon and Docherty, 2012) asked the same question - i.e whether the crisis led to the paradigmatic shift - but did not use text mining to answer this question. I cannot therefore write a targeted literature review presenting the findings of authors who worked on this question before me. What I attempt to do in this section is to present the main authors I used to guide my research and ground my hypotheses.

My work is focused on *mainstream economics*, I used this term taking the definition from Colander:

*“Mainstream consists of the ideas that are held by those individuals who are dominant in the leading academic institutions, organizations, and journals at any given time, especially the leading graduate research institutions. Mainstream economics consists of the ideas that the elite in the profession finds acceptable, where by ‘elite’ we mean the leading economists in the top graduate schools.”* (Colander et al., 2004, p. 490)

Colander’s 2004 article is central to understand the economic profession and how economics is evolving. Colander’s view differ from the one of Kuhn (1970), since for the former revolutionary changes in the profession of economics occur incrementally without scientists noticing it. His conception could nevertheless be partially reconciled with Kuhn’s view of “normal science” which proceeds incrementally.

The important contribution from Colander is to define the mainstream economics as *“a dynamic entity, which generates a self-reproducing, evolving, complex system of interacting ideas”* (Colander et al., 2004, p. 485). This means that economics should not be seen as a monolithic coherent fixed paradigm but rather as an ever evolving entity. Moreover, Colander distinguishes between orthodox economics and mainstream economics: *‘Orthodoxy generally refers to what historians of economic thought have classified as the most recently dominant ‘school of thought,’ which today is ‘neoclassical economics’.*” (Colander et al., 2004, p. 490). For Colander, orthodoxy is a backward-looking static view of economics which is interesting to use mainly to stress the changes occurring in today’s economics.

Colander’s views are to be understood as views from within mainstream economics. He is critical of the mainstream but his criticisms remain acceptable from the dominating paradigm stand. He himself has been highly critical of economic heterodoxy and political economy, sometimes in a singularly contemptuous way according to Thornton (2015). I chose to ground some of my hypotheses on Colander’s views not because I find them particularly convincing but because his views are influential within the mainstream and because he worked extensively on the changes of modern economics. By doing so, my work evaluates some aspects of mainstream economics in its own terms, and not from the standpoint of critical heterodox theories.

Based on this definition of mainstream economics I chose to analyze abstracts coming from a variety of the most influential economic journals, each having a different focus, style, methodological or ideological sensibility, and board of editors. Through this diversity of journals, I hope to capture the core of this dynamic mainstream economics about which Colander writes.

Colander stresses the point that mainstream economics is always evolving and was already evolving away from neoclassical economics in 2004: *“We argue that economics is moving away from a strict adherence to the holy trinity – rationality, selfishness, and equilibrium – to a more eclectic position of purposeful behavior, enlightened self-interest and sustainability.”* (Colander et al., 2004, p. 485). Colander goes further and argues that what is happening at the ‘edge’ of mainstream economics is influencing the key future developments of mainstream economics itself. He uses the notion of ‘edge’ to better reflect his

understanding of mainstream economics as a dynamic entity with a ‘core’ – the main orthodox research area and topics and methodologies on which most of economists usually work – and with ‘edge’ where the research being done challenges the orthodoxy present in the ‘core’ and where “*ideas that previously had been considered central to economics are being modified and broadened, and the process is changing the very nature of economics*” (Colander et al., 2004, p. 487).

He argues that the key predictor for future changes in the mainstream is the ‘variance of acceptable views’<sup>4</sup> held within the economic profession. If this variance increases, this signals that changes are about to occur soon in the economics profession since: “*If the variance of views increases, while the core remains relatively unchanged, the static characterization of the profession will not change, but its dynamic characterization will.*”(Colander et al., 2004, p. 487). For him this variance has already been increasing since the late 90s but he fell short of proposing a measurement of this variance<sup>5</sup>. I propose a way to measure this variance and to test Colander’s statement by looking at the variance of lexical diversity in a sample of mainstream economics journal abstracts presuming the crisis accelerated this move toward more diversity of ideas.

**Hypothesis 1.** *The variance of accepted views within mainstream economics was already increasing since the late 90’s and the rate of increase went up after the crisis.*

**Hypothesis 2.** *Rationality, Selfishness and Equilibrium-related concepts are less and less frequent as economics moves toward more complexity.*

Colander (2010) and Colander et al. (2009) are two articles analyzing directly the role of economics and its failure regarding the crisis. For them, economics should not be blamed for being unable to predict the crisis, which he thinks was unpredictable, but for the overuse of models not taking into account enough complexity like the dynamic stochastic general equilibrium (DSGE) model (Colander, 2010, p. 419) and for the fact that economists were weak at communicating the limitations and difficulties of the models they were using (Colander et al., 2009, p. 255). Colander goes on to explain what led the economic profession to fail to predict the crisis and elaborates on the poor usage of models. For instance, Colander criticizes the fact that before the crisis derivatives were studied with the lens of a general-equilibrium model in which they are primarily seen as efficiency increasing tools. In this context, the loss of information due to securitization or the impact it had on the systemic risk were neglected in the modeling process. For him mathematical models should be improved and transform economics into a new area of ‘complexity economics’. This stand has been harshly criticized by Thornton (2015, p. 19) : “*Colander’s analysis of progress in economics seems guilty of an old-fashioned misconception in equating the use of computers and mathematics with better science. This runs the risk of producing a more scientific rather than scientific economics.*”

Colander sees the source of the economists’ failure in the structure of institutional incentives in academia itself, where “hands-off applied research”<sup>6</sup> is more rewarding for economists than what he calls “hands-on” applied research which is more embedded in the concreteness of institutions and the real

<sup>4</sup>Colander et al. (2004) use here the word ‘variance’ in its non-statistical meaning of ‘variation’ or ‘difference’ and not the statistical definition:  $\sigma^2 = (1/n) \sum_{i=1}^n (x_i - \mu)^2$  since taking the statistical variance of ideas makes no sense given the qualitative nature of ideas.

<sup>5</sup>Instead he simply mentions that “[...]mainstream economists today such as William Baumol, George Akerlof, Thomas Schelling, Truman Bewley, and Paul Krugman, in important aspects of their thinking, are working outside of what is generally considered the orthodoxy of the profession. Yet, their ideas are widely accepted and discussed within the mainstream of economics. It is such work that has increased the variance of acceptable views in the profession.”(Colander et al., 2004, p. 487)

<sup>6</sup>Colander (2010, p. 422) defines it as “research written primarily for other economic researchers”. It’s a kind of research faraway from real-world problems and understanding the “real economy”.

economy. For him this is one of the reasons why after the crisis, in the science of economics, “*significant change is highly unlikely*” (Colander, 2010, p. 422).

**Hypothesis 3.** *Major changes at the very core of economics did not occur after the crisis.*

**Hypothesis 4.** *The usage of DSGE model should be decreasing since the crisis (because the crisis showed how irrelevant they are when confronted with real-life complexity).*

Dow (2015) analyses the concept of uncertainty and what she calls “fundamental uncertainty”. For her, this Keynesian concept is much deeper than “quantifiable risk” which is normally the form by which uncertainty enters mainstream economic models. For her, notwithstanding the fact that the crisis increased “uncertainty in economic life” (Dow, 2015, p. 33), fundamental uncertainty is precluded in economic theories. Dow gives the following definition of fundamental uncertainty:

*Fundamental uncertainty with respect to beliefs, as explored by Keynes (1921 [1973]), arises from the openness (organicness) of the economic system whereby the future is not knowable even in principle. The ultimate source of uncertainty is therefore the nature of the subject matter, such that uncertainty is aleatory. Conventions and institutions evolve and behavior may be creative, such that the units of analysis and their inter-relations are not pre-determined and the structure within which these inter-relations occur is itself not pre-determined. (Dow, 2015, p. 34)*

**Hypothesis 5.** *The focus on quantifiable risk increased in mainstream economics, but the focus on fundamental uncertainty did not.*

A remarkably central aspect of economics is its reliance on modeling and mathematics. The simple fact that the word stem ‘model’ is present at least once in 41.9%<sup>7</sup> of my abstracts collection (this is the most present stem in all abstracts) is revealing. The impact that the crisis had on this key feature of economic science is worth analyzing since any change in this deeply grounded practice would mean a sizeable shift in the way economists do their profession. For this matter, to ground my hypothesis I rely on three authors: Bigo and Negru (2014); Lawson (2009, 2006)

*“A pervasive feature of the discussions that took place in the economic forums was a drive to improve the existing mathematical apparatus and/or to produce newer, better models. Although many economists genuinely see themselves as challenging dominant methodology, the same economists continue to embrace formal modeling. In other words, to conclude this section, during the academic events that followed 2007, bar a few exceptions, I observe a near-total absence of papers questioning, let alone suggesting a reduction in, the emphasis on mathematical modeling.” (Bigo and Negru, 2014, p. 336)*

**Hypothesis 6.** *The reliance on the usage of mathematical modeling did not experience any significant changes after the crisis.*

*Social reality, in other words, is of a nature that is significantly at variance with the closed systems of isolated atoms that would guarantee the conditions of mathematical deductivist modelling. That is why modern economics has continually failed on its own terms. It is also why, as a step on the road to this failure, economics is inescapably profuse with assumptions accepted by everyone as widely unrealistic,[...]. (Lawson, 2009, p. 765)*

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<sup>7</sup>‘model’ appear in 8456 abstracts out of my 20,216 abstracts collection, this is a 41.9% frequency. Check table 3 for more information.

Mathematical modeling being at the core of economics, the wish to perfect modeling, as strongly expressed by Colander (2010), reveals a framework belonging to *normal science* where anomalies are integrated incrementally but do not lead to radical changes. The conception from Lawson (2009) is much more radical since he thinks economics should break away from the key feature of using deductivist mathematical models. This dichotomy stresses the mainstream stand of Colander for whom the betterment of mathematical modeling and the move toward ‘complexity economics’ is in itself a revolutionary change of the profession.

A particular question I wanted to research was the impact that the crisis had on behavioral economics. This sub-discipline being relatively new and original in both its methods and research focus, I wondered whether the crisis pushed this sub-discipline from the edge of the profession toward the core of economics by giving it more credit (and more anomalies to work on). On this very idea Wilkinson and Klaes (2012) wrote:

*“All economics is behavioral in the sense of examining how people choose to act and allocates resources in different types of situation. However, over the last decades the standard model of economics rationality, based largely on the assumption of expected utility maximization, has come under increasing criticism from both outside and inside the economics profession. The recent global financial crisis has exacerbated this situation. There are large number of empirical anomalies that the standard model fails to explain. Behavioral economics attempts to answer many of these criticisms by taking a broader approach to studying economic phenomena.”*(Wilkinson and Klaes, 2012, p. X of the preface)

**Hypothesis 7.** *The crisis strengthened the position of behavioral economics within mainstream economics.*

### 2.3 Text Mining and Content Analysis

Feldman and Sanger (2006) define text mining as:

*“[...]a knowledge-intensive process in which a user interacts with a document collection over time by using a suite of analysis tools. In a manner analogous to data mining, text mining seeks to extract useful information from data sources through the identification and exploration of interesting patterns. In the case of text mining, however, the data sources are document collections, and interesting patterns are found not among formalized database records but in the unstructured textual data in the documents in these collections.”* (Feldman and Sanger, 2006, p. 1)

As such, text mining involves:

*“The preprocessing of document collections (text categorization, information extraction, term extraction), the storage of the intermediate representations, the techniques to analyze these intermediate representations (such as distribution analysis, clustering, trend analysis, and association rules), and visualization of the results.”* (Feldman and Sanger, 2006, p. X of the Preface)

Visualization of the results is central to text mining methodology as this represents a way of extracting knowledge and to understand the massive data that have been processed. This is essential since the normal way of interacting with text – which is simply reading the text – is no longer possible given the

huge size of the documents collection. This is why I chose in this thesis to present most of the results in a graphical form, directly in the text and not in the Appendix.

The main limitation of using text mining comes from the nature of language itself. A few basic difficulties include: on the one hand, some words could have different meanings (polysemy) or connotations depending on the time at which they are used, the person using them, or their phrasal context; On the other hand, different words could have the same meaning (synonymy). At the root of the problem is the fact that natural language is meant to be used by humans and not by machines. To increase efficiency in human communication, common-sense knowledge is simply often forgotten because it is assumed that the reader or listener knows it already. In a similar way, a lot of ambiguities are kept in the language, as we assume the reader or listener will be able to understand them. These two points are hard for a computer to figure out. Human language grammar is simply too heterogeneous and irregular to be fully comprehensible by machines. These difficulties make it difficult to deduce or directly prove causation between phenomena using text mining techniques, since these techniques are based on a poor understanding of language.

Since causation is hardly provable with text mining techniques, my thesis is not focused on one problem or question to be answered. I used several text mining techniques as a way of exploring text data but not as a way of scientifically explaining phenomena. The hypotheses presented in the previous section are tools to guide my exploration effort in the vast amount of data I collected.

[Grimmer and Stewart \(2013\)](#) explore the main limitations and advantages of working quantitatively with political texts. Even though these authors come from the fields of political and social sciences, their hindsight and warnings apply directly to my subject, since I am using similar methods. They describe clearly how text mining techniques are reducing the complexity of human language and transforming it into numbers. The most shocking step, they argue, is to treat text as a ‘bag of words’ where the word order does not matter ([Grimmer and Stewart, 2013](#), p. 6).

The authors singled out 4 key principles of quantitative text analysis:

1. *All quantitative models of language are wrong—but some are useful.*
2. *Quantitative methods for text amplify resources and augment humans.*
3. *There is no globally best method for automated text analysis.*
4. *Validate, Validate, Validate. ([Grimmer and Stewart, 2013](#), p. 3)*

These 4 principles make it clear that quantitative text analysis is not the panacea to fully understand huge document collections and stress the need to validate results and interpretations coming from text mining. The danger here is the over-interpretation of text mining outputs.

In text mining jargon, the difference is made between ‘deep natural language processing’ (NLP) and ‘shallow NLP’. Deep NLP requires more human effort but could lead to inferences as sentences’ structure and meaning are taken into account. Deep NLP could only be applied on a small body of text. Shallow NLP uses statistical methods that could be used on a very large number of documents, and though it is robust, it is often useless. For deep NLP, there will be more errors but it leads directly to usable knowledge, there is a trade off. In my thesis, I rely mostly on Shallow NLP techniques.

## 2.4 On The Usage of Abstracts

I chose to analyze mainstream economics through abstracts of scientific articles coming from the most influential mainstream journals. I made this choice partly for practical reasons, the first of which is simply that handling the full text data of circa 29,000 articles would have been much more computationally demanding and probably beyond the power of my computer. Moreover, it would have cost a lot to the university of Neuchâtel. Reducing the number of articles selected was an option but I would have lost a lot of information and been left sometimes with just a handful of articles for a given review in a given year. An alternative solution would have been to use JSTOR's bibliometric tool 'Data for Research' (DfR), but I would have lost flexibility for handling my data and lost the possibility of using text mining techniques like term co-occurrences and clustering. Moreover DfR strictly limits the amount of downloadable raw data.

Beyond these practical reasons, there are also some strong theoretical justifications for using abstracts. From an information perspective, abstracts have the highest information density in a scientific article. Usually written by authors, they are meant to summarize and present the research question, the main findings and the method used. Since abstracts lack space for examples or technicalities, they normally introduce the main theme of the paper succinctly and effectively. Even when the paper does not present empirical findings, as is the case for purely theoretical or methodological papers, abstracts still present a selection of the most important elements from the paper such as the key argument or point of view held. This selection is done not by a machine, but by the author (usually), who is arguably the person knowing the most about the article. I argue therefore that this selection of the most important elements of the paper is a valid one.

It is possible to argue against this somewhat optimistic view about the content of abstracts by stating that the first goal of an abstract is to catch the attention of peers and publishers and not to objectively summarize the most important elements of a paper. On the so-called 'academic market' this attention catch is of utmost importance for the author since one's academic career can be changed by the publication of a paper in the most influential journals. Following this view and assuming rational economists, one expect them to write an abstract strategically, taking into account the expectation of their future readers. In an extreme case scenario, they no longer summarize the most important part of their paper but simply write what they think are the most effective succession of words (100-150) to catch the attention of and impress their reader. The problem with this view is the strength of the constraint forcing the abstract to be connected with the text which follows. Having no link at all is not possible and will be rapidly detected by most readers. What remains possible is to adapt the formulations, the vocabulary or what is being stressed, to the estimated expectations of the audience.

This latter phenomenon likely happens frequently as scholars adapt their abstract to the journal they are submitting them to. In my dataset itself, I was able to detect this phenomenon when finding duplicate titles revealing two different abstracts related to one original research: one abstract coming from a working paper of the National Bureau of Economic Research (NBER) and the other abstract made for the peer-reviewed published paper which followed. Most of the time the abstracts were almost completely similar (with sometimes minor changes in the typography or punctuation) but occasionally the abstract were completely different with no single sentence alike.

What I argue here is that even if abstracts are strongly modified to reflect what the audience (publisher, reviewer or academic peers) wants to read, *a fortiori* when they are modified in such a way, they will still be holding the most information-dense content possible to extract out of an article. Indeed, when particular care is being paid to show the 'right' wording, the 'right' tone and the 'right' formulation, the

abstract is finely enriched with words reflecting the expectation about what economics ought to be like, what should be of interest and what is deemed scientific by ‘the community of practitioners’. Since the subject of my thesis is the study of economic thought and its evolution, these elements are precious as they reflect the paradigmatic dimension present in economics.

## 3 Methodology

Before presenting the data and text mining techniques I used in this thesis, I want to stress the special nature of a text mining methodology and its main limitations. The word ‘mining’ reflects this nature well as it supposes one will find something - usually after much effort - but with no claim to understand what is found. With text mining I will be discovering textual pattern, mined from a 28,974 abstracts collections but I will struggle to find the explanations of what I will find. Simply listing all the interesting patterns I have found would have been too minimalist and descriptive for a thesis. This is why I will try to comment on each ‘stone’ or ‘jewel’ found in the mining process and try to make the most educated guess I can to explain why the stone is the way it is. In other words, I will present speculations or hypotheses about the underlying processes which lead to such observable patterns.

To help me in this task, I have some tools that strongly determine what could be found and what could not. The first kinds of tools I have are simply the software allowing me to analyze parts of the data and manipulate them in order to extract meaningful information. My mastery of these tools is limited and limits my efficiency in the mining process as well. The other more subtle kind of tool is my representation of what is of interest and what is not. The amount of information extractable being too vast, I have to select patterns, questions and topic, which I think are relevant. This is a highly subjective choice I made using mostly what I have learned during my studies and reading the academic literature. At a more unconscious level, my values, my views (for examples on the political and social dimensions of economic systems) as well as the position I give to economics in the social sciences all contributed to influence my selection. Text mining is in some way paradoxical as it is on the one hand strongly *positivist* (using empirical data to produce objective measures through quantitative analysis) and on the other hand *postpositivist*, giving the researcher’s subjectivity an important role from the start of the research process.

To deal with this paradox I chose to pick statements from different economists which could guide my search in a more objective way. These were the hypotheses presented in section 2.2. I used these to guide my search of information, but whenever in the mining process I found some interesting enough patterns that were unrelated to any of the hypotheses I made, I presented them as well since discovering unexpected patterns is inherent to text mining methodology.

### 3.1 Data

For my thesis, I relied on text mining techniques using mostly the open source data mining software RapidMiner 5.3 completed by the free text mining extension available on its internal marketplace. In my case, the main documents collection consisted of the 28,974 abstracts from the 16 most influential economic journals and the National Bureau of Economic Research.

#### 3.1.1 Source

I extracted the data from the econlit database which regroups the majority of scientific economic journals. The abstracts are from the first 16 journals with the highest h-index impact factors<sup>8</sup>. This factor is computed by the research division of the Federal Bank of St. Louis and is accessible online on the [IDEAS website](#)<sup>9</sup>. According to Google Scholar: “*The h-index of a publication is the largest number h such that*

<sup>8</sup>The full list consulted on March 13, 2015 contained the following journals: The Quarterly Journal of Economics, Econometrica, Journal of Financial Economics, Review of Economic Studies, Journal of Economic Perspectives, Journal of Political Economy, Review of Financial Studies, American Economic Review, Journal of Monetary Economics, Journal of Finance, Journal of Econometrics, Economic Journal, Journal of international Economics, Journal of Public Economics, Journal of Development Economics, European Economic Review.

<sup>9</sup><https://ideas.repec.org/top/top.journals.hindex.html>

at least  $h$  articles in that publication were cited at least  $h$  times each.” The h-index is therefore a measure of impact taking into account quality and quantity of the papers published since only the most cited papers influence it. It remains subject to classical bibliometric flaws and weaknesses like the fact that being highly cited does not always represent a good indicator of quality (a paper could be so bad that many other authors will judge it necessary to criticize it and cite it). The rankings are computed on data gathered with the RePEc project<sup>10</sup>, in which, according to the [website](#): “publishers self-index their publications and authors create online profiles from the works indexed in RePEc. Citation analysis is performed by the CitEc project, abstract views and paper downloads are counted by the LogEc project, and the various rankings are then established. Rankings are typically updated around the 3rd to 5th day of each month. Some rankings are updated more frequently. All data is experimental.” All together, I collected and kept, after the cleaning and preprocessing procedures, 18,535 abstracts from these 16 journals.

I also collected 10,439 abstracts from the working papers of the National Bureau of Economic Research (NBER). Only abstracts which were published after 1999 were kept. The time range for my data run therefore from 1999 to the first quarter of 2015. I chose to include the NBER abstracts for 3 reasons:

1. Their influence (as shown by the highest h-index impact factor of all the publication series) and the fact that the NBER is a major source of funding for economic research.
2. Their broad ideological diversity.
3. Their policy focus.

Adding the NBER dataset to the Journals dataset led to the creation of the 28,974 row dataset. See [figure 2](#) for a graphical view of the number of abstracts collected per journal.

### 3.1.2 Creation of Database and Cleaning Procedure

Using the software [import.io](#), I downloaded from the econlit database for each journal article the following variables: Title, Abstract, Year of Publication, Month of Publication, Authors, Reference. I proceeded 1 result page (containing 50 results) at a time. For each journal, I created an excel document containing all the variables as well as all the abstracts for the period 2000-2015.

Since a lot of NBER working papers were also published in the form of an article in the academic journals I had selected, I deleted duplicates. To do this, I used the command line in excel applying it on abstracts and titles. The problem here was the inability of excel to detect duplicates in the presence of minor typographic differences like the presence of a point or a comma. In order to solve this problem I used rapidminer and for every title and abstract I stripped all signs or characters which were not either a word or a number. I then used the ‘find duplicate’ command in excel again, this time with greater success as 2239 duplicates could be found<sup>11</sup>. When I found duplicates were coming from NBER and an economic journal, I systematically deleted the NBER abstracts and not the corresponding journal abstract. The reasons behind this choice are: NBER abstracts were already representing circa one third of the abstracts from my dataset and I wanted to diminish this influence in order to let other journal’s abstracts remain

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<sup>10</sup> “RePEc (Research Papers in Economics) is a collaborative effort of hundreds of volunteers in 82 countries to enhance the dissemination of research in Economics and related sciences. The heart of the project is a decentralized bibliographic database of working papers, journal articles, books, books chapters and software components, all maintained by volunteers. The collected data is then used in various services that serve the collected metadata to users or enhance it.” Excerpt extracted from the [RePEc website](#)

<sup>11</sup> This substantial number of duplicate shows in itself the considerable impact that NBER has on leading economic research. It represent a 12.6% of all published works from these 16 leading reviews. Percentage estimate comes from the comparison of the 2,239 deleted duplicates with the 18,535 remaining non-NBER abstracts (from which 2,239 were published first as a NBER working paper). This estimate is solely based on my dataset and is prone to mistakes, remaining duplicates and the likely incompleteness of the dataset due to my collection procedure.

relevant in the analysis.

The collected abstracts were not ‘clean’ in that they contained a lot of irrelevant words such as the JEL classification number, whether the abstract was written by the authors or not, or whether it was copyrighted by Elsevier publishing etc. Using excel, I tried to delete most of these words not belonging to the scientific abstract *per se*. I’ve also deleted abstracts when:

1. The abstracts contained less than 50 words (usually they were not complete or simply restating the title of a book review).
2. The cell supposed to contain the abstract was either a report from the editorial board, the presentation of a new board member, an erratum, a blank cell, an index or some other kind of text which was not an abstract of a scientific article.
3. The abstract cell was simply blank.

After cleaning the abstracts I used excel to create a new variable containing simply the word count in each abstract. A first inspection of the mean of the abstract length per year showed no particular trend in the abstract length as seen in figure 4.

### 3.1.3 Preprocessing Procedure Steps

To start processing the dataset efficiently with the text mining tools, I applied the following preprocessing procedure steps:

1. Discretize the year attribute into two classes (pre/post 2008). ‘pre2008’ is the period going from 1999 to 2008 (2008 included) ‘post2008’ is the period from 2009 to 2015. This choice to set the second period beginning in 2009 was made based on an estimation of the lag necessary for the crisis to be themed and thought in scientific articles. This estimation was based on the observation of the evolution of the yearly frequency of the words like ‘financial crisis’, ‘securitization’ or ‘credit risk’ which all experienced a sharp rise in 2008-2009 as seen in graph 7. I did not choose 2008 as the splitting year since the collapse of Lehman Brothers happened in fall 2008 and represents the peak of the crisis. Moreover, 2008 is the year in which most countries from the OECD fell into recession<sup>12</sup> (contraction of quarterly real GDP over at least two quarters) which represents the time when adverse real economic effect started to be felt and measured. For all these reasons, even though the first turmoil of the crisis started in 2006, I chose 2009 as a reasonable point from which the effect of the crisis should be felt in economics research papers<sup>13</sup>.
2. Extract a random sample of 4,000 abstracts from NBER in order to avoid it having an overwhelming influence.
3. Perfectly balance the dataset between the two classes (pre/post) in order to have exactly the same number of abstracts per period. The dataset was reduced to two groups of 10,108 abstracts, and the selection was made randomly under the only constraint that 10,108 abstracts had to be picked by the rapidminer’s operator for each period. I chose 10,108 abstracts since it was the highest number common to the two periods. Due to this balancing procedure the balanced dataset had 3619 NBER abstracts left and 16,597 abstracts from the 16 academic journals.

<sup>12</sup>Quarterly real GDP growth data accessible on the OECD website here: <http://stats.oecd.org/Index.aspx?QueryName=350&QueryType=View&Lang=en>

<sup>13</sup>It could be argued that given a publication lag which range from one to two years in many top-ranking review, 2009 is actually too early to start looking for changes. Against this argument are the data showing clearly that obviously crisis-related topic are experiencing frequency change starting in 2008-2009.

### 3.1.4 Processing Procedure Steps

The main text mining transformation procedures I applied on the dataset were:

1. Tokenize<sup>14</sup> each abstract into a list of tokens. In my case, most of the tokens were words since the delimiter to transform the abstracts into tokens was simply the space symbol, which means that every combination of character or number separated by a space before and after was considered a token.
2. Filter stopwords for the basic English words like ('a', 'the', 'is', 'about', 'again' etc..). This was done to eliminate words carrying almost no relevant information for my analysis.
3. Transform all cases into lower cases in order to avoid having similar words being considered different because of upper/lower cases difference.
4. Stemming with the Porter algorithm which: *"reduces all words with the same root to a single form, the 'stem' by stripping the root of its derivational and inflectional affixes; in most cases, only suffixes that have been added to the right-hand end of the root are removed"* (Willett, 2006, p. 219)<sup>15</sup>.
5. Generate n-grams (combination of tokens directly following each other). The maximum size of an n-gram was set to 4 contiguous tokens. Using n-grams enabled me to extract concepts and ideas that are often described with more than one word (e.g: 'financial crisis') and to disambiguate the meanings of some words. For example, the word 'depression', which could refer to a psychological condition or to the economic turmoil of the 30s, could be better disambiguated when the preceding word is known. The creation of the bi-gram 'great depression' allows this disambiguation.
6. Set the pruning parameters under which words should not be considered. I chose to ignore words which were appearing in less than at least once in 50 different abstracts out of the 20,216 abstracts collection. This is equivalent to a pruning limit at a 0.25% frequency.
7. Compute the relative term frequency of each remaining word in each abstract and represent these frequencies in a  $20,216 \times 3522$  matrix with each line representing an abstract and each column representing a word. For more details on the computation of the relative term frequency see section [3.2.2](#).

For every abstract processed, rapidminer creates a variable containing the tokenized, stemmed and filtered abstract. I added this variable to my dataset for further analysis of lexical diversity within abstracts. To see a concrete example of these processed abstracts which are at the base of my analysis see Appendix [A](#).

### 3.1.5 Data Characteristics

The majority of my variables are simply textual data (Authors, Title, Abstracts, Journal, Reference) and the only numerical variables are: the year, the date (including month) and the number of words per abstract<sup>16</sup>. The length of these abstracts varies with the journal's editorial policy limit on the numbers of terms allowed. For most journals, the limit is between 100-150 words. As seen in figure [1](#). To be able

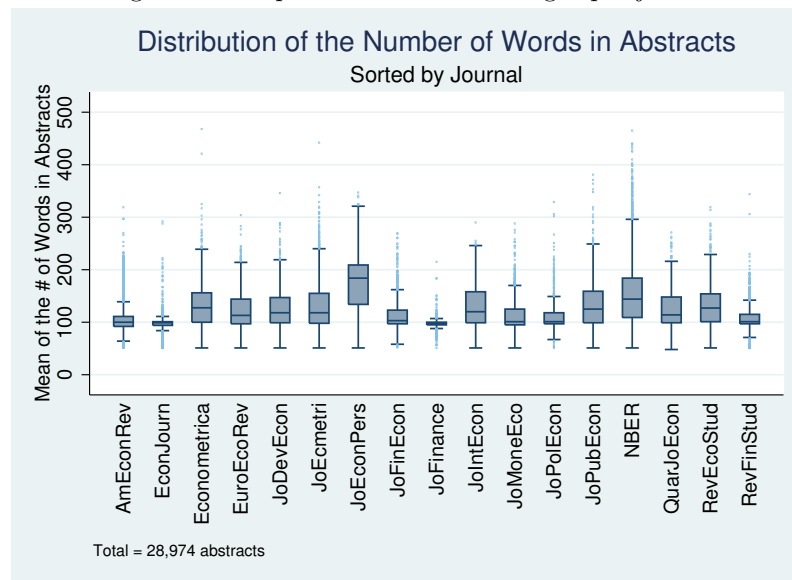
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<sup>14</sup>Tokenization is a process by which a string of characters (a text) is divided into subunits (the tokens) like words, sentences, syllable, or letters.

<sup>15</sup>For a overview of the porter algorithm see the full paper by Willett (2006).

<sup>16</sup>The words in abstracts variable was computed in excel, by simply counting the words in each cleaned abstract

Figure 1: Box plot of the abstract length per journal



The blue horizontal line represent the median, the lower limit of boxes are at the 25th percentile, the upper limit at the 75th percentile. The whiskers end at 1.5 time the interquartile range, under the 25th percentile for the lower whisker and above the 75 percentile for the upper whisker. Light blue points represent outsiders.

to represent the journal variable in figures, the journal name were abbreviated<sup>17</sup>.

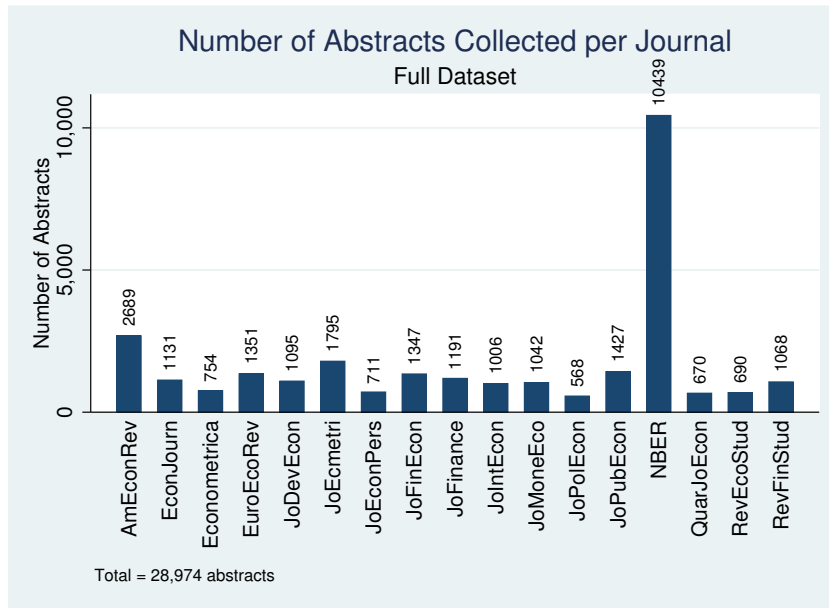
Figure 1 reveals for instance that the American Economic Review seems to be more strict about respecting abstract length limits compared to NBER or the Journal of Economic Perspectives which show a greater interquartile range.

Figure 2 shows substantial variation in the number of abstracts collected according to the source considered. The overwhelming importance of the NBER abstracts could clearly be seen. The differences in abstracts per journal comes mostly from the different publication rhythm of each journal. For example, since 2014, the American Economic Review (AER) has a monthly rhythm of publication as opposed to the Quarterly Journal of Economics, which publishes an issue every 3 months. The number of articles per issue varies and could also explain the variation of the number of abstracts collected per journal.

Figure 3 shows that the distribution of abstract length is highly similar before and after the crisis, but not entirely. The distribution looks like a skewed normal distribution with a high Kurtosis caused by the number of abstracts having a number of words around the limit (100 words). The slight skewness to the right is explained simply by the fact that the number of words per abstract has a clear inferior bound (50 words minimum, given the pruning applied) but different upper bound policies and possibilities to derogate from this policy according to each journal considered. The most puzzling element here can be seen for the period of 1999-2008 during which a relatively high number of short abstracts just over 50 words is visible. This is far higher than for the second period. I tried to find a pattern in the dataset which could explain this phenomenon but I did not succeed to find a meaningful answer. It does not seem to be associated with either a journal or a year and is seemingly unassociated with a type of abstract.

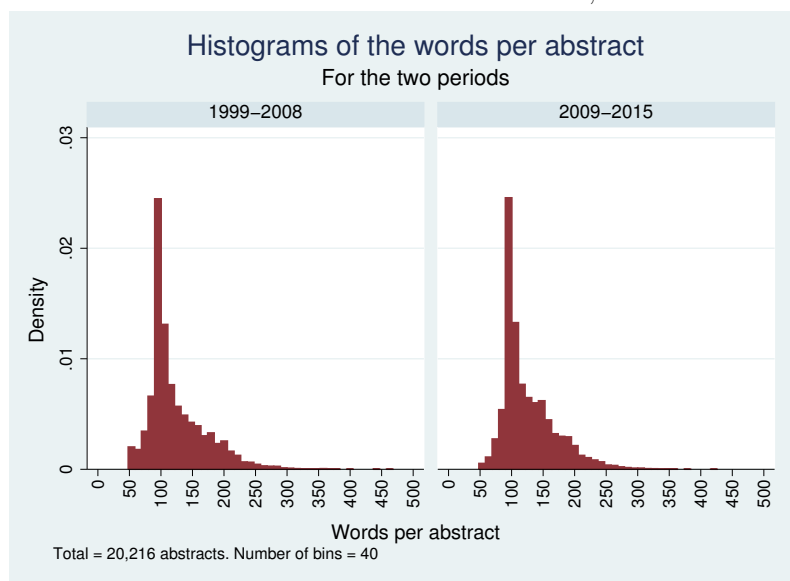
<sup>17</sup>The abbreviations are: AmEconRev for the American Economic Review, EconJourn for the Economic Journal, Econometrica was short enough not to be abbreviated, EuroEcoRev for the European Economic Review, JoDevEcon for the Journal of Development Economics, JoEconPers for the Journal of Economic Perspective, JoFinance for the Journal of Fiance, JoFinEcon for the Journal of Financial Economics, JoIntEcon for the Journal of International Economics, JoMoneEco for the Journal of Monetary Economics, JoPolEcon for the Journal of Political Economy, JoPubEcon for the Journal of Public Economics, QuarJoEcon for the Quarterly Journal of Economcis, RevEcoStud for the Review of Economic Studies, RevFinStud for the Review of Financial Studies

Figure 2: Abstracts collected per journal



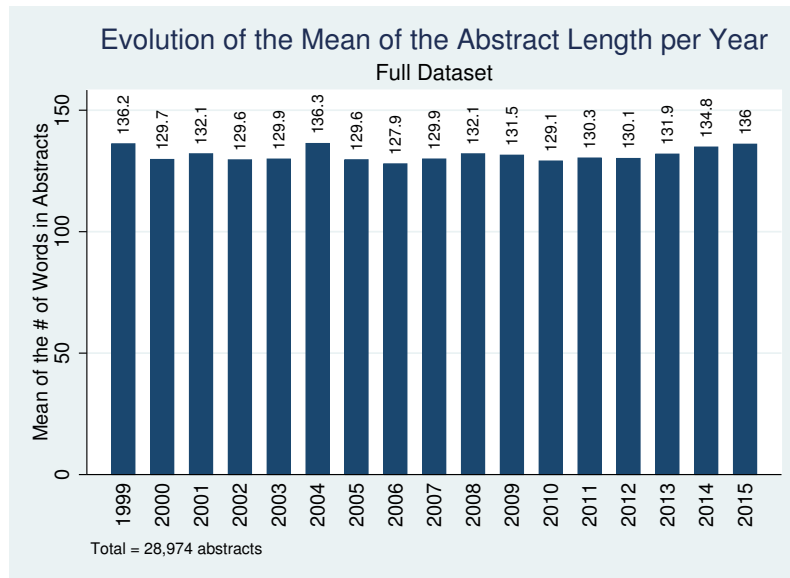
Note: Unbalanced dataset

Figure 3: Distribution of the number of words in abstract, before and after the crisis



Note: Balanced dataset, meaning that there is exactly 10,108 abstracts for each of the two period

Figure 4: Mean of abstract length



Note: Unbalanced dataset

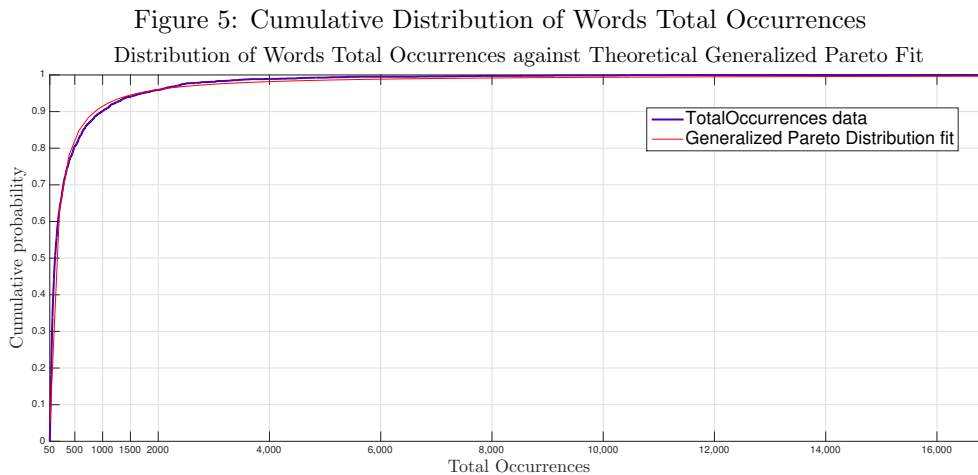
Several different factors could have played a role in causing this phenomenon: a change in editorial policies bringing up the number of words per article or a change in the way abstracts are considered by authors. This latter possibility could have come with the full digitization of scientific publications and the fact that abstracts have become one of the key elements used by potential readers reviewing many different journals to decide whether they will invest time to read the paper. Making a truly concise abstract could be a strategy to catch their attention.

Figure 4 shows an apparent absence of trend in the evolution of abstract size. This is an important characteristic, since major parts of my analysis rely on the assumption that the size of abstracts does not evolve.

Figure 5 confirms that the word occurrences are distributed according to a Pareto distribution. These distributions are found across many remarkably different phenomena ranging from the distribution of city population size, to intensity of earthquakes and people’s annual income among others (Newman, 2005, p. 325). It is a well-studied phenomenon that word occurrences in English are supposed to follow this kind of distribution as well (also referred to as Zipf’s law or power law<sup>18</sup>). Figure 5 is therefore simply confirming what was to be expected from a sample of English texts : “most words are rare and a few are very common” (Solé et al., 2010, p. 21). The surprising element is the fact that the filter stop word preprocessing procedure, the stemming and the fact that my text corpus is not made of books (on which Zipf’s law is often tested), but of very short text abstracts did not affect the validity of Zipf’s law on my dataset as made clear by the almost perfect match between the theoretical Pareto distribution and the total occurrences data observable in figure 5.

“Language is a system of interacting units. As such, we can map their relations onto a graph in the hope that such mapping will capture fundamental traits of language under a global picture” (Solé et al., 2010, p. 21) therefore language could be seen, in some aspects as a network. Network theory is

<sup>18</sup> “Cumulative distributions with a power-law form are sometimes said to follow Zipf’s law or a Pareto distribution, after two early researchers who championed their study. Since power-law cumulative distributions imply a power-law form for  $p(x)$ , ‘Zipf’s law’ and ‘Pareto distribution’ are effectively synonymous with ‘power-law distribution’” (Newman, 2005, p. 327)



Note: Word occurrences computed after processing the 20,216 abstracts coming from the balanced dataset. 3522 different word stems or n-grams were found to be present in more than 0.25% of the documents. The fitted value and parameters for the generalized Pareto fit were computed on Matlab using maximum likelihood estimation through the distribution fitting tool, the theta parameter - which is threshold value for the fat tail of the distribution - was set to 49 since my pruning limit eliminated any possibility of finding words occurring less than 50 times. At the upper right corner- with 16,753 total occurrences - the word stem 'model' is represented.

rich in information about so called 'scale-free network', networks whose nodes interconnectedness level follow a power law, exactly as the word occurrences in my dataset are following a power law. The main characteristics of such networks - the most well known being the world wide web - are according to [Barabási and Bonabeau \(2003\)](#):

- Their robustness to accidental failure of some random nodes
- Their vulnerability to coordinated, targeted attacks against the most connected nodes (called 'hubs')

I explain how such findings from network theory could bring insights for understanding my results and economics as a whole in the discussion section (section 5.1) of this thesis.

## 3.2 Text Mining Techniques Applied

### 3.2.1 Term Occurrences

In order to test the hypothesis presented in section 2.2, I need to be able to analyze the evolution of the usage of different concepts ideas and methods. To do this, the most basic statistic at my disposal is simply the total number of times a word is occurring in the entire document collection and the total number of different documents in which each word occurred. Rapidminer text processing operator provides this information under the form of a simple word list with this basic information for each word.

To better answer my research question, I slightly modified the operator so as to have the total number of occurrences of each given word for each of the two periods (pre2008 and post2008). This augmented wordlist enabled me to use excel to calculate the percentage increase or decrease between the two periods of interest. This enabled me to easily identify the most frequently occurring words as well as the words whose frequency experienced the biggest change across the periods. For a look at excerpts from this word list see Appendix B. I chose to produce 3 tables : table 3 which shows the most occurring terms and

their evolution; table 4 which shows the terms which experienced the biggest rise in occurrence between the two periods; table 5 which shows a selection from the top 100 words which experienced the sharpest drop. These three tables reveal parts of the data that are especially meaningful to interpret and easy to locate.

The weakness of this method is its inability to show the timing of the changes in frequency of a given word. This weakness could preclude the finding of a major shift in the frequency of a word if this shift was just happening for a short period of time and directly followed by a shift in the opposite direction. Such a variation would go undetected as it would keep the overall sum of occurrence for the given period almost unchanged. To deal with this weakness, a more sophisticated method is to look at the yearly evolution of the relative term frequency.

### 3.2.2 Relative Term Frequency Evolution

Rapidminer provides a simple way to compute the relative term frequency of a term in a document. The code for this computation is given in Appendix C. To calculate the relative term frequency, rapidminer uses cosine normalization. “This normalization ensures that the  $l^2 - norm$ <sup>19</sup> of the [document] vectors will all be one”<sup>20</sup>. Cosine normalization, in this case, means that the absolute frequency of each term (number of times the word appears in the document) is divided by the square root of the sum of the squared absolute frequencies of each term present in the document. Given this normalization, cosine similarity of two vectors is the dot product of the two vectors. As a consequence of this normalization, words appearing, for example, once among a 60 word-long abstract are given more weight than words appearing once time in a 130 words long abstract.

Given the diversity of vocabulary in the human language and the small size of the abstracts, the relative term frequency of a randomly chosen word in a given economic abstract is likely to be zero. To analyze the evolution of the relative term frequency of a given word, I took its yearly mean over all the abstracts and plotted the evolution of this mean. For the plotting part, I relied on Stata, mostly because of the flexibility and the aesthetics of the graphing tools.

This methodology assumes that the difference in the number of abstracts per year does not affect the mean of relative term frequency<sup>21</sup>. Looking at the evolution of term frequency is a highly flexible and powerful method as it makes it possible to focus directly on the usage of a specific term while taking into account the variation in abstract length.

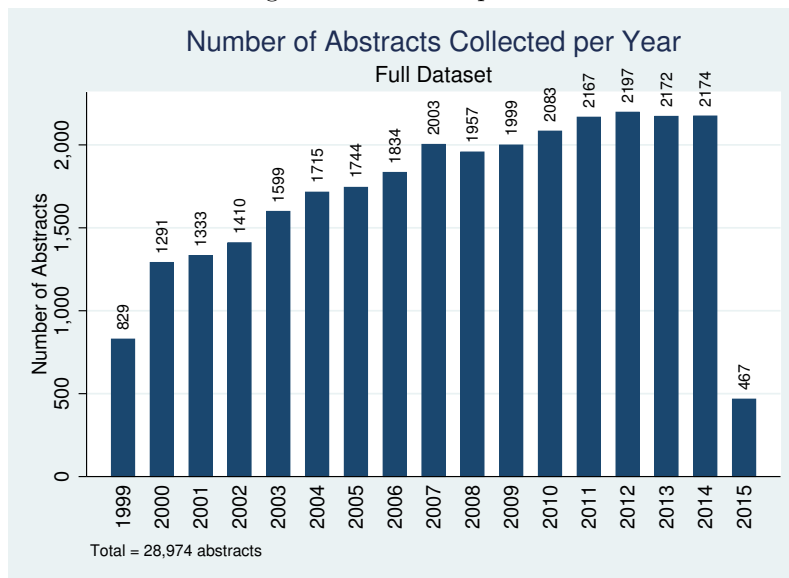
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<sup>19</sup>The  $l^2 - norm$  of a  $n$ -dimensional vector  $\mathbf{X}$  can be defined as  $|\mathbf{X}| = \sqrt{\sum_{k=1}^n |x_k|^2}$  (definition taken from: <http://mathworld.wolfram.com/L2-Norm.html>)

<sup>20</sup>This information comes from Ingo Mierswa and is detailed in the reply # 5 of the forum discussion accessible here: <https://rapid-i.com/rapidforum/index.php?topic=3728.0>

<sup>21</sup>This variation in the number of abstract per year could be seen in figure 6.

Figure 6: Abstracts per Year



### 3.2.3 Variance of the Vocabulary in Abstracts

According to hypothesis 1 based on Colander et al. (2004), the variance of ideas within the mainstream should have been increasing already since the beginning of 2000. I expect the crisis to have strengthened this phenomenon and thus to be able to observe a difference between the two periods (pre/post 2008). To measure this ‘variance of ideas’, I look at the evolution of lexical diversity within the abstracts.

On this measure deBoer (2014, p. 140) clearly states that:

*“The simplest method for measuring lexical diversity lies in simply counting the number of different words (NDW) that appear in a given text. This figure is now typically referred to as types. This metric benefits from simplicity in both concept and in measurement, and can be easily generated from simple computer programs. However, the problems with NDW are obvious. The figure is entirely dependent on the length of a given text.”*

Since abstract size did not evolve significantly (see figure 4), I could keep constant the number of abstracts selected per year in order to make sure that the overall length of the text corpus for each year was comparable. To test hypothesis 1, given the similar size of abstracts, the most simple way to approach the variance of views in economics after the crisis was to calculate the total number of different words occurring above a given threshold in the two subsamples of abstracts: one before the crisis and the other after the crisis. In order to avoid having too many unimportant words<sup>22</sup> I pruned away all the words appearing in less than 0.25% of all documents for each period and compared then the total word diversity of two 10,108 long samples of abstracts. These preliminary results showed that from the pre2008 sample only 3511 stemmed words or n-grams were more frequent than 0.25%, as opposed to the 3695 stemmed words from the post2008 sample. This preliminary result tends to show that the lexical diversity augmented after 2008.

To test the hypothesis more precisely I looked at the yearly evolution of lexical diversity. Keeping the same parameters as for the general period comparison was not possible because of the decreased number

<sup>22</sup>Words which are appearing too rarely in abstracts to be of significance.

of abstracts available per year and the constraint that for each year exactly the same number of abstracts should be used. This led me to drop the years 1999 and 2015 for which not enough abstracts were available (589 abstracts for 1999 and 349 for 2015). Then I selected 1019 abstracts for each year. 1019 is the number of abstracts remaining after the processing and balancing procedure for the year 2000. This is the smallest abstract collection for the remaining year and therefore represents the highest number of abstracts possible to include without dropping another year (2000). Given the smaller size of my text collection, I could not keep the pruning of words below the 0.25% frequency since it would have meant that any word present in at least 3 documents would have been included. This number is too small to be statistically significant and is therefore too prone to random variation. This is why I chose to set the pruning at 1%, meaning that any word stem of n-grams appearing at least in 10 different abstracts (out of the 1019 yearly collection) would be counted. Results of this procedure could be seen in figure 15 in the next section. They show a slight increase of lexical diversity.

### 3.2.4 Association Rules and Word Co-occurrences

The method of association rule was first developed for market basket analysis. In a market basket context, the goal is to discover which items were often bought together. An association rule usually has the form  $A \Rightarrow B$  or  $A, D \Rightarrow E$  implying: when products A and D were bought E was also often bought. In this case, A and D are called the premises of the rule and E the conclusion. In a text mining, items are not products but simply terms or n-grams. In the context of my thesis each abstract represents a word basket, and association rules are describing the co-occurrences of words within abstracts.

To describe the strength and quality of the associations several statistical concepts were developed. The most important ones are *support*, *confidence* and *lift*.

In text mining, the *support* of the rule  $A \Rightarrow B$  is defined as the number of times A and B appear together in the document collection divided by the total number of documents. More formally, support of rule  $A \Rightarrow B = \text{support}(A \cup B)$ , or in other words it is simply the proportion of documents containing both terms A and B.

The *confidence* of a rule of the form  $A \Rightarrow B$  is:  $\text{supp}(A \cup B) \div \text{supp}A$ . It's an estimate of the probability of observing B given A and it ranges between 0 and 1.

The *lift* of the rule  $A \Rightarrow B$  is defined as:  $\text{supp}(A \cup B) \div (\text{supp}A \times \text{supp}B)$ . It is the ratio of the observed support of the rule to that of the hypothetical support of A and B if A and B were independent. The closer to 1 the lift value is, the more independent the two terms are, and therefore the less interesting they are.

To create association rules, I used rapidminer. The process document operator was slightly changed in order to compute binary term occurrence and not relative term frequency. In the hope of finding interesting rules, I included a variable containing the corresponding journal for each abstract. This variable as well as all the terms were binomialized in order to be usable by the FP-Growth operator<sup>23</sup> generating frequent itemsets which are needed for the computation of the association rule.

### 3.2.5 Clustering

Clustering is a data mining technique used to explore data structure by regrouping similar items/documents together into clusters. It belongs to unsupervised learning techniques as it does not require labeling

<sup>23</sup>Documentation on this operator and the list of frequent itemsets are available here: [http://docs.rapidminer.com/studio/operators/modeling/associations/fp\\_growth.html](http://docs.rapidminer.com/studio/operators/modeling/associations/fp_growth.html)

of the data or preexisting knowledge or hypotheses about what is being searched for. Therefore with this technique I did not test any hypothesis, but explored the thematic structure of subgroups of economic abstracts after the crisis. The technique regroups the abstracts thematically and makes it possible to see the main areas of research.

A good clustering model is one for which distance within the cluster is small (documents being clustered together are very similar) but distance between clusters is high (each cluster should contain a kind of document completely different from that of the other clusters).

A distance function is central to the procedure as it is the only way to evaluate how similar documents are. The k-mean clustering algorithm I used relies on squared Euclidian distance. To use this distance function, all data need to be numerical and comparable (normalized). This is the case with the relative term frequency computed by rapidminer as explained in section 3.2.2.

To implement clustering on my text collection, I had to transform the  $20,216 \times 3522$  term-document matrix created after processing each document. The 3522 columns (one for each word having a frequency above 0.25%) were full of zeros since they were appearing in very few documents and applying clustering algorithms directly on this term-document matrix would not have produced optimal results. To reduce the number of dimensions of my matrix, I used a technique called *latent semantic indexing* which relies on the linear algebra matrix transformation technique called *singular value decomposition (SVD)*. This technique allows a dimension reduction of the term-document matrix in a provably optimal way (Feldman and Sanger, 2006). Proof and precise mathematical description of this technique can be found in Feldman and Sanger (2006, pp. 89-90). This technique overcomes both major problems of textual analysis: polysemy and synonymy by taking into account the context in which words are used.

Using this technique I was able to reduce my term-document matrix into a  $20,216 \times 80$  matrix. Columns no longer contained the term frequency of individual words, but rather the result of the singular value decomposition procedure. These new artificial dimensions cannot be interpreted for themselves since they contain the information of many unidentifiable word vectors. From this matrix I selected all the 10,108 abstracts dating from the 2009-2015 period and ran the clustering k-mean algorithm, setting the initial number of cluster seeds to 15.

The k-mean algorithm proceeds as follow<sup>24</sup>

1. **Initialization** : K number of cluster seeds are randomly created. Seeds are treated by the algorithm as initial centroids (which are a multidimensional cluster center).
2. **Assignment** : Each document is assigned to the closest cluster seed (according to Euclidian distance to the seed). This is computed based on their 80 SVD dimensions.
3. **Update the centroids** : Centroids are recomputed taking into account the position in the 80-dimensional space of the each newly-assigned document. This updating procedure led to the need to reassign some documents for which the new centroid moved further away than the next closest centroid from a different cluster .
4. **Reiterate** : Step 2 and 3 are reiterated until centroids are stable which means that no document will be reassigned to any new cluster.

One of the weaknesses of this algorithm is that the final cluster produced could be significantly affected by the initial random affection of seeds at the beginning of the process and the number of different clusters chosen. To be less dependent on the random choice of initial seeds, I used an improved version of the

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<sup>24</sup>For more information see rapidminer documentation available here: [http://docs.rapidminer.com/studio/operators/modeling/clustering/k\\_means.html](http://docs.rapidminer.com/studio/operators/modeling/clustering/k_means.html).

k-mean algorithm called ‘k-mean ++’ which was developed by David Arthur and Sergei Vassilvitskii and presented in their paper : [Arthur and Vassilvitskii \(2007\)](#). This could be implemented with rapidminer as an option in the k-mean algorithm.

To choose the right number of initial clusters I first used two performance measures of clustering models: the average within cluster distance as well as the Bouldin index ([Davies and Bouldin, 1979](#)). According to these two measures, 13 clusters seemed to be the best initial number of clusters to choose (Lowest Bouldin score for average within cluster difference of 0.003).

After each document was assigned to a cluster, my task was to understand what made documents from one cluster similar and what differentiated one cluster from the other. For this task, I read a small selection of documents for each cluster and tried simply to see whether I could detect a special thematic coherence. As I was struggling to find coherent patterns among abstracts from the same cluster, I chose to look at them quantitatively using almost the same procedure as described in subsection [3.1.3](#) and [3.1.4](#) but this time only on abstracts from the same cluster. To visualize the most compelling information about the document contained in a cluster, I collected for each cluster 3 pieces of information:

1. The top 3 most occurring words from the abstract collection of a cluster.
2. The 3 next most occurring word from the top 20 of the cluster which were not in the general top 25 of the entire abstract collection as seen in table [3](#).
3. The top 3 most occurring n-grams.

I have collected this different information as it reveals key different aspects of a cluster. The top 3 words reveal the most important words of the cluster. The next 3 most occurring words in the top 20 of the cluster but not in the top 25 of the general abstract collection reveal traits of the cluster which differentiate it from the general abstract collection, in other words ‘what makes it special’. The 3 top n-grams often allow disambiguation of the top 3 words and give much more conceptual clarity, giving an indication on how words should be interpreted. Using this technique on the 13 clusters helped me, but still a majority of clusters remained hard to classify. I chose to slightly increase the number of clusters to 15 and repeat the procedure to see if it would help make the clusters more distinguishable. Doing this helped a lot and as the results from table [2](#) show, this led to the creation of easily distinguishable clusters.

This reveals a well-studied weakness of the cluster Bouldin metric: the best measures do not assure the best information retrieval possibilities.

### 3.3 Qualitative Methodology

Some words are so hard to disambiguate and understand that looking at the evolution of their relative frequency carries little useful information. To test hypothesis [5](#) for example, it is necessary to differentiate when uncertainty is meant in a quantifiable way, as a parameter subject to human estimation or when it is carrying the meaning of ‘fundamental uncertainty’. This is necessary to validate my interpretation and make sure I was not blinded by a combination of number and wishful hypothesis testing.

To delve into this question, the most direct and simple way was to read a random selection of abstracts containing the word ‘uncertainty’ and try to understand and classify the usage of this word. This needs to be done since ‘uncertainty’ appears with the adjective ‘fundamental’ placed before it only once.

Here subjectivity plays a large role since the way I understand the definition given by [Dow \(2015\)](#) directly influences how I am going to classify the usage of the different words. Moreover without the time

spent reading each article, I could have misunderstood the usage of these words and how the authors truly meant them.

By looking at the term frequency evolution of words present in at least 50 different abstracts (0.25% pruning limit), I've excluded words from my analysis which could carry a lot of insight into economics because of their low frequency. Looking at what kind of words are absent or singularly rare could be useful as they say what is excluded from the mainstream, or what does not belong to it. The choice of less frequent words which should be considered important is more complicated, as they rely on more subjective representations.

Without carrying out a full comprehensive analysis of these words, I chose to make a case study of how the word 'capitalism' appears in only 15 abstracts of my 20,216 abstract dataset. This word is of special interest because of the social, reflexive and critical connotations it usually carries. It normally assumes power relations and individuals embedded in structures which are representations left out of mainstream economics ([Palermo, 2007](#)). I chose this word also because of its importance in heterodox economic approach like, for example marxist economics, post-keynesian or social economics. By looking at this word, I focus on a term outside the normal bounds of mainstream economics, which happens to appear within few mainstream journals. My goal through the usage of this word is to analyze the place left for heterodox views within the mainstream.

## 4 Results

### 4.1 Term Occurrences Analysis

This section shows the most basic form of analysis that I used: the analysis of the term occurrence variation. Thanks to this technique, I evaluated the change in term occurrence on two parts of the data. The first part was made of abstracts coming from the period 2009 and after, which I name ‘Post2008’ and the second part was made of abstract published between 2000 and 2009, which I named ‘Pre2008’

Table 3 in Appendix B shows the first 40 most frequent words in economics abstracts. I chose to analyze first the most frequent words as they represent the very core of the economics profession and to test hypothesis 3 I had to focus on the core of the discipline. Results in table 3 show that most changes of stems carrying thematic meaning<sup>25</sup> are relatively small, generally below 20%. Only two word stems show an increase greater than 40%: *financi* and *risk* with 45% and 41.2% increase respectively. Given the already exceptionally high frequency of these words, these changes are to be considered as important shifts in the core of mainstream economics.

A group of state-related word stems (tax, state, countri, growth, polici) are declining in importance. Although relatively mild, this decline shows a compelling trend in economics: nation-states and what is theirs (taxation, policies and growth) are becoming less and less relevant. This could be explained first by the overall globalization of the world economies: this globalization and the increased interconnectedness are relegating the role of the State in the economies to a secondary one. On the increased focus on global problems and themes, the full word list table<sup>26</sup> reveals that the stem ‘global’ appeared 384 times before 2009 and 680 times from 2009 onward. A second explanation could be the diminishing status of macroeconomics due to the greater interest among economists for the less ideologically oriented and more evolving world of microeconomics, where most of the cutting-edge research has been accomplished during the past two decades<sup>27</sup>. To mirror this decline in nation-state themes, the sizable increase of the 5th most frequent word stem ‘firm’ (+ 24.1% from 4565 occurrences before 2009 to 5665 after 2008) is worth noting. Some less frequent words tend to show as well the rise of micro analysis like: ‘micro’ (+ 39.2% from 125 to 174) ‘micro data’<sup>28</sup> (+ 45.6% from 57 to 83 ) ‘micro level’ (+173.3% from 15 to 41) ‘microstructure’ (+39% from 38 to 53). Contradicting this idea is the fall in occurrence of the word ‘microeconomics’ which fell from 73 to 61 occurrences (-16.4%), the fact that the word stem ‘macro’ experienced a + 64% increase (from 84 to 138) and that the word macroeconomics saw almost no decline (from 519 to 510).

This example illustrates the limit of text mining techniques as it can reveal interesting patterns and trends in a document collection but it does not provide means to prove the underlying causes behind these phenomena. Using such a technique, I had to pay special attention to my possible cognitive bias since on such a large collection of words (3522) it is easy to look for the words reinforcing my hypotheses and not for the ones which would lead to its rejection. There is no perfect recipe against such cognitive bias. One security though, when exploring data like mines, is to systematically try to find what in the data could contradict the hypotheses I am testing with the wish to prove it. In this case again, cognitive bias could arise quickly as one can easily turn a blind eye, by being stricter and more rigorous as to what represents a valid contradiction of my hypothesis. This problem arises in all sciences, but is particularly

<sup>25</sup>Words unlike ‘suggest’, ‘find’, ‘show’ or ‘find’ which say something about the evolving style of abstract but not conceptual evolution

<sup>26</sup>The word list table is available upon request at [h.roquet@gmail.com](mailto:h.roquet@gmail.com)

<sup>27</sup>On this topic see the article “A golden age of micro” published in The Economist on the 19th of October 2012 and accessible online here: <http://www.economist.com/blogs/freeexchange/2012/10/microeconomics>

<sup>28</sup>the occurrences of the alternative spelling ‘microdata’ were added manually to the occurrences of ‘micro data’ as rapidminer created two stems for this one concept

salient when using data mining tools - or text mining tools - which by definition provide the researcher a huge amount of information to analyze among which she/he will be free to choose from.

Table 4 in Appendix B, shows the words whose term occurrence changed the most between the two periods. I've highlighted the 14 stems related to finance or the crisis, which are present in this table. All these words have a high rank (above 1000 except for one), which means that they are occurring relatively rarely. The fact that the top 4 words which increased the most in occurrences are all related to the crisis completes the first findings of table 3 where it was found that among the most frequent words, *financi* is the stem which experienced the biggest increase. In table 4, I find that the biggest increases overall are as well connected to the crisis. Together these results show that the global financial crisis seem to be what caused the most disruption in mainstream economics during the last 15 years. To confirm this finding, a graph of the yearly evolution of some of these terms experiencing a strong increase after the crisis is presented in figure 7 in section 4.2.

Table 4 reveals as well a few methods gaining influence in economics like the Dynamic Stochastic General Equilibrium or 'DSGE' +292.3% (from 26 to 102) between the two periods. The stem 'field experi' experienced a rise of +529.2% (from 24 to 151) and the stem 'regress discontinu' experienced a +378.9% rise (from 19 to 103). Given that all of these methods are strongly grounded on mathematical techniques, this result constitutes an element in favor of hypothesis 6. The rise of the occurrence of DSGE contradicts hypothesis 4. Even though Colander (2010) singled out the over-reliance of such models as being problematic for not taking into account enough complexity, economists are more and more relying on them. However, complexity does seem to make its way with the fact that firms are modeled more and more as heterogeneous ('heterogen firm' +250%).

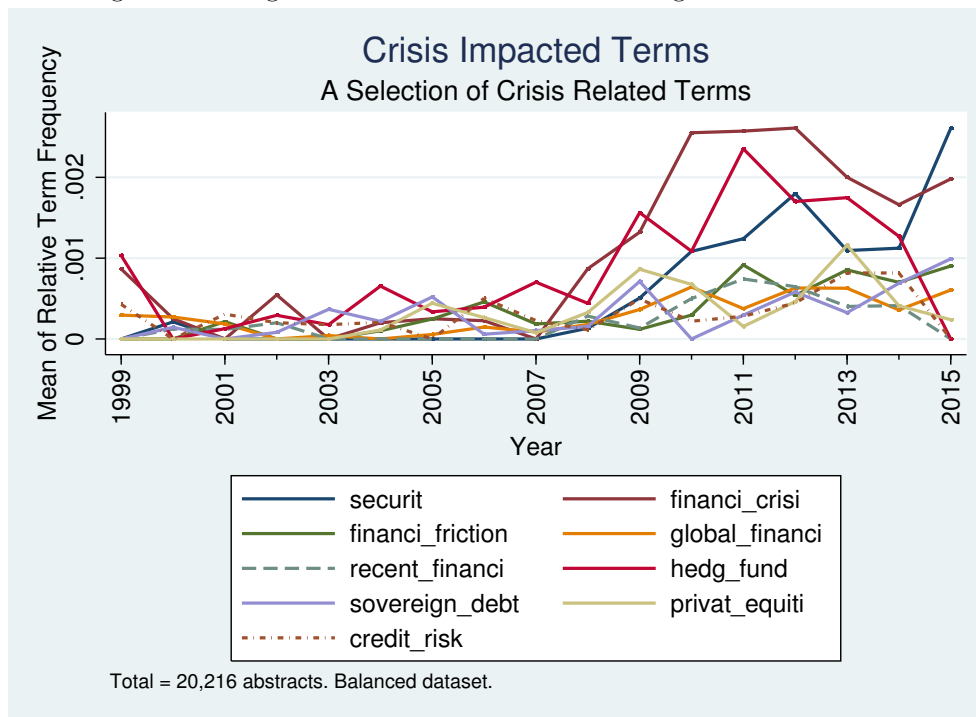
Looking at the stems which experienced some of the sharpest drops in frequency in table 5, I've noticed two meaningful categories. Words related to imperfect competition or market failure ('antitrust', 'monopoli', 'olligopoli', 'collus') and words with a social dimension ('socioecon', 'happi', 'leisur', 'altruist', 'social secur', 'life expect'). I interpret these findings in next section as they reappear with a similar but more precise methodology together with the drop of occurrence for 'britain' and 'japanes' visible in the table.

## 4.2 Relative Term Frequency Evolution

Figure 7 shows that some obviously crisis-related topics terms started to be more in use in abstracts after 2008. I chose these terms to test my methodology on words which *had to* increase. For instance, the absence of any change in the word stem 'financi crisi' would have discredited my methodology. The words I selected were all connected to finance and these results corroborate what was already found with the strong rise in the occurrence of the stem 'financi' in the post2008 period (+45%). Indeed, finance-related topics are becoming more and more the subject of academic research. Their timely evolution between 2008 and 2009 also shows the lag after which the financial crisis began to be discussed in mainstream journals and is the main reason why I chose January 1st of 2009 to divide my dataset between before and after the crisis groups. The relatively low frequency of these words make them subject to higher variation but this graph shows clearly that even at low frequencies changes are observable.

To test hypothesis 3 in a more precise way than simply looking at the difference in term occurrence of the 40 most frequent words between the two periods, I looked at the yearly evolution of the mean of

Figure 7: Strong After Crisis Evolution of the Usage of Selected Words



Notes: N=20,216 abstracts coming from 16 Journals and NBER. The mean of the relative term frequency is calculated per year

the relative term frequency of 13 of the most frequent stem in economics (all of them in the top 25 most present stem). I consider these words to reflect the very center of the profession in term of topics and methods. I did not include in the graph the terms: ‘find’ ‘paper’ ‘show’ and ‘rate’ which I considered carrying too little information on economics itself.

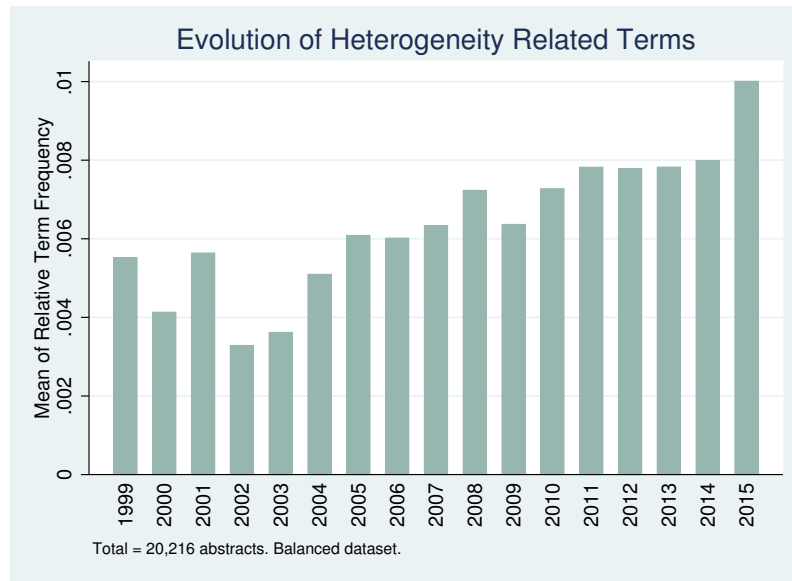
Figure 8 shows results which support hypothesis 3, since most of the lines show no clear trend. Only the word ‘risk’ has an upward trend, which seems to have been reinforced by the crisis given its observable strongest rise between 2008 and 2009. This particular small increase in the relative word frequency of this widely-used word supports hypothesis 5 but incompletely since, to be fully controlled, one would also need to look at the evolution of ‘fundamental uncertainty’ (Dow, 2015) and make sure ‘risk’ is mostly used in a way which supposes it is quantifiable. To test this I had to use a more qualitative methodology and read a selection of abstracts containing these words. I present the results of the more qualitative methodology in section 4.6.

The considerable variation observable in the word stem ‘model’ are somewhat surprising since this stem is the most frequent one and from this high frequency I expected more constancy (as the random variation in the mean of the relative term frequency should be decreasing with the number of times the word is appearing). For the overall period, no trend is detectable for ‘model,’ but a sharp drop in its frequency can be observed between 2008 and 2009. The drop is hard to interpret as we observe a strong rise of the frequency of ‘model’ in 2010 already. Given the publication lag and the deepening of the crisis in 2009 it is unlikely that its effects in academia was already over by 2010. Because of this, I cannot interpret the fluctuation of the stem ‘model’ as coming from the financial crisis.

The fact that the word ‘model’ has a relative frequency clearly above any other words from the economic profession during the entire period studied is in itself revealing of the way economic research is

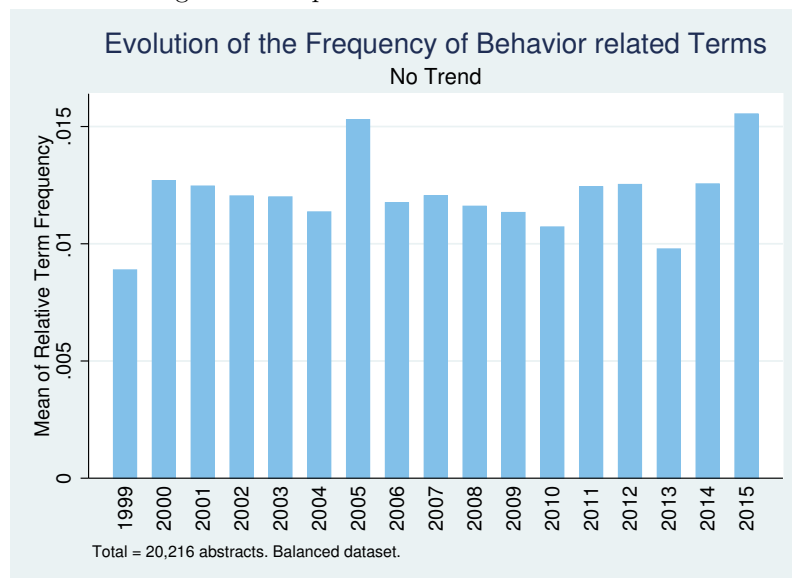


Figure 9: Heterogeneity making its way



Note: With the stem "heterogen" multiple words and N-grams are included like: heterogeneity, heterogeneous, heterogeneous-firms, model-heterogeneous, unobserved-heterogeneity

Figure 10: Impact on Behavioral Economics



Note: Due to a failing of the porter algorithm to detect the similar root between the british English and the american spelling of the word (behaviour and behavior) I've added manually their frequency to the stem "behav" in order to find the true frequency of the stem "behav"

Figure 11: Dynamic Stochastic General Equilibrium

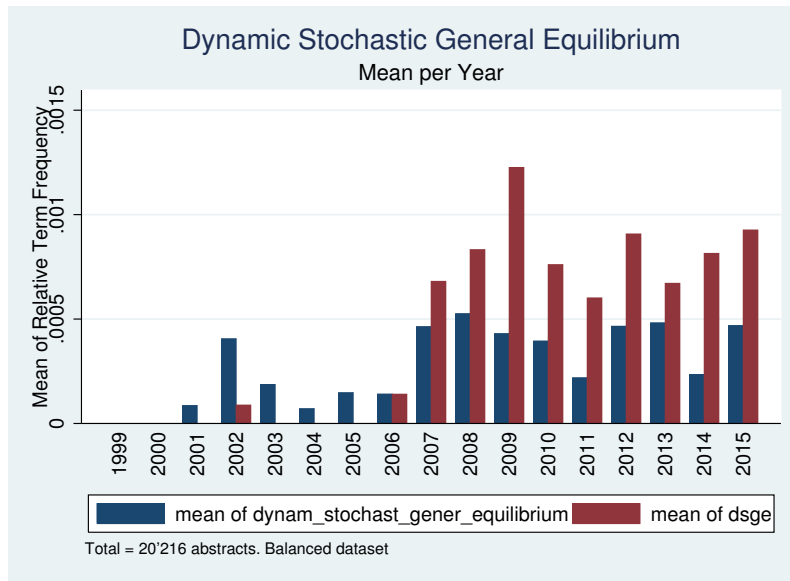
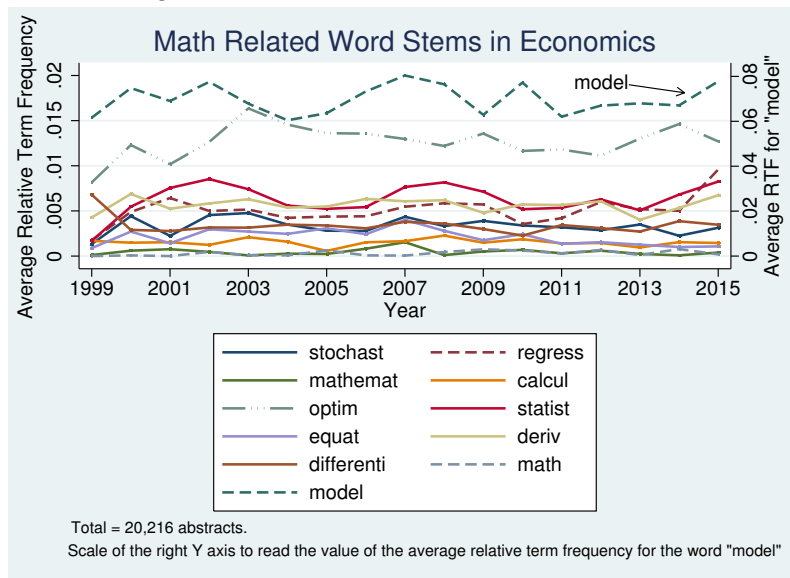


Figure 12: The influence of math in Economics

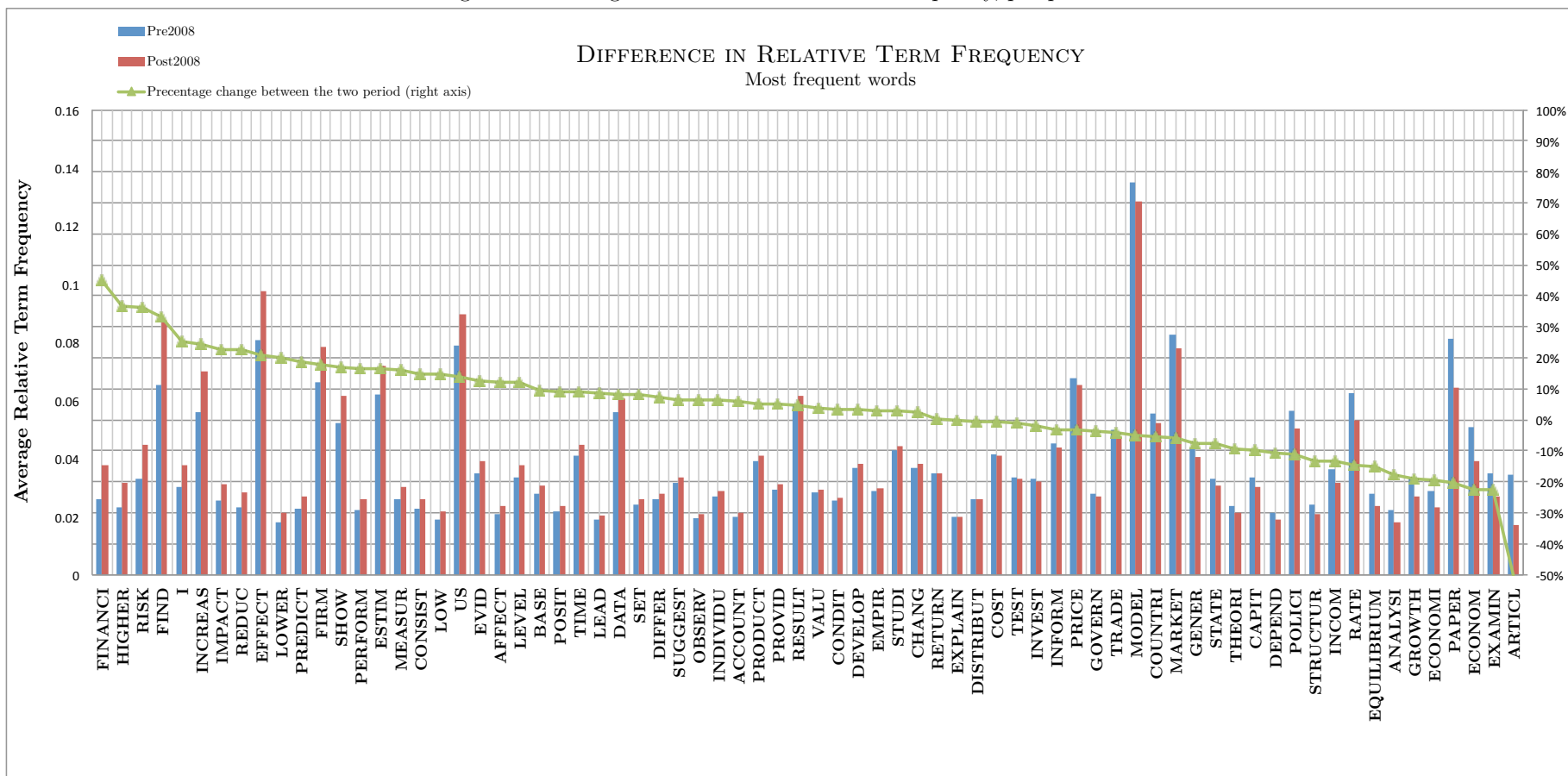


added the stem ‘math’ which was not included in their selection. The graph I made strongly confirm the findings of [Bigo and Negru \(2014\)](#). Indeed mathematical modeling did not experience any significant change after the crisis as seen in figure 12. This reveals a key constancy in one of the most important methodological aspects of modern economics and could also be considered as data supporting hypothesis 3.

On hypothesis 3, figure 13 is the most telling one as it made visible that, for the 72 most frequent words in economics, changes in relative frequency stay within a  $\pm 20\%$  range. The only exception to this are the word ‘risk’ and ‘financi’ which were already analyzed in section 4.1 and some words carrying no

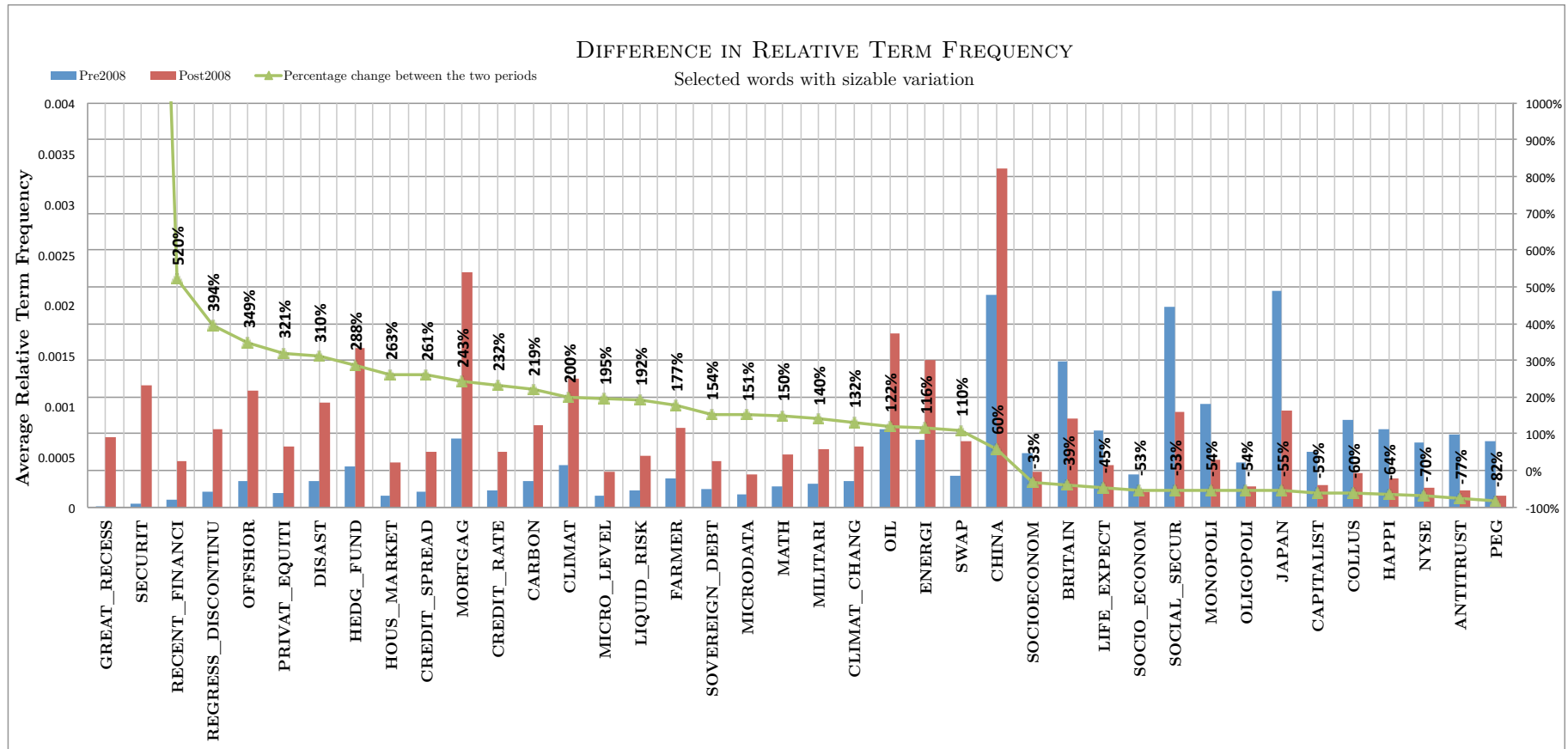
economic meaning like ‘higher’ ‘article’ ‘examin’ and ‘find’. If the crisis had impacted in a major way the core of mainstream economics we would have observed more variation in figure 13. This clearly supports hypothesis 3 with the exception of the greater role that finance and risk are taking in the core of the mainstream economics since the crisis.

Figure 13: Average value of the relative term frequency, per period.



N=20,216 Abstracts. Balanced dataset. Sorted by descending order of change. Stemmed with Porter Algorithm. The graph shows all the stems present at least once in more than 1900 documents.

Figure 14: Biggest Difference in Relative Term Frequency



N=20,216 abstracts. Balanced dataset. Stemmed with Porter Algorithm. The graph shows only a selection of stems present in more than 0.25% of abstracts. The bar charts shows the actual average value of the relative term frequency per period, the value should be read on the left y axis. The green line shows the percentage change between the 2 periods, its value should be read on the right y axis. Selection of stems was partly based in table 4. The two word stems on the very left have experienced such a rise in frequency that their percentage increase were not suitable for the already broad right scale I had chosen. ‘Great Recession’ experienced a 8237% increase in its relative term frequency (this is comparable with the 7900% increase in term occurrence visible in table 4. The word stem ‘securit’ (which is the stem for ‘securitization’) experienced as well a particularly dramatic increase of 3379%. I’ve manually added the average frequency of ‘chines’ to China’s stem, ‘british’ to Britain’s stem and ‘japanes’ to Japan’s stem in order to better reflect how often subjects or data related to these country are subject to economic research.

Figure 14 shows variation in the mean of relative term frequency just as figure 13 does. The only difference is the smaller left y-axis scale chosen to better reflect the changes occurring at lower frequency and the bigger right y-axis scale chosen to display higher percentage change. This graph shows a selection of words which experienced a strong variation in the mean of their relative term frequency over the two periods. By strong I considered here rises above 100% and drops below -30%. The only exception is China whose 60% rise in frequency is worth comparing to the drop in frequency of ‘Japan’ and ‘Britain’. This observation shows a shift in focus worth noting but foreseeable. As China economic role in the world rises with its GDP growth, more economists are carrying out research on it. Potential explanations for the fall of research being linked with Japan or Britain goes from the sluggish (viewed less interesting) Japanese economy to the loss of influence of British researchers. These are speculations I propose to the reader’s thoughts.

This figure shows where the major changes in mainstream economics are occurring. The fact that these words are occurring on average at an average frequency 60 times<sup>29</sup> lower than the average frequency of the words presented in figure 13 shows how secondary these words are. The left axis reveals this information more precisely. I cannot use this graph to reject hypothesis 3 since the changes present in figure 14 are not at the core of the economic discipline; they are secondary. However, this graph supports well the idea that economics is a dynamic ever evolving entity as presented by Colander et al. (2004).

The figure shows a remarkably high proportion of finance-related terms<sup>30</sup> among the words which experienced a sharp rise. This tends to show that since the crisis happened, economists are focusing more and more on finance-related domains some of which strongly connected with the global financial crisis (mortgag, hous market, securit, swap for example). However, two terms which could be associated to finance are also undergoing a strong decline (‘PEG’ and ‘NYSE’). Both are acronyms ‘PEG’ stands for the *price/earnings to growth ratio* and is a financial indicator of the quality of a stock and ‘NYSE’ is the acronym for the New York Stock Exchange. The fall in frequency for PEG is probably not related to the crisis but more to the complexification of finance which led to the fall of relevance of this ratio as increasingly new complex financial products are *engineered* and more complex indicators to understand them are used. The fall in frequency of ‘NYSE’ could also be easily explained by the globalization of finance which lead the NYSE - which was once the center of world finance - to lose its importance. These are pure conjectures from my part and should not be taken as proven by my data. Again, text mining does not allow to prove causation but reveals pattern in the data that are revealing some phenomenon. Further deeper research should be done to really prove such links.

Figure 14 reveals as well the increasing focus on climate change themes: climate (+ 200%) and carbon (+219%). Their is no direct reason that these words would be impacted by the financial crisis and looking at their yearly evolution revealed that, indeed there was a preexisting upward trend as could be seen in table 26 in Appendix H. This upward trend could be explained by the strengthening media attention to the topic and the ongoing global warming problem. A parallel could be drawn with the increased focus on energy and oil also visible in the figure.

The figure reveals as well a drop in the frequency of “society-oriented” words which are: ‘socioeconomic’ ‘social security’ ‘life expectancy’ ‘happi’. It could be interpreted as a trend away from topics which are not typically subject to economics inquiry but more within the competence of sociology, psychology or political science. If this is true, the science of economics is closing itself to more interdisciplinary research within the realm of other social sciences. To really support this claim, a thorough analysis of these terms

<sup>29</sup>The average relative frequency for all the words in figure 13 is: 0.03926 while the average frequency for the words in figure 14 is 0.00065

<sup>30</sup>I consider the following word stems are related to finance: great recess, securit, recent financi, privat equiti, hedg fund hous market, credit spread, mortgag, credit rate , liquid risk, sovereign debt, swap

would be required. The text mining methodology I'm using - again - do not allow to clarify this points but reveals an intriguing pattern about economics which would be worth delving into. The presence of research trend could also explain such phenomenon but a longer historical research would be necessary to see whether researchers' focus follows a cyclical trend.

Another compelling finding not related to any hypothesis is the drop in frequency of words related to "imperfect competition". I mean by that 'collus', 'monopoly', 'oligopoly' and 'antitrust'. My intuition is that oligopoly, monopoly and collusion have been modeled and studied in such a thorough manner that researchers are moving away from these topics where new genuine findings are hard to produce.

What figure 14 reveals is that most of the major changes in frequency which happened between the two periods are probably linked to the crisis but that these changes are occurring at low frequency. This is both troubling and reassuring. On the one hand, given the fact that the global financial crisis and the recession which followed are clearly the major economic events since the oil shock of 1973 (or the great depression) I am reassured to see that it's the most important factor of change in the economic profession. Economics is not completely disconnected from reality (as some are arguing) and is reacting to major real economic problems. On the other hand, the changes which are happening are not making it to the most frequent words, which means they are happening at the periphery of mainstream economics. This is no sign for a paradigm shift and a scientific revolution but rather a sign of a normal science evolving slowly and trying to make sense out of 'new' finance-related problems.

### 4.3 Variance of the Vocabulary in Abstracts

I try to test hypothesis 1, which stated that the variance of acceptable idea within mainstream economics is increasing. The most basic approach to test this hypothesis is to look at the evolution of lexical diversity of the vocabulary used in abstracts with the methodology presented in section 3.2.3.

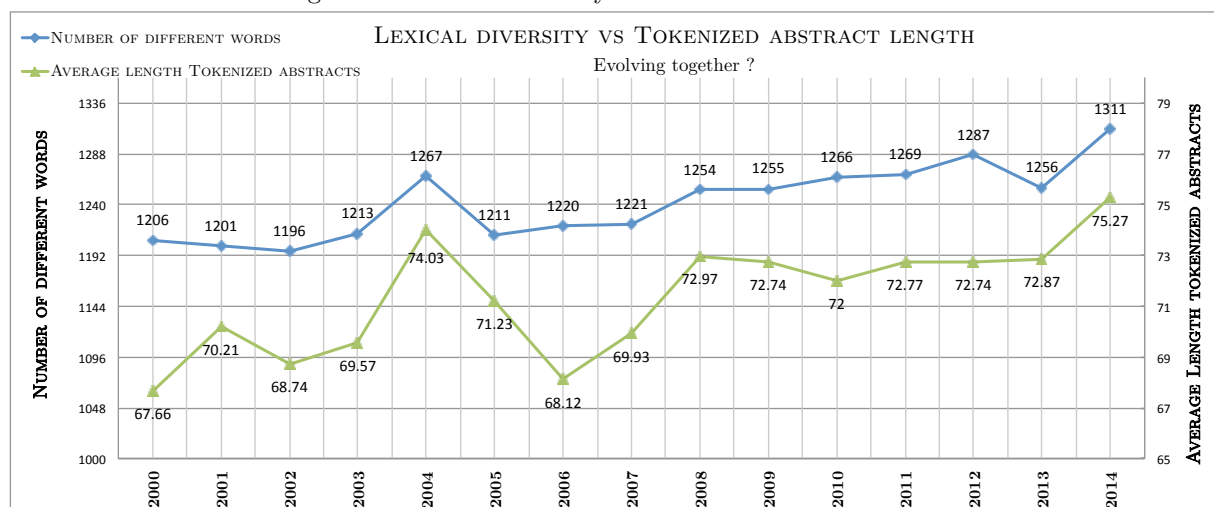
To check the robustness of my preliminary results showing a higher number of stemmed words used in the abstracts after 2008 (3695 words for 2009-2015 and 3511 for 1999-2008), I conducted a t-test on the similarity of the mean for the tokenized abstracts' length for the two periods. The result of the test, visible in Appendix D show that abstracts from the 2009-2015 period are significantly (but slightly) longer than the ones for the preceding period. This constitutes a problem for my analysis of the evolution of lexical diversity since this measure is impacted by the total text corpus length, which varies with the average tokenized abstract length.

To look more precisely at how these phenomenon are linked, I choose to analyze the evolution of the tokenized abstract length per year and plot it against the evolution of the NDW per year (methodology described in section 3.2.3) A graphical representation of the results can be seen in figure 15. This figure shows that from 2008 to 2012 the lexical diversity - measured by NDW - increased while the average length of tokenized abstracts stayed almost constant (except for the small drop in 2012). This tends to confirm hypothesis 1 but for the remaining part of the graph, where the average length of tokenized abstracts is evolving, the interpretation becomes more complicated. For instance, looking at the peak of 2004, the question which should be asked is: what is the expected rise in lexical diversity that we await when the average abstract length rises - from 69.57 in 2003 to 74.03 in 2004 - for 1019 abstracts and how does it compare with the empirical measured rise in lexical diversity from 1213 to 1267 ? Knowing the exact number of abstracts per year (1019) one can easily reconstruct the absolute number of additional words present in 2004:  $1019 \times (74.03 - 69.57) \cong 4545$  additional words, but to compute the expected rise in lexical diversity that such an additional number of words should cause is much more complicated

as it necessitates knowledge on the probability of appearance of each word and their probability to be different from the first 1213 words already appearing in more than one percent of the abstracts from 2004. Without this information I am left to interpret what the graph is showing in a rough way.

When the trends of the two lines are different (one going up and the other going down and vice versa) one can already interpret the trend in lexical diversity as not being decided by the rise or fall of abstract length. This happens after 2000, 2005, 2010, 2011 and 2012. Moreover when the tokenized abstract length is almost not evolving (as between 2008 and 2012) the evolution of the lexical diversity could be interpreted for itself and, as we observe it, it turns out to be a small but steady rise for this period. This goes well with hypothesis 1 but does not prove it since this increase in lexical diversity could be explained by many different factors.

Figure 15: Lexical Diversity and Tokenized Abstract size



Total =15,285 abstracts. 1019 abstracts for each year. Y axes were rescaled in order to better show the variation of both variable. Only the words appearing in more than 10 different documents per year were included in the word count (pruning at 1%)

If Colander et al. (2004) are right, this increase in variance comes from the opening up of mainstream economics to more and more concepts and ideas from the edge of the profession. The problem is the limitations of my methodology which does not enabled me to check this causation link. I cannot therefore reject alternative possible explanations which could cause this increase in lexical diversity. It would have been necessary to control for possible editorial policy changes toward higher English requirement during the same period which would have pushed toward a vocabulary diversification/higher lexical diversity.

Another factor which might have played a role is the origins and publication rate of non-native speakers. Non-native speakers use a noticeably different vocabulary (as you have probably noticed reading this thesis) and although their personal English lexical diversity (the number of different of words they use in English) is likely to be lower than the lexical diversity of a native English-speaker, they might be using uncommon English words with a far higher frequency than an average native English speaker would have, or simply different words. Given the rising supremacy of the English language in academia around the world and most specifically in research, more and more researchers whose first language is not English are trying to publish in English. This could have pushed the lexical diversity up (or down).

To analyze this problem more precisely, I chose to study the lexical diversity per abstract and not for the overall corpus. For this matter, I worked with the ‘word bag’ that rapidminer created after processing

each document. This word bag is simply the abstract stripped of all punctuation marks, numbers and stop words. No n-grams were produced for this stage of the analysis as they represent noise when abstracts are not pruned. The additional step I had to go through was to eliminate tokens which were appearing more than once in each ‘word bag’. I did it with an excel function and this led to the creation of a variable containing all different words that each abstract contains. Graphing the mean of the number of different words per abstract - the token diversity - shows a tiny upward trend as could be seen in Appendix E. To refine my analysis and to check whether lexical diversity evolves differently depending on the journal, the same measure was computed for each journal. Appendix F shows this somewhat crowded results.

When comparing the token diversity evolution to the simple abstract length (not tokenized, not filtered) evolution, one sees, as expected, that they follow each other very closely. The Spearman correlation coefficient for these two variables is 0.9002 (calculated on the 20,216 abstracts balanced dataset) and confirms the strong link between the two variables. The first thing to note in the figure in Appendix F is the fact that trends and levels differ by journal. The remaining problem though is the impossibility to say whether the changes in trends come from the increased abstract length or from a true increasing concept diversity within abstracts.

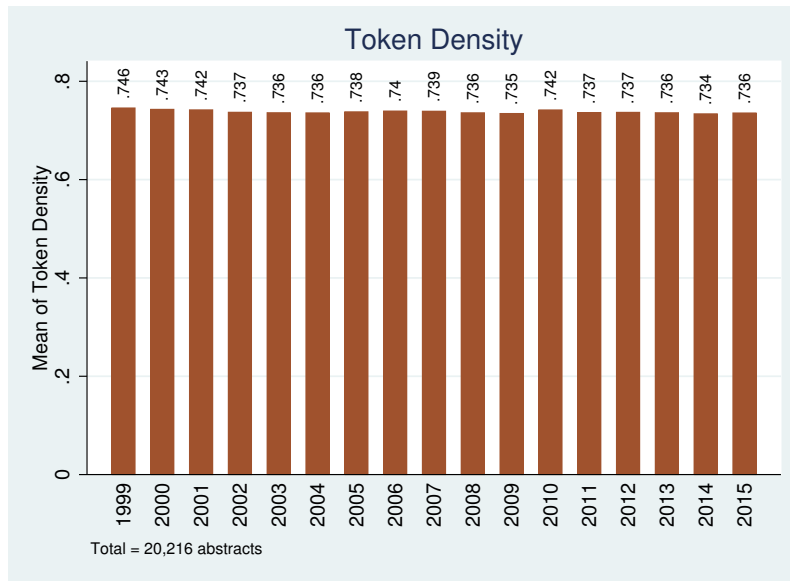
Facing this strong link I normalized the number of different tokens found in every abstract by the abstract length in order to analyze the evolution of the normalized token diversity. I’ve called the result of this normalization ‘token density’ as it simply represents how frequent different tokens are in an abstract and represent therefore the conceptual density present in abstracts. The closer to 1 is ‘token density’ the more dense is the abstract<sup>31</sup>. Averaging the token density per year for the entire dataset, one can see no trend at all. This statistic is remarkably stable and almost perfectly flat as seen in figure 16. This tends to confirm that no major changes happened in individual abstract style as authors are still presenting the same amount of information (relative to abstract size). This allows us to exclude the possibility that the overall increase in lexical diversity, as presented in figure 15, comes from a change in the density of how abstracts are written.

However, I cannot exclude alternative explanations - like the increased presence of non-native English authors - for the slight rise of lexical diversity observed. To conclude on hypothesis 1, I could only say that my data weakly support it for the period after the crisis only and that the change of lexical diversity observed after 2008 is truly mild.

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<sup>31</sup>But a score of one is impossible to reach since it would mean an abstract full of exclusively different key words, without stop-words (connector, determinants etc., which were filtered out during the processing of the abstracts). I did not normalize by the number of filtered token, because I considered the frequency of stop words as relevant to the measurement of ‘token density’

Figure 16: Token Density

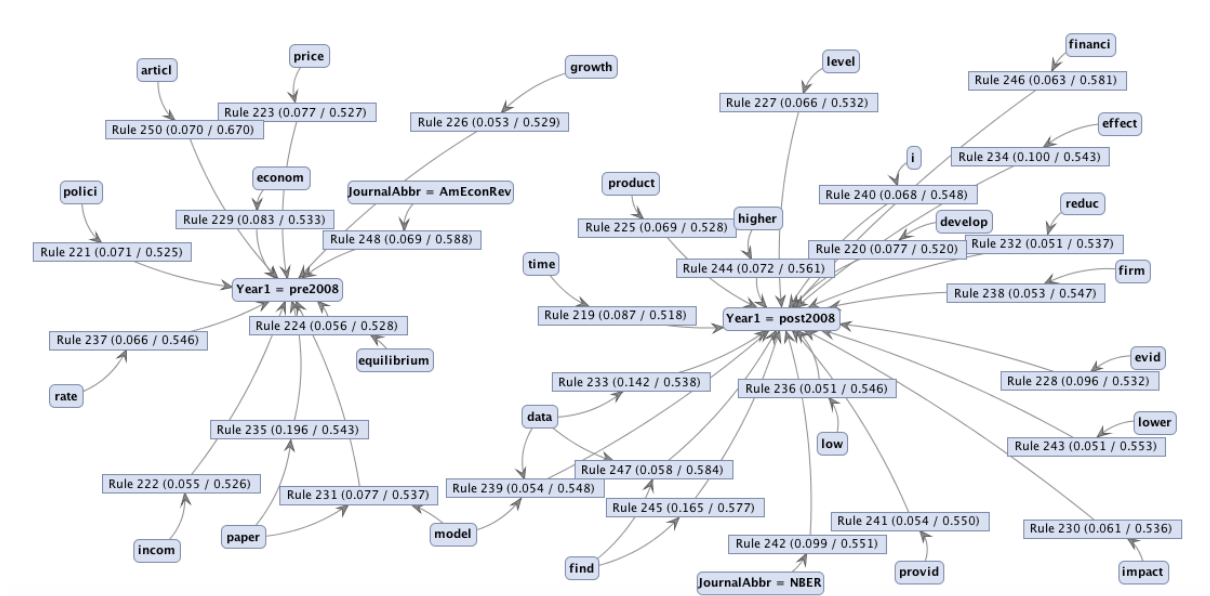


Note: Token density is the number of different tokens present in an abstract divided by the total length of the abstract, including stop words.

#### 4.4 Association Rules and Word Co-occurrence

I used the technique of association rule first to look which words were most associated with the two periods (pre/post crisis). The graphical result of this procedure can be seen in figure 17. To make the comparison of rules associated with the two periods easier, I used the balanced dataset.

Figure 17: Association Rule



Note: Total = 20,216 Abstracts. The first number of a rule is the support, the second number represent the confidence. Balanced dataset. Stemmed with Porter Algorithm. Minimum support for the creation of association rules = 0.005, Minimum confidence = 0.1.

Figure 17 displays clearly the weakness of the association rules found. Except for the rule *articl*  $\Rightarrow$  *pre2008* which has a confidence of 0.67 (and a support of 0.077), all the other rules have a confidence between 0.5 and 0.6. Given the fact that the conclusions (the two periods) are already related to 50% of the abstract each due to the balancing procedure, only confidence level well above 0.5 are worth analyzing. The fact that figure 17 shows very few examples of such rules is a sign that the word usage did not evolve much between the two periods. This finding represents another evidence in support of hypothesis 3.

Many different kinds of findings arise from this graph. The rule *equilibrium*  $\Rightarrow$  *pre2008* confirms part of hypothesis 2 based on Colander et al. (2004), for whom equilibrium, rationality and selfishness is losing ground; since the rule shows that equilibrium is slightly more related to the pre2008 period than the post2008 period. The confidence of this rule being only 0.528, this represents a weak evidence that ‘equilibrium’ is a notion losing ground in economics. This weakness shows that the pace of change is particularly slow.

The other findings are not related to my hypothesis but still worth noting. For example the rules *articl*  $\Rightarrow$  *pre2008* and *paper*  $\Rightarrow$  *pre2008* show a stylistic evolution in abstracts. ‘Article’ was more used before 2009 than after (confidence 0.67), this could be partially explained by the fact that this word is being increasingly replaced by the word ‘paper’. The low support of ‘articl’(0.07) compared to the high support of ‘paper’ (0.196) shows that this replacement has already largely taken place. But the fact that the word ‘paper’ itself is more associated with the pre2008 period shows as well that abstracts from the post2008 period contain less and less direct reference to the ‘paper’ they are summarizing. It might come from the fact that more and more researchers are considering useless to mention ‘this paper’ (or ‘this article’) at the beginning of their abstract.

Stems associated to results and empirics like ‘evid’, ‘effect’, ‘find’, ‘impact’, ‘data’ are all more associated with the post2008 period. I interpret these findings as rise in the straightforwardness of abstract, where results and what they are based on (the evidence, the data) are expected to appear. The parallel interpretation is that there are even less and less purely theoretical or reflexive abstracts, which are based on no data, have no evidence or show no result. As such, it could also represent a move to confront model more directly to data.

The fact that the *American Economic Review* (AmEconRev) is more associated with the pre2008 period (with a confidence of 0.588) could be simply explained by the fact that most of the abstracts I collected from this review are from the pre2008 period. This can be explained by the fact that I failed to collect abstract from 2013 to 2015 from this review<sup>32</sup>.

The rule *NBER*  $\Rightarrow$  *post2008* could be easily explained with a similar fact : the NBER working paper publication rate increased the last 15 years<sup>33</sup>. Strengthening this phenomena in my dataset is the fact that no article was collected from the *American Economic Review* between 2013-2015; this led to a increase in the prevalence of NBER abstracts since NBER abstracts which would have been otherwise deleted from the dataset - the ones about studies which were also published as an article in the *American Economic Review* - remained in my dataset for this period.

The rule *financi*  $\Rightarrow$  *post2008* with a confidence of 0.581 is the second strongest rule for the post2008 period after *data, model*  $\Rightarrow$  *post2008*. This finding confirms what was already found with term occurrence analysis of section 4.1: the strongest sizeable change in mainstream economics after the crisis is its shift toward more and more finance-related topics.

<sup>32</sup>I realized this problem very late in the analysis and was therefore not able to correct the dataset. The origin of this problem lies probably in a mistake during dataset manipulation as I was constructing the dataset. It should not have affected significantly any of the result given the size of the remaining abstract collection

<sup>33</sup>This increased yearly rate is clearly observable in the dataset by simply plotting the number of abstract collected per year for NBER

With association rule I was able to study the co-occurrences linked to a particular word. This technique simply reveals which words are co-occurring together in an abstract and what is the quality of this co-occurrence. Given the binominalization applied on the journal variable and on the period variable I was able to find rules taking these two variables into account. Table 1 shows a selection of rules. Association rule is more an exploratory tool than a scientific tool proving causation. My interpretation of these rules should be seen as an educated guess pointing toward a possibly interesting pattern.

Rule one reveals how strongly Monte-Carlo methods together with the stem ‘model’ are associated with the *Journal of Econometrics*. The support of the rule shows that this rule is present in approximately 1% of the abstracts. The confidence shows the probability of observing the conclusion ‘journal of econometrics’, ‘carlo’ given that the abstract contains ‘model’ and ‘mont’: it is 82% which reveals how strongly the journal of econometrics is using monte-carlo methods. The singularly high lift confirms that the premise and the conclusion are very far from being independent (a lift value of one shows independence). This kind of information reveals a strong methodological specialization of a journal and would represent a valuable hindsight if I were to develop my analysis further by studying more precisely mainstream journal characteristics.

Rule 2 shows how rationality-related words are co-occurring with the stem behavior. The numbers can be understood as for Rule one but the interpretation is more complex. Together with Rule 3 these rules could be showing how behavioral economics is challenging the rationality assumption and this often with experimental methods. But this should be further researched as the data are too laconic to fully support this interpretation. Behavior could as well have been used in a non-critical way, simply stating the rational behaviors of agents in abstracts. Lift of rule 3 shows the existing link between experiment-related methods and behavior. This confirms a particular trait of behavioral economics which relies more on experimentation than traditional economics.

Rule 4 shows a dependency between ‘heterogen’ and ‘individu’. This could be a sign of the complexification of economic models which are no longer assuming homogeneous rational individual. Confirming this is the absence of any rule with the stem ‘homogen’. Problem with this interpretation is the level of co-occurrence used to build my association rules. Since co-occurrence in entire abstracts are represented, it could well be that the stem ‘heterogen’ does not refer to ‘individu’ but some other words in the abstract which happen to contain a full form of the ‘individu’ stem.

Rule 5 shows what growth is strongly associated with. The low confidence level comes probably from the fact that ‘growth’ is a current word in economic abstracts. Therefore the probability of observing ‘model’ ‘technolog’ given that ‘growth’ is present in an abstract is low. The lift value of 2.77 confirms however that these words are dependent and that a common practice in economics is to model growth together with technology. Since in many macroeconomic models technological growth (and behind it innovation) is at the root of economic growth, it is not a surprising result.

Rule 6 confirms that the global thematic and finance gained influence in mainstream economics after the crisis.

The confidence of Rule 7 shows that when ‘model’ and ‘polici’ are appearing together, the topic is likely at 9% to be related to monetary questions and optimum. The lift shows a high dependence, revealing probably the strength of the practice of modeling monetary policy problems and looking at the optimal policy at the same time. Again, this rule is a hint toward such an interpretation but does not prove it.

Rule 8 reveals something obvious: tax is strongly associated with government and income.

Support of Rule 9 shows the proportion of abstract containing the rich/poor opposition. The meaning

of this co-occurrence remains ambiguous since both words are often used as adjective not at all related to socio-economic conditions (rich data, poor results etc...).

Rule 10 reveals the importance of taxation-related topics in the *Journal of Public Economics*. There is a 10 percent chance to observe a abstract containing the word ‘taxation’ (only word for the stem ‘taxat’).

Table 1: Selected co-occurrences

Rule #	Premise	Conclusion	Support	Confidence	Lift
1	model, mont	JoEcmetri, carlo	0.0098	0.82	41.95
2	ration	behavior	0.0060	0.19	2.43
3	experiment	behavior	0.0052	0.23	2.87
4	heterogen	individu	0.0054	0.16	2.33
5	growth	model, technolog	0.0053	0.05	2.77
6	global	Year1 = post2008, financi	0.0070	0.21	3.34
7	model, polici	optim, monetari	0.0051	0.09	9.91
8	tax	incom, govern	0.0053	0.08	7.00
9	rich	poor	0.0066	0.34	9.61
10	JoPubEcon	taxat	0.0067	0.10	5.65

Association rules created on the binominalized term document matrix to which the period variable ‘Year1’ was added as well as a binominalized variable containing abbreviation of Journal names. Minimum support for the creation of association rules = 0.005, Minimum confidence = 0.1. For a definition of support, lift and confidence see section 3.2.4

## 4.5 Clustering

With clustering I am no longer looking at the impact of the crisis on the mainstream but simply at the structure of the mainstream itself and whether similar abstract could be regrouped in different enough clusters and if this is the case: what are the key differentiating elements. A first graph of the centroids of each of the 15 clusters projected on each of the 80 SVD dimensions can be seen in figure 18. This figure shows first that clusters do seem to have significantly different centroids and this for more than one dimension represented on the x-axis (each dimension resulting from the singular value decomposition procedure). Since we want clusters to be as different as possible, it’s a good sign.

But what is really of interest is the content of each cluster. The result of the methodology described in section 3.2.5 can be seen in table 2. It reveals a dense selection of the main key words about each cluster. The first problematic element is cluster 13 which contains almost 50% of the abstracts and is not differentiable from the overall abstract collection characteristics. Its top 3 words are in the top 4 of the most frequent words from the entire abstract collection (as identified in table 3). Its top 20 words are present in the top 25 words of the entire abstract collection (almost identical) and the 3 most frequent n-grams are too diverse to give any conceptual precision.

This cluster reveals the existence of a huge group of abstracts which are too close to each other to be assigned to any of the other more thematically precise clusters. I’ve tested the ‘cohesion’ of this huge cluster by increasing the number of clusters up to 30, but it did not lead to any meaningful break up. An oversized (2849 abstracts) cluster remained present also with 29 much smaller other cluster at its sides. This could be interpreted as either a failing of the clustering algorithm to differentiate within this mass of abstracts or a true high conceptual similarity for 50% of the dataset. The first option looks unlikely given the quality of the other clusters analyzed which are highly differentiable and show high

within-cluster homogeneity. I am therefore left with the second interpretation, there is considerably large group of very homogeneous abstracts. Confirming this interpretation is the fact that the average within similarity performance measure is 0.004 for cluster 13 just like most of the other homogeneous clusters.

Reading more precisely a random selection of abstracts from this cluster, I've noticed two patterns: the strong prevalence of using 'model' (appearing in 2028 abstracts) and applying them to singularly different problems (adoption, portfolio optimization, social security, financial intermediaries, automated payment and air pollution, just to quote a random selection found in the cluster).

This cluster does not regroup thematically coherent abstracts. So what is making the k-mean algorithm considering this abstracts close to each other? My hypothesis is that this cluster is giving a glimpse at the normal way of doing economics. These abstracts are homogeneous in the way they approach an issue and report about it in a mostly quantitative or mathematical way but they are heterogeneous in topics. What unifies them is their methodology. The diversity of research questions picked by economists makes it almost impossible for the clustering algorithm to cluster abstracts thematically. This is why cluster within-similarity arises from the methodological traits of the cluster. This provides compelling evidence supporting Lawson's claim that the defining element of mainstream economics is its mathematical modeling methodology (Lawson, 2006, p. 493) and also:

*"Certainly the contemporary discipline is dominated by a mainstream tradition. But whilst the concrete substantive content, focus and policy orientations of the latter are highly heterogeneous and continually changing, the project itself is adequately characterised in terms of its enduring reliance, indeed, unceasing insistence, upon methods of mathematical modelling. In effect it is a form of mathematical deductivism in the context of economics."* (Lawson, 2013, p. 950)

I argue that this highly heterogeneous and continually changing focus, together with the strong static methodological unity is causing the k-mean algorithm to constitute such a oversized cluster as cluster 13.

Looking at the other clusters briefly summarized in table 2 one detects coherent thematic clusters. Cluster 0 being focused on the stock market. Cluster 1 on industries, production and firms issues at a macro level. Cluster 2 on financial markets, financial crisis and their link with country-level questions. Cluster 3 is focused on special mathematical methods. Cluster 4 is about firms but with a more micro level of analysis than cluster 1. I let the reader look at the rest of table 2 to see the main thematics emerging from these different clusters since they are obvious enough to be read from the table directly. What these thematic clusters reveal are sub-fields of economic research, where high similarity in the wording and in the topics are observable. The presence of two clusters focusing exclusively on social thematic (cluster 12 for education, and cluster 8 for health) shows where economists are focusing when going outside the more traditional economic topics (firms, growth, bank, productivity etc...).

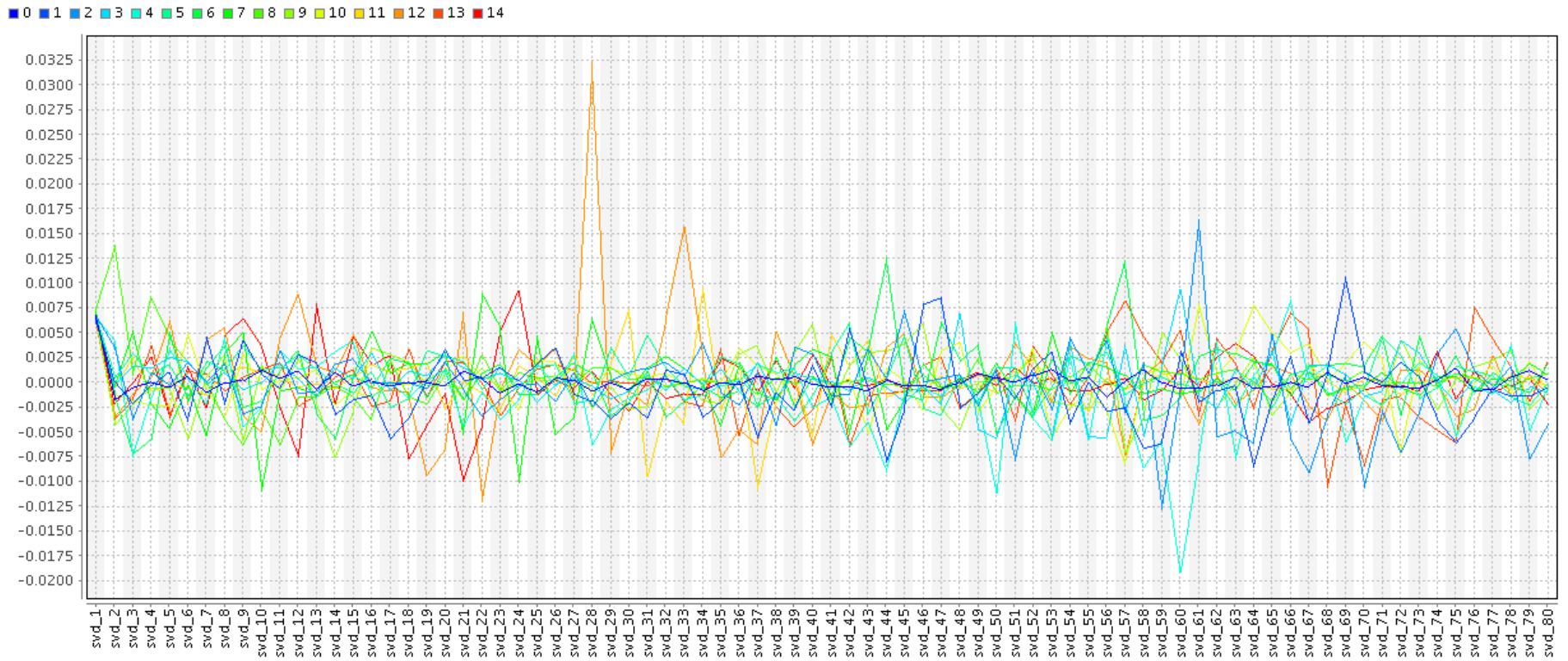
The absence of any cluster related to heterodox methodologies or topics is a remarkable fact and supports the claim that mainstream economics remained 'monolithic' even after the crisis (King, 2013, p. 17). I assume that heterodox papers would have been clustered together (at least some of them) but this should be tested, for example by extracting abstract from 2-3 heterodox reviews and mixing them in the dataset and applying the clustering algorithm. This represent a possible area of development to improve the validity of the interpretation of my results.

Studying the evolution of the size of these clusters in time would be interesting in order to see the importance of these main areas of research to the science of economics. But since the process of clustering could be strongly affected by random elements like the initial cluster seed or the evolution of vocabulary,

the results would be difficult to link with the true importance of these areas of research. This is also a reason why the size of these clusters should not be interpreted too much. It could well be that in cluster 13 many abstracts are related to education but not being considered part of the education cluster (number 12) because of special wording. Looking at the relative frequency of family of terms is a better approach than clustering for looking at the importance of a thematic in a collection of documents.

I tested the cluster thematic made visible in table 2 against some (around 10) randomly chosen abstracts for each cluster and each time most of the abstracts were confirming the thematic emerging from table 2. This is a weak subjective fact supporting the usage of the simple procedure I've developed in order to identify the nature of document clusters. More objective testing should be done to see how it performs against human cluster classification for example.

Figure 18: Centroid plot view. K-Mean ++ Clustering. 15 Clusters



N=10,108 abstracts from 2009 to 2015. Stemmed with Porter Algorithm. Single value decomposition was applied in order to reduce the number of dimensions to 80

Table 2: Overview of cluster's content

Cluster	# of abstracts	Top 3 Words	Different from general top 25	Top 3 N-grams
0	294	stock, return, market	investor, option, liquid	stock return, stock market, stock price
1	205	industri, firm, product	competit, demand, labor	manufactu industri, industri level, product market
2	374	financi, market, countri	crisi, capit, credit	financi crisi, financi market, financi development
3	645	estim, model, method	asymptot, distribut, parameter	mont carlo, finit sample, maximum likelihood
4	860	firm, product, market	export, invest, valu	firm level, product firm, r d
5	179	fund, manage, perform	return, investor, mutual	hedg fund, mutual fund, fund manag
6	472	polic, monetari, model	inflat, optim, shock	monetari polic, fiscal polic, interest rate
7	215	volatil, model, price	return, option, stock	stochast volatil, impli volatil, time vari
8	267	health, insur, care	health insure, coverag, medic	health insur, health care, insur coverag
9	313	tax, income, rate	tax rate, optim, taxat	tax rate, incom tax, tax polic
10	124	exchang, rate, price	currenc, shock, volatil	exchang rate, interest rate, nomina exchang
11	256	bank, loan, market	lend, credit, liquid	central bank, balanc sheet, financi crisi
12	493	test, school, student	educ, teacher, asymptot	test score, test statist, unit root
13	4970	model, effect, us	$\emptyset$	interest rate, labor market, unit state
14	441	risk, model, market	asset, avers, premium	risk avers, risk share, asset price
Total =	10108			

N=10,108 abstracts from 2009 to 2015. Stemmed with Porter Algorithm. Single value decomposition was applied in order to reduce the number of dimensions to 80. K-mean + algorithm was used to created the 15 clusters. Top 3 words = the 3 most occurring words in the cluster. Different from general top 25 = The 3 first words (top 3 words being excluded) or n-grams which are appearing in the top 20 most occurring words from the cluster but are not in the top 25 words of the general dataset as visible on 3 in Appendix B . Top 3 n-grams = the first 3 most occurring n-grams from the cluster. All words or n-gram are presented in frequency order (the word at the left of each column is always the most frequent word)

## 4.6 Qualitative Methodology: Uncertainty and Capitalism

The concept of ‘fundamental uncertainty’ is so infrequent that no bi-grams could be created for it. The only time it appears in the balanced 20,216 abstract dataset is - ironically - under the form of ‘nonfundamental uncertainty’<sup>34</sup>. The concept of uncertainty is in itself post-Keynesian and belong as such to a branch of heterodox economics Lawson (2006, p. 500). Focusing on this term is therefore a way to look at the place left within mainstream economics to a concept from outside its boundaries. To test hypothesis 5 more rigorously than by looking at the relative frequency evolution of the stem ‘uncertainty’ in my abstract collection, I chose to read some of the abstracts directly. Checking simply the evolution of the word stem ‘uncertainty’ would not be rigorous enough since it could be used with another meaning as the one presented by Dow (2015). The only possibility to check whether uncertainty was used with a meaning approaching fundamental uncertainty was to find all abstracts containing ‘uncertainty’ and read through them in order to determine whether fundamental uncertainty was meant with other words. The problem being the fact that the stem ‘uncertainty’ was occurring 1086 time in 658 different documents (rise from 523 to 563 between pre2008 and post2008). In order to reduce my work I took a random sample of 30 abstracts and went through them one by one in order to understand how ‘uncertainty’ was used.

The results are that, most of the time, uncertainty is modeled either as a shock or a parameter to estimate and factor in. Over the 30 randomly-chosen abstracts, 29 modeled uncertainty this way confirming Dow (2015). The only abstract where uncertainty was considered as something more fundamental used the phrase “We investigate a model with uninsurable idiosyncratic uncertainty about liquidity need”<sup>35</sup>. This reveals well that even then, uncertainty is not fundamental and represent a parameter in a model and therefore do not correspond to the concept of ‘fundamental uncertainty’ presented by Dow (2015).

These results, together with the increased focus on risk visible in table 3, support hypothesis 5. The crisis increased ‘fundamental uncertainty in economic life’ (Dow, 2015) but this was translated into mainstream economics as an increased focus on modeling risk and uncertainty as parameters or shocks. The concept of ‘fundamental uncertainty’ did not enter mainstream economics in any significant way.

Looking at usage of the cleaving word *capitalism* in the dataset, I was able to find 15 abstracts (out of 20,216) containing it. How the word is used is enlightening: 4 out of the 15 times it was used in the expression ‘crony capitalism’ and was used to describe particular regional form of capitalism (Malaysian, Est-Asia, Western-Europe). One similar article was about Russian ‘oligarch capitalism’. These articles are using the word in a negative targeted way, focusing only on special regions.

One 2015 article<sup>36</sup> by Acemoglu and Robinson was placing Piketty in the “tradition of the great classical economists, like Marx and Ricardo, in formulating general law of capitalism”. The connotation of the word seems neutral, even though the author is intensely critical of Piketty’s work and the possibility to formulate such general law. With *capitalism* is meant the entire economic.

One NBER abstract was about a review of the major publication “Cambridge History of Capitalism” published in 2014. The NBER working paper<sup>37</sup> is strikingly telling as the title itself reveals the problem around the word *capitalism*, which is put between quotation marks in the working paper but not in the

<sup>34</sup>This happens in the abstract of the following article: Duffy, John, and Eric O’N. Fisher. (2005). Sunspots in the Laboratory. *American Economic Review*, 95(3): 510-529.

<sup>35</sup>Abstract from the paper: Telyukova, I. A. and Visschers, L. (2013). Precautionary money demand in a business-cycle model. *Journal of Monetary Economics*, 60(8):900 – 916.

<sup>36</sup>Full reference for the article: Acemoglu, D. and Robinson, J. A. (2015). The Rise and Decline of General Laws of Capitalism. *Journal of Economic Perspectives*, 29(1):3-28

<sup>37</sup>The working paper is accessible here : <http://www.nber.org/papers/w20658>

original Cambridge publication. The review itself begins with a phrase revealing the unease of mainstream economists when confronted with such broad historical work. The review begins with: “*What is an economist to make of two volumes containing one thousand pages on the history of capitalism? Is it another Non-Communist Manifesto, echoing Rostow (1960)?*”.

One other NBER working paper<sup>38</sup> analyzes the benefits in the work place of ‘shared capitalism’. Meant is a capitalism in which employee would access some level of ownership, profit sharing or hold stock options of the firms they work in. The word is here used positively (with ‘share’) and describes the possibly better - understand more efficient - organization of workplaces.

In an other abstract<sup>39</sup> the word is used more critically. The broader acceptance of ‘free market capitalism’ among Democrats and Republicans is seen a one (out of five) factor which could explain the inequality rise in the US during the ‘last two generations’. The precision ‘free market’ shows probably the need to precise what is meant with *capitalism* since the word has a broad definition. That ‘free market’ is used pejoratively (implying that ‘non-free market capitalism’ would not have led to such a rise of inequality in the U.S) reveals a critical stand against economic liberalism but not capitalism *per se*.

Another abstract is simply relating the interview of the director of the center on ‘Capitalism and Society’ at Columbia. It reveals a failing in the cleaning procedure of the dataset since this abstract is not from a research paper.

Then comes the second allusion to Marx with the term ‘contradiction of capitalism’ used in a NBER working paper<sup>40</sup> in order to describe the conflicting interests arising when ‘Economics has firms maximizing value and people maximizing utility, but firms are run by people’. This contradiction of capitalism is treated as an agency problem leading to suboptimal situations and justifying the need for regulations.

The next abstract<sup>41</sup> mentions ‘Schumpeter’s 1950 vision of modern capitalism’ with a lot of monopolies which could be swept by creative destruction. The word is used in reference of Schumpeter but has a neutral connotation, it seems to refer to the general traits of the economic system.

The word capitalism appears also once ironically in the mouth of an imaginary business cycle economist which would have said after much economic turmoil due to the world financial crisis “welcome to free market capitalism”. The abstract<sup>42</sup> is critical and underlines the negative aspects of the global financial system. Again, “free market capitalism” is used in a particularly negative way.

Elionor Ostrom used the word capitalism in an 2010 paper<sup>43</sup>. The word is used in this broad sense of an institution which together with the State defines key parameters of economic and social life. The abstract is highly critical as it both mentions limits to ‘traditional mathematical modeling’ and findings contradicting game theory.

The last abstract used the word capitalism while quoting a title from a article by Paul Krugman appearing in the *New York Times Magazine* on October 20, 2002 and titled: “For Richer: How the Permissive Capitalism of the Boom Destroyed American Equality.” Critically used, but again with an adjective (in this case ‘permissive’), enabling the author to direct its attack on a problematic kind of capitalism.

<sup>38</sup>The working paper is accessible here : <http://www.nber.org/papers/w14230>

<sup>39</sup>Reference: Bonica, A., McCarty, N., Poole, K. T., and Rosenthal, H. (2013). Why hasn’t democracy slowed rising inequality? *The Journal of Economic Perspectives*, 27(3):103–123.

<sup>40</sup>Working paper accessible here :<http://www.nber.org/papers/w16490>

<sup>41</sup>Reference: Schmalensee, R. (2000). Antitrust issues in schumpeterian industries. *The American Economic Review*, 90(2):pp. 192–196

<sup>42</sup>Reference: Rogoff, K. (1999). International institutions for reducing global financial instability. *Journal of Economic Perspectives*, 13(4):21

<sup>43</sup>Reference: Ostrom, E. (2010). Beyond markets and states: Polycentric governance of complex economic systems. *The American Economic Review*, 100(3):pp. 641–672.

From this short overview two results appear: First, the word capitalism is often used together with adjectives. This restricts the scope of the critical points raised with its usage since when ‘crony capitalism’, ‘free market capitalism’ or ‘permissive capitalism’ are used, *capitalism* in itself is not being challenged or criticized. With ‘shared capitalism’ the analysis is different since it was presented as a positive amelioration to be implemented to boost productivity while cutting supervision costs. This is arguably a ‘capitalist’ way to look at the question of ‘shared capitalism’ as it is more focused on the firms than on the workers. Second, even when capitalism appeared, it was not with key heterodox economic concepts often associated with capitalism such as: power, institutions, commodification, history and social relations<sup>44</sup>. This displays a strong degree of paradigmatic cohesion in which heterodoxy or pluralistic views are simply not being published in the top 16 influential reviews in economics, even when looking at a term more typically used in heterodox economics.

Together with the remarkably low number of occurrences of the word capitalism, this constitutes another evidence supporting the claim that “*Economics is unique among the social sciences in having a single monolithic mainstream, which is either unaware of or actively hostile to alternative approaches.*” (King, 2013, p. 17). It also reveals the unwillingness to think the economic system as a whole, at a high level of generalization.

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<sup>44</sup>For general references on heterodox economics see the work of Mearman (2007) and Lawson (2006) and on the notion of ‘Power’ from a marxist standpoint see Palermo (2014)

## 5 Discussion

The results presented in the previous 6 subsection of section 4 are diverse, and this is why I have tried to interpret most of them separately already. What I want to address in this discussion is: the broad picture that my results are depicting, what they say about mainstream economics and what could possibly explain this broad picture.

### 5.1 Main Results

Before delving into the discussion a brief reminder of the main results found is necessary.

From the term occurrences table in Appendix B, we discovered how most of the top 40 words in economics did not experience major changes except the word stems ‘financi’ and ‘risk’ which underwent a significant rise in their frequency. We saw as well how the stem ‘model’ dominates by a large margin the vocabulary used in abstracts. By looking at the yearly evolution of key words, we were able to better visualize the absence of other major changes in economics after the crisis (figures 13 and 8). We saw that the key fundamental reliance on mathematical techniques did not evolve with figure 12. Meanwhile I was able to detect many significant but less fundamental changes by looking at figure 14 as well as tables 4 and 5. We found weak evidence of a slight increase in lexical diversity after the crisis, visible in figure 15. By using association rules, we found that few words are associated with either period of my analysis with a strong confidence. However, we were able to confirm that the stem ‘financi’ is the second most associated term with the post-crisis period after data and model (occurring together). Applying clustering techniques on the 10,108 abstracts from 2009 to 2015 we were able to discover 14 meaningful small clusters of abstracts and 1 dominating cluster being not differentiable from the general mainstream as seen in table 2. Last but not least, looking at the place of key central heterodox economics concepts of ‘fundamental uncertainty’ and ‘capitalism’ in mainstream abstracts, we discovered in section 4.6 a near total preclusion of their usage with a heterodox meaning.

Taken together, these results constitute reasonable evidence that economics did not experience a paradigm shift after the global financial crisis. At the same time, these results do seem to contradict heterodox critiques of mainstream economics, for whom mainstream economics is a static science constructed only in the defense of neoliberal ideology and incapable of integrating contradicting empirical evidences (Colander et al., 2004; Lawson, 2006). On the contrary, my results show some variation happening. First of all, there is a reorientation toward more finance-related topics but also among other changes on can mention: new mathematical methods becoming more popular (DSGE modeling, regression discontinuity), old ones losing ground (regression model, linear regression<sup>45</sup>), an evolving country focus (less abstracts about Britain, Japan, and Latin America more on China). The results are showing a dynamic science but the question is how deep this dynamism goes? Or, in other words: how close to the core of the discipline are major variations observable? Between the two opposite views from Colander et al. (2004) for whom mainstream is highly dynamic and Thornton (2015) for whom mainstream is not as dynamic as it claims, what do my data show?

So far in this thesis, I’ve treated the core of mainstream economics loosely as being represented by the most used words of the profession. According to this loose definition, the core changed little except for a larger focus on risk and finance-related topics. A more precise definition of what characterizes the core of mainstream economics is given by Lawson:

<sup>45</sup>Results from the full word list dataset. Available on request.

*The truth is that modern mainstream economics is just the reliance on certain forms of mathematical (deductivist) method. This is an enduring feature of that project, and seemingly the only one; for the mainstream tradition it is its unquestioned, and seemingly unquestionable, essential core.* Lawson (2006, p. 489)

Comparing these insights with my data about the evolution of math-related terms, especially figure 12, I can assert again, in a more rigorous way, that the core of the discipline - its reliance on mathematical deductivist methods - did not change and therefore the crisis did not impact economics in a fundamental way. A possible explanation of this phenomenon is given by Thornton:

*“New insights are generally absorbed into mainstream economics in [a] way that does not threaten core tenets of mainstream thought, with the more revolutionary insights being adopted within political economy. This is apparent in the production of various schisms: neoclassical Keynesian versus post-Keynesian economics, old and new institutional economics, old and new behavioural economics. We might well find a similar dualism in complexity economics, where it is only ever absorbed into the economic mainstream via its bastardisation.”* Thornton (2015, p. 18)

These two quotations help explain why, even after the crisis, no cluster containing abstracts using more heterodox methodologies could be found and why heterodox terms are absent from mainstream abstracts (as seen in section 4.6). Mainstream economics is indeed ‘monolithic’ (King, 2013, p. 17) and the mechanism which ensures this level of unity is the reliance on the mathematical modeling methodology. This mechanism is defended by Colander et al. (2004, p. 492) when he argues that heterodox economists should adopt an orthodox methodology to be recognized in the mainstream. Another example of this mechanism was criticized already in 2001 by Lipsey when he wrote:

*“[...]to get an article published in most of today’s top rank economic journals, you must provide a mathematical model, even if it adds nothing to your verbal analysis. I have been at seminars where the presenter was asked after a few minutes, ‘Where is your model?’. When he answered ‘I have not got one as I do not need one, or cannot yet develop one, to consider my problem’ the response was to turn off and figuratively, if not literally, to walk out.”* Lipsey (2001, p. 184)

I argue therefore that this strong mathematical modeling methodological paradigm, worsened by institutional incentives within academia that promote ‘hands-off applied research’ (Colander, 2010, p. 422) caused the absence of major changes within mainstream economics, even in the face of the global financial crisis.

As a supporter of a pluralistic approach, I regret this phenomenon and would welcome the opening-up of mainstream economics to a wider variety of methods. Modeling and math are useful, and they often bring clarity and precision to analyzes and should continue being used. They are not, however, always superior to less formalized methods which are trying to explain the complex present by calling in history, social relations and power among other conceptual tools. A shift toward a ‘social ontology’ as defined by Lawson (2006, p 495-497.) is what economics needs most.

But how to get there? From the scale-free distribution of word stems within economics seen in figure 5, and the network characteristic of language (and the connection between language and thoughts) the optimal strategy for heterodox economists trying to bring changes within mainstream economics<sup>46</sup> could

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<sup>46</sup>For a reflection on a more specific the strategy for Post Keynesian to follow in order to impact mainstream economics and their failure at entering mainstream economics after the crisis see Rochon and Docherty (2012).

be to coordinate their effort against the strongest word stems with a special focus on the dominating one: the stem ‘model’. Following a network analogy, this stem is the biggest ‘hub’ in the networks of mainstream economic ideas, and scale-free networks are particularly vulnerable to ‘coordinated attacks’ on hubs as explained by [Barabási and Bonabeau \(2003, p. 62\)](#). The problem lies in the complexity of economics idea networks and its social dimensions. Nods are words reflecting ideas in the heads of economists, which are social relational beings, within institutions (universities, editorial board etc.) which influence some of their thoughts. Moreover economists usually carry a training in mainstream economics (the normal economic curriculum). They have an interest also at keeping the *status quo* given the *sunk cost* that their mathematical abilities would represent if they were to depart from the mathematical modeling methodologies they learned after much effort. These factors and many others are playing a role and strengthening the inertia and stability of the dominating paradigm.

For all these reasons, the task of changing mainstream in a significant way is not an easy one. If the analogies hold, the stability and robustness of scale-free networks might be playing against major changes as well. However, major changes in the mainstream are not impossible. Looking back at history to find examples of disruptive moments in economics, one finds Keynes’ *The General Theory of Employment, Interest, and Money*. It was even Keynes’ stated goal to impact economics and the strategy he adopted was to bring his ‘obvious’ ideas to a high level of abstraction in order to get attention from his fellow economists colleagues. Or in his words:

*“For if orthodox economics is at fault, the error is to be found not in the superstructure, which has been erected with great care for logical consistency, but in a lack of clearness and of generality in the premises. Thus I cannot achieve my object of persuading economists to re-examine critically certain of their basic assumptions except by a highly abstract argument and also by much controversy”* ([Keynes, 1936](#), Preface)

## 5.2 Caveats

The first main weakness of my work is the fact that by using many different methods I did not use any of them very deeply. I was facing a quality/quantity trade-off of my methods usage. To be able to generalize some of my results, I needed different methods, producing different results, which is why I kept my techniques diversified. However, the diversity of methods makes my results easily criticizable since I was not able to refine my methods.

The diversity of methods and results is therefore both the strength and the weakness of this thesis. The diversity of results enabled me to give an overview of mainstream economics, but at the same time this overview is not completely rigorous. This is coherent with the nature of text mining, which is first and foremost an exploratory method.

Another main weakness of my work is the size of the dataset. The balanced dataset comprised only 20,216 abstracts from 17 publications sources over 15 years. I applied text mining techniques and looked at the yearly evolution of words appearing at least 50 times. For those words which appeared so rarely the yearly average of relative term frequency is subject to much random variation. Taking into account more abstracts from more journal would increase the robustness of my results, especially those about relatively rare words (appearing less than that once in 100 abstracts).

Another main caveat is the choice to work exclusively with abstracts from the most influential mainstream scientific journals. By restricting my analysis only on those journals, I was not taking into account areas of mainstream economics much more sensitive to changes. For instance, focusing on text data from

blogs, websites or op-eds from influential mainstream economists would have probably revealed more changes in the mainstream than what my actual data are showing. An analysis of text data from international economic institutions like the OECD or the IMF would also have probably revealed greater level of change in economic thought during the 1999-2015 period. However, because of the considerable role that scientific journals - *a fortiori* the most influential ones - have in shaping the boundary of mainstream economics, I think my approach remains a valid attempt at studying the core of mainstream economics.

One could also criticized my overly American focus. Choosing more reviews from Europe and Asia and analyzing working paper from other sources than only the NBER (e.g the CEPR or the german CESifo) would have increased the international scope of my analysis and bring more diversity in my depiction of mainstream economics. However, since I wanted to focus on the very core of mainstream economics, the same line of defense apply as in the last paragraph: given the key centrality of American reviews and academic institutions for mainstream economics, I do not think that the American bias of my data takes the validity of my results away.

## 6 Conclusion

The diversity of my findings and the flexibility of text mining gives room for a wide range of possible research developments. Before concluding on today's state of mainstream economics, I want to present some of the most interesting and promising research possibilities<sup>47</sup> which could be carried out to extend the analysis of mainstream economics.

For example, it could be of interest to carry out in-depth cluster analysis, trying different clustering algorithms and comparing the results. To test the performance of the clustering algorithm, introducing abstracts from heterodox economics or other disciplines into the dataset and running clustering algorithms again would constitute an improvement as well. Developing the method further, it could be possible to build a classification model able to assign abstracts to the corresponding clusters and detect heterodox abstracts. Looking at the evolution of clusters' composition per year would also bring interesting hindsight on the evolution of economics.

To broaden the scope of our understanding of economics as a whole, the same clustering methodology could be used on a selection of the most influential heterodox journals in economics. In a similar fashion, applying clustering analysis on abstracts from more pluralistic sciences (e.g. Political Science or Sociology) could also help interpret the clustering result from economics itself. For this purpose, implementing a comparative approach could help bring scientific rigor to the interpretation of the results.

It would be possible to deepen association rules analysis in order to try to disambiguate words' meanings in a more complete way. For this purpose, the creation of more precise association rules at the phrase level (as opposed to abstract level) could provide much robust results and a mean to validate some of my findings.

Another possible development of my work would be to deconstruct the hidden ideology behind the mainstream by focusing on selected stems and their utilization. The 4 stems from the top 15 words in economics: 'market', 'price', 'firm' and 'trade' would be good candidates for such an analysis as they could easily be linked to neoliberalism.

Using some simple text mining technique as I did, it could be possible to build a basic indicator of scientific dynamism. Simply counting the number of words above a given frequency threshold which experienced a sizable yearly variation (above a predetermined limit) of their average relative term frequency could provide a basic indication of the changes happening within a science. To refine this measure weight could be attributed to each word varying above the threshold according to their importance in term of absolute occurrences, or their rank in the sorted word list. This very basic indicator could be improved by taking into account a measure of the similarity of entire word lists between two years. Altogether this could constitute a rough indicator of scientific dynamism which could be used to analyze development of different sciences and compare them.

At the end of my thesis, after having constructed and analyzed a dataset from some of the most influential journal in economics as objectively as I could, I would like to conclude on the state of mainstream economics on a critical - more subjective - tone. I consider challenging the actual state of mainstream economics as being an important task given the influence that the science of economics has on real-world issues. Indeed, mainstream economics is one of the most influential sciences in terms of policy. The heterogeneity of its topics of choice: finance, education, health, management, environmental policy, labor regulations, fiscal and monetary policies etc. are wide reaching and give economists a say on a broad variety of topics at a high political and societal level. The source of their strength lies mostly in the

<sup>47</sup>Palliating to the caveats mentioned in section 5.2 represents also a research possibility.

scientific appearance of their methods which remained vastly ‘unquestioned and unquestionable’ within mainstream economics as my results show.

This is more than problematic. It has a real impact as policies and economic activities affect substantial parts of human life. By failing to adopt ‘social ontology’<sup>48</sup> and acknowledge the true depth of the social realm and the impossibility of encompassing it all with variations of one mathematical deductivist approach, mainstream economists will stand as zealous - often unconscious - defenders of the *status quo* in which: “*Instead of economy being embedded in social relations, social relations are embedded in the economic system.*” (Polanyi, 1944). The methodological reliance of such mathematical deductivist approach does not preclude completely the integration of social ‘parameters’ in economics models but it hides from economic analysis key social aspects which cannot be reduced into a formalized abstract model. A key example of such social aspects of economic activities was noted by Polanyi in his analysis of the spread of markets disembedded from society. For him this phenomenon has intrinsic adverse consequences since through the commodification of land and labor, societies and nature are transformed and subdued as life itself becomes objectified into a commodity. Many such central economic phenomenon and their wide ranging social consequences can not be analyzed within the methodological framework of today’s mainstream economics.

Conscious of this problem, my aim was to explore the state of mainstream economics and look at signs of transformation after the crisis. I did it in an empirically-grounded way, using mostly quantitative tools. Although the changes I found are mostly small, a few signs of hope are visible.

Economists have been so harshly criticized after the crisis (and partly discredited) that within the mainstream introspection began. The best example of this is given by Colander (2013, 2010) and Colander et al. (2009). While he still advocates better mathematical models and a shift toward ‘complexity economics’, he argues for more ‘hands-on’ applied research. My hope is that by more rigorously confronting themselves to empirics, mainstream economists will open the profession to various approaches and develop into a pluralistic science. The increased usage of the words ‘data’ and ‘evidence’ among other as well the undeniable impact that the 2007-2008 financial crisis had on redirecting economic research toward finance and risk, are positive signs that empirics is being taken increasingly seriously. The shift of economics into a ‘complexity area’ (Holt et al., 2011) might be the first step toward acknowledging the depth of the social realm.

Where it will lead, no one knows, as mainstream economics itself is a complex embedded evolving network of ideas, people, institutions and more.

What I know though, is that it does matter.

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<sup>48</sup>As defined by Lawson (2006, p 495-497.)

## 7 Bibliography

- Akerlof, G. A. and Shiller, R. J. (2010). *Animal Spirits: How Human Psychology Drives the Economy, and why it matters for global capitalism*. Princeton University Press.
- Arthur, D. and Vassilvitskii, S. (2007). K-means++: The Advantages of Careful Seeding. In *Proceedings of the Eighteenth Annual ACM-SIAM Symposium on Discrete Algorithms*, SODA '07, pages 1027–1035, Philadelphia, PA, USA. Society for Industrial and Applied Mathematics.
- Barabási, A.-L. and Bonabeau, E. (2003). Scale-free Networks. *Scientific American*, 288(5):50–59.
- Bigo, V. and Negru, I. (2014). Mathematical Modelling in the Wake of the Crisis: a Blessing or a Curse? What does the Economics Profession say? *Cambridge Journal of Economics*, 38(2):329–347.
- Colander, D. (2010). The Economics Profession, The Financial Crisis, and Method. *Journal of Economic Methodology*, 17(4):419–427.
- Colander, D. (2013). The Systemic Failure of Economic Methodologists. *Journal of Economic Methodology*, 20(1):56–68.
- Colander, D., Goldberg, M., Haas, A., Juselius, K., Kirman, A., Lux, T., and Sloth, B. (2009). The Financial Crisis and the Systemic Failure of the Economics Profession. *Critical Review*, 21(2-3):249–267.
- Colander, D., Holt, R., and Jr., B. R. (2004). The Changing Face of Mainstream Economics. *Review of Political Economy*, 16(4):485–499.
- Davies, D. L. and Bouldin, D. W. (1979). A Cluster Separation Measure. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, PAMI-1(2):224–227.
- deBoer, F. (2014). Evaluating the Comparability of Two Measures of Lexical Diversity. *System*, 47(0):139–145.
- Dow, S. C. (2015). Addressing Uncertainty in Economics and the Economy. *Cambridge Journal of Economics*, 39(1):33–47.
- Dukelow, F. (2015). Pushing Against an Open Door. *Comparative European Politics*, 13(1):93–111.
- Feldman, R. and Sanger, J. (2006). *The Text Mining Handbook: Advanced Approaches in Analyzing Unstructured Data*. Cambridge University Press.
- Gagliardi, F. and Gindis, D. (2011). Overcoming the Impasse in Modern Economics. *Competition & Change*, 15(4):336–342.
- Goodchild, P. (2012). What is Wrong with the Global Financial System? *Journal of Interdisciplinary Economics*, 24(1):7–28.
- Gorton, G. B. (2010). *Slapped by the Invisible hand: The Panic of 2007*. Oxford University Press.
- Granovetter, M. (1985). Economic Action and Social Structure: The Problem of Embeddedness. *American Journal of Sociology*, 91(3):pp. 481–510.
- Grimmer, J. and Stewart, B. M. (2013). Text as Data: The Promise and Pitfalls of Automatic Content Analysis Methods for Political Texts. *Political Analysis*, 21(3):1–31.

- Hall, P. A. (1993). Policy Paradigms, Social Learning, and the State: The Case of Economic Policymaking in Britain. *Comparative Politics*, 25(3):275–296.
- Hargreaves Heap, S. P. (2013). What is the Meaning of Behavioural Economics? *Cambridge Journal of Economics*, 37(5):985–1000.
- Holt, R. P., Jr., J. B. R., and Colander, D. (2011). The Complexity Era in Economics. *Review of Political Economy*, 23(3):357–369.
- Jessop, B. (2010). The ‘return’ of the National State in the Current Crisis of the World Market. *Capital & Class*, 34(1):38–43.
- Keynes, J. M. (1936). *The General Theory of Employment, Interest, and Money*. Macmillan Cambridge University Press.
- King, J. E. (2013). A Case for Pluralism in Economics. *The Economic and Labour Relations Review : ELRR*, 24(1):17–31.
- Kocher, E. (2014). Politique Économique et Hégémonie Néolibérale dans les Médias. Master’s thesis, Université de Lausanne.
- Kuhn, T. S. (1970). *The Structure of Scientific Revolutions*. University of Chicago Press, second enlarged edition.
- Laidler, D. (2010). Lucas, Keynes, and the Crisis. *Journal of the History of Economic Thought*, 32(1):39–62.
- Lawson, T. (2006). The Nature of Heterodox Economics. *Cambridge Journal of Economics*, 30(4):483–505.
- Lawson, T. (2009). The Current Economic Crisis: Its Nature and the Course of Academic Economics. *Cambridge Journal of Economics*, 33(4):759–777.
- Lawson, T. (2013). What is this ‘School’ called Neoclassical Economics? *Cambridge Journal of Economics*, 37(5):947–983.
- Levitt, S. D. and List, J. A. (2008). Homo Economicus Evolves. *Science*, 319(5865):909–910.
- Lipsey, R. G. (2001). Successes and Failures in the Transformation of Economics. *Journal of Economic Methodology*, 8(2):169–201.
- Lo, A. W. (2012). Reading About the Financial Crisis: A Twenty-One-Book Review. *Journal of Economic Literature*, 50(1):151–178.
- Mearman, A. (2007). Teaching Heterodox Economics Concepts. *Handbook for Economics Lecturers*.
- Michel, J.-B., Shen, Y. K., Aiden, A. P., Veres, A., Gray, M. K., Team, T. G. B., Pickett, J. P., Hoiberg, D., Clancy, D., Norvig, P., Orwant, J., Pinker, S., Nowak, M. A., and Aiden, E. L. (2011). Quantitative Analysis of Culture Using Millions of Digitized Books. *Science*, 331(6014):176–182.
- Neuendorf, K. A. (2002). *The Content Analysis Guidebook*. Sage Publications Thousand Oaks, CA.
- Newman, M. (2005). Power Laws, Pareto Distributions and Zipf’s law. *Contemporary Physics*, 46(5):323–351.

- 
- Palermo, G. (2007). The Ontology of Economic Power in Capitalism: Mainstream Economics and Marx. *Cambridge Journal of Economics*, 31(4):539–561.
- Palermo, G. (2014). The Economic Debate on Power: a Marxist Critique. *Journal of Economic Methodology*, 21(2):175–192.
- Polanyi, K. (1944). *The Great Transformation: The Political and Economic Origins of our Time*. Beacon Press.
- Rampell, C. (2009). ‘Great Recession’: A Brief Etymology. *New York Times*, March 11th.
- Reinhart, C. M. and Rogoff, K. (2009). *This Time is Different: A Panoramic View of Eight Centuries of Financial Crises*. Princeton University Press.
- Reinhart, C. M. and Rogoff, K. S. (2008). This Time is Different: A Panoramic View of Eight Centuries of Financial Crises. Working Paper 13882, National Bureau of Economic Research.
- Rochon, L.-P. and Docherty, P. (2012). Engagement with the Mainstream in the Future of Post Keynesian Economics. *Review of Political Economy*, 24(3):503–518.
- Shiller, R. (2008). *The Subprime Solution: How Today’s Global Financial Crisis Happened, and What to Do about It*. Princeton University Press.
- Solé, R. V., Corominas-Murtra, B., Valverde, S., and Steels, L. (2010). Language Networks: Their Structure, Function, and Evolution. *Complexity*, 15(6):20–26.
- Thornton, T. (2015). The Changing Face of Mainstream Economics ? *The Journal of Australian Political Economy*, 75:11–26.
- Wilkinson, N. and Klaes, M. (2012). *An Introduction to Behavioral Economics*. Palgrave Macmillan.
- Willett, P. (2006). The Porter Stemming Algorithm: Then and Now. *Program*, 40(3):219–223.



## 8 Appendices

### A Tokenized and Stemmed Abstract: An Example

Example abstract from the following paper: Irvine, P. J. and Pontiff, J. (2009). Idiosyncratic return volatility, cash flows, and product market competition. *Review of Financial Studies*, 22(3):1149–1177.

**1. Original abstract:** Over the past 40 years, the volatility of the average stock return has drastically outpaced total market volatility. Thus, idiosyncratic return volatility has dramatically increased. We estimate this increase to be 6% per year. Consistent with an efficient market, this result is mirrored by an increase in the idiosyncratic volatility of fundamental cash flows. We argue that these findings are attributable to the more intense economy-wide competition. Various cross-sectional and time-series tests support this idea. Economic competitiveness facilitates reinterpretation of the results from the cross-country  $R^2$  literature, as well as the US idiosyncratic risk literature.

**2. Tokenized and filtered for stop-words:** years volatility average stock return drastically outpaced total market volatility thus idiosyncratic return volatility dramatically increased estimate increase year consistent efficient market result mirrored increase idiosyncratic volatility fundamental cash flows argue findings attributable intense economy wide competition various cross sectional time series tests support idea economic competitiveness facilitates reinterpretation results cross country r literature idiosyncratic risk literature

**3. Stemmed and without duplicates words:** year volatil averag stock return drastic outpac total market thu idiosyncrat dramat increas estim consist effici result mirror fundament cash flow argu find attribut intens economi wide competit variou cross section time seri test support idea econom competit facilit reinterpret result countri literatur risk

## B Term occurrences results table

Table 3: 40 Most Frequent Words, sorted by descending order of total occurrences

Rank	Total occurrences	Word	In # of documents	Pre2008	Post 2008	$\Delta$ in %
1st	16753	model	8456	8480	8273	-2.4%
2nd	11170	effect	6436	5037	6133	21.8%
3rd	10458	market	5463	5342	5116	-4.2%
4th	10264	us	7809	4765	5499	15.4%
5th	10230	firm	3695	4565	5665	24.1%
6th	9119	find	6791	3922	5197	32.5%
7th	9107	price	3966	4639	4468	-3.7%
8th	8912	estim	4463	4155	4757	14.5%
9th	8521	paper	7352	4685	3836	-18.1%
10th	7798	increas	5054	3485	4313	23.8%
11th	7727	rate	3932	4182	3545	-15.2%
12th	7441	<b>countri</b>	3433	3784	3657	-3.4%
13th	7361	data	5455	3561	3800	6.7%
14th	7183	result	5743	3480	3703	6.4%
15th	6854	trade	2824	3424	3430	0.2%
16th	6677	<b>polici</b>	3414	3494	3183	-8.9%
17th	6626	show	5484	3014	3612	19.8%
18th	5590	product	2855	2692	2898	7.7%
19th	5416	inform	2959	2696	2720	0.9%
20th	5399	time	3677	2593	2806	8.2%
21st	5369	cost	3077	2671	2698	1.0%
22nd	5280	econom	3482	2956	2324	-21.4%
23rd	5127	gener	3961	2631	2496	-5.1%
24th	5108	<b>risk</b>	2415	2118	2990	41.2%
25th	5051	<b>tax</b>	1541	2706	2345	-13.3%
26th	4993	studi	4226	2436	2557	5.0%
27th	4829	chang	3085	2398	2431	1.4%
28th	4738	develop	3503	2295	2443	6.4%
29th	4596	return	2385	2261	2335	3.3%
30th	4573	level	3368	2160	2413	11.7%
31st	4552	incom	2191	2421	2131	-12.0%
32nd	4504	test	2267	2277	2227	-2.2%
33rd	4486	capit	2227	2373	2113	-11.0%
34th	4477	evid	3624	2113	2364	11.9%
35th	4316	i	2516	1902	2414	26.9%
36th	4286	invest	2263	2143	2143	0.0%
37th	4196	growth	2080	2296	1900	-17.2%
38th	4153	<b>financi</b>	2270	1695	2458	45.0%
39th	3956	<b>state</b>	2407	2025	1931	-4.6%
40th	3911	suggest	3457	1894	2017	6.5%

N=20,216 Abstracts. Balanced Data set. Stemmed with Porter Algorithm. Out of 3522 stemmed words and N-grams present in more than 0.25 % of abstract. The 'rank' column shows the position of importance of the stems (least important = 3522<sup>rd</sup>)

Table 4: Words with the biggest percentage increase, sorted by descending scale of change  $\Delta$ 

Rank	Total occurrences	Word	In # of doc	Pre2008	Post 2008	$\Delta$ in %
2698th	81	<b>great_recess</b>	63	1	80	7900.0%
1678th	156	<b>securit</b>	58	5	151	2920.0%
3183rd	64	<b>recent_financi</b>	58	7	57	714.3%
1055th	295	<b>financi_crisi</b>	249	36	259	619.4%
1549th	175	field_experi	157	24	151	529.2%
1688th	155	disast	72	26	129	396.2%
2411th	95	<b>privat_equiti</b>	51	16	79	393.8%
2288th	100	exogen_variat	98	17	83	388.2%
1446th	192	offshor	62	33	159	381.8%
2147th	110	regress_discontin	103	19	91	378.9%
2891st	74	<b>global_financi</b>	66	14	60	328.6%
1204th	253	<b>hedg_fund</b>	101	51	202	296.1%
1917th	128	dsge	93	26	102	292.3%
2457th	92	<b>financi_friction</b>	73	19	73	284.2%
2383rd	96	<b>credit_rate</b>	62	20	76	280.0%
918th	351	<b>mortgag</b>	153	77	274	255.8%
2465th	91	us_novel	91	20	71	255.0%
2490th	91	<b>credit_spread</b>	53	20	71	255.0%
2166th	108	heterogen_firm	104	24	84	250.0%
3450th	53	suggest_evid	53	12	41	241.7%
3131st	66	<b>hous_market</b>	54	15	51	240.0%
2637th	83	identif_strategi	81	19	64	236.8%
1376th	205	climat	116	47	158	236.2%
3246th	61	chief_execut_offic	61	14	47	235.7%
1744th	147	risk_take	96	34	113	232.4%
1865th	134	fuel	88	31	103	232.3%
3385th	56	exploit_variat	54	13	43	230.8%
3392nd	56	polici_intervent	53	13	43	230.8%
2912th	73	affect_firm	71	17	56	229.4%
1973rd	124	farmer	61	29	95	227.6%
1843rd	136	carbon	66	32	104	225.0%
2547th	88	<b>liquid_risk</b>	57	21	67	219.0%
2874th	75	percentil	57	18	57	216.7%
1970th	124	back	79	30	94	213.3%
1209th	252	discontin	211	61	191	213.1%
2268th	102	complianc	68	25	77	208.0%
3455th	53	effect_stronger	51	13	40	207.7%
1603rd	167	chines	111	41	126	207.3%
2280th	101	extens_margin	73	25	76	204.0%
1445th	192	destin	110	48	144	200.0%
2875th	75	<b>sovereign_debt</b>	57	19	56	194.7%

Note: N=20,216 Abstracts. Balanced dataset. Stemmed with Porter Algorithm. Out of 3522 stemmed words and N-grams present in more than 0.25 % of abstract. The 'rank' column shows the position of importance of the stems (least important = 3522<sup>rd</sup>). In bold are finance related topics

## B TERM OCCURRENCES RESULTS TABLE

Table 5: Selection of words in the top 100 biggest percentage drop, sorted scale of change  $\Delta$

Rank	Total occurrences	Word	In # of docs	Pre2008	Post 2008	$\Delta$ in %
2221st	105	peg	56	88	17	-80.7%
3059th	69	nasdaq	51	56	13	-76.8%
2587th	86	factor_price	65	69	17	-75.4%
2236th	104	<b>antitrust</b>	54	83	21	-74.7%
2342nd	98	devalu	55	78	20	-74.4%
2279th	101	nyse	74	79	22	-72.2%
2790th	77	provid_inform	76	58	19	-67.2%
1873rd	133	polici_rule	102	100	33	-67.0%
1615th	165	japanes	88	124	41	-66.9%
2563rd	87	market_maker	52	65	22	-66.2%
3055th	69	purchas_power	57	51	18	-64.7%
1909th	129	<b>happi</b>	52	95	34	-64.2%
3345th	58	inform_technolog	50	42	16	-61.9%
2966th	72	regim_switch	53	52	20	-61.5%
1436th	194	underwrit	89	140	54	-61.4%
2865th	75	increas_return	65	54	21	-61.1%
1853rd	135	<b>collus</b>	70	97	38	-60.8%
3277th	60	econom_analysi	58	43	17	-60.5%
3105th	67	time_model	54	48	19	-60.4%
2181st	108	softwar	57	77	31	-59.7%
1957th	125	east	82	88	37	-58.0%
2416th	94	ordinari	85	66	28	-57.6%
3110th	67	interest_group	50	47	20	-57.4%
2354th	97	sticki_price	83	68	29	-57.4%
2848th	76	chicago	53	53	23	-56.6%
2524th	89	<b>capitalist</b>	62	62	27	-56.5%
1890th	131	capit_gain	68	91	40	-56.0%
3239th	62	capit_labor	55	43	19	-55.8%
221st	1412	exchang_rate	604	976	436	-55.3%
1841st	136	price_level	86	94	42	-55.3%
2298th	100	britain	76	69	31	-55.1%
2075th	116	ventur_capit	67	80	36	-55.0%
2898th	74	fama	62	51	23	-54.9%
2328th	99	output_gap	65	68	31	-54.4%
2931st	73	borrow_constraint	52	50	23	-54.0%
2140th	111	<b>leisur</b>	78	76	35	-53.9%
2343rd	98	latin_america	55	67	31	-53.7%
3135th	66	bid_ask_spread	52	45	21	-53.3%
688th	499	economist	378	340	159	-53.2%
710th	480	central_bank	291	327	153	-53.2%
3401st	56	<b>socio_econom</b>	50	38	18	-52.6%
3080th	68	return_scale	56	46	22	-52.2%
2896th	74	<b>oligopoli</b>	64	50	24	-52.0%
1580th	171	<b>monopoli</b>	133	115	56	-51.3%
3030th	70	world_trade	55	47	23	-51.1%
2678th	82	durabl_good	53	55	27	-50.9%
2613th	85	tax_reform	56	57	28	-50.9%
2539th	88	<b>altruist</b>	70	59	29	-50.8%
813th	408	<b>social_secur</b>	195	273	135	-50.5%
1811th	139	forward_look	111	93	46	-50.5%
1693rd	154	<b>life_expect</b>	84	103	51	-50.5%

N=20,216 Abstracts. Balanced Data set. Stemmed with Porter Algorithm. Out of 3522 stemmed words and N-grams present in more than 0.25 % of abstract. The 'rank' column shows the position of importance of the stems

## C Code for the computation of the relative term frequency in Rapidminer

```

int numTerms = wordList.size();
double totalTermNumber = 0;
for (float value: frequencies)
    totalTermNumber += value;

double [] wv = new double[numTerms];

if (totalTermNumber > 0) {
    double length = 0.0;
    for (int i = 0; i < wv.length; i++) {
        wv[i] = frequencies[i] / totalTermNumber;
        length += wv[i] * wv[i];
    }

    length = Math.sqrt(length);

    if (length > 0.0)
        for (int i = 0; i < wv.length; i++)
            wv[i] = wv[i] / length;
}
return wv;

```

For more details see: <https://rapid-i.com/rapidforum/index.php?topic=3728.0>

## D T-test on the mean of abstract length between the two periods

Figure 19: t test on the mean with equal variances

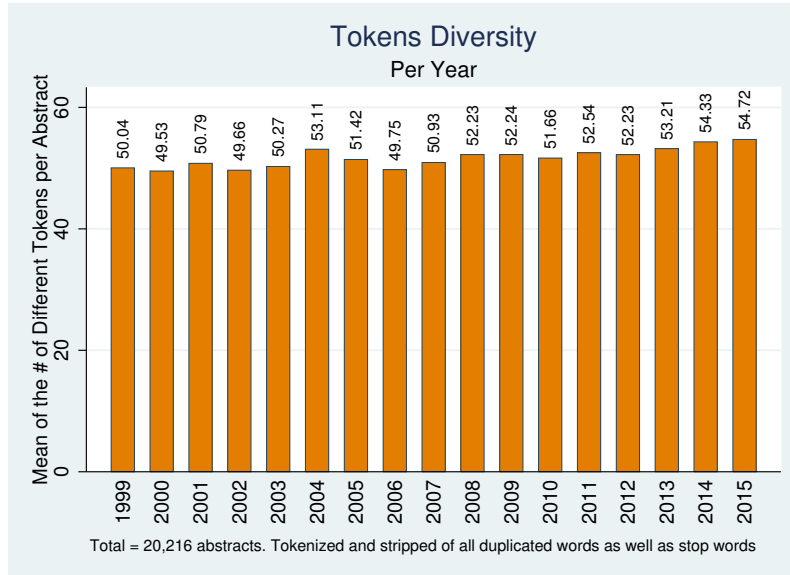
Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
post2008	10108	72.83261	.2327735	23.40271	72.37633	73.28889
pre2008	10108	70.23684	.2472411	24.85726	69.7522	70.72148
combined	20216	71.53472	.1700289	24.17521	71.20145	71.868
diff		2.595766	.3395757		1.93017	3.261362
diff = mean(post2008) - mean(pre2008)				t = 7.6441		
Ho: diff = 0				degrees of freedom = 20214		
Ha: diff < 0		Ha: diff != 0		Ha: diff > 0		
Pr(T < t) = 1.0000		Pr( T  >  t ) = 0.0000		Pr(T > t) = 0.0000		

The null hypothesis of the equality of means is strongly rejected. The probability of observing an absolute value of T above the t statistic computed (t-stat = difference mean / difference standard error = 7.64) is 0.000 which is well under the normal p-value threshold of 5%.

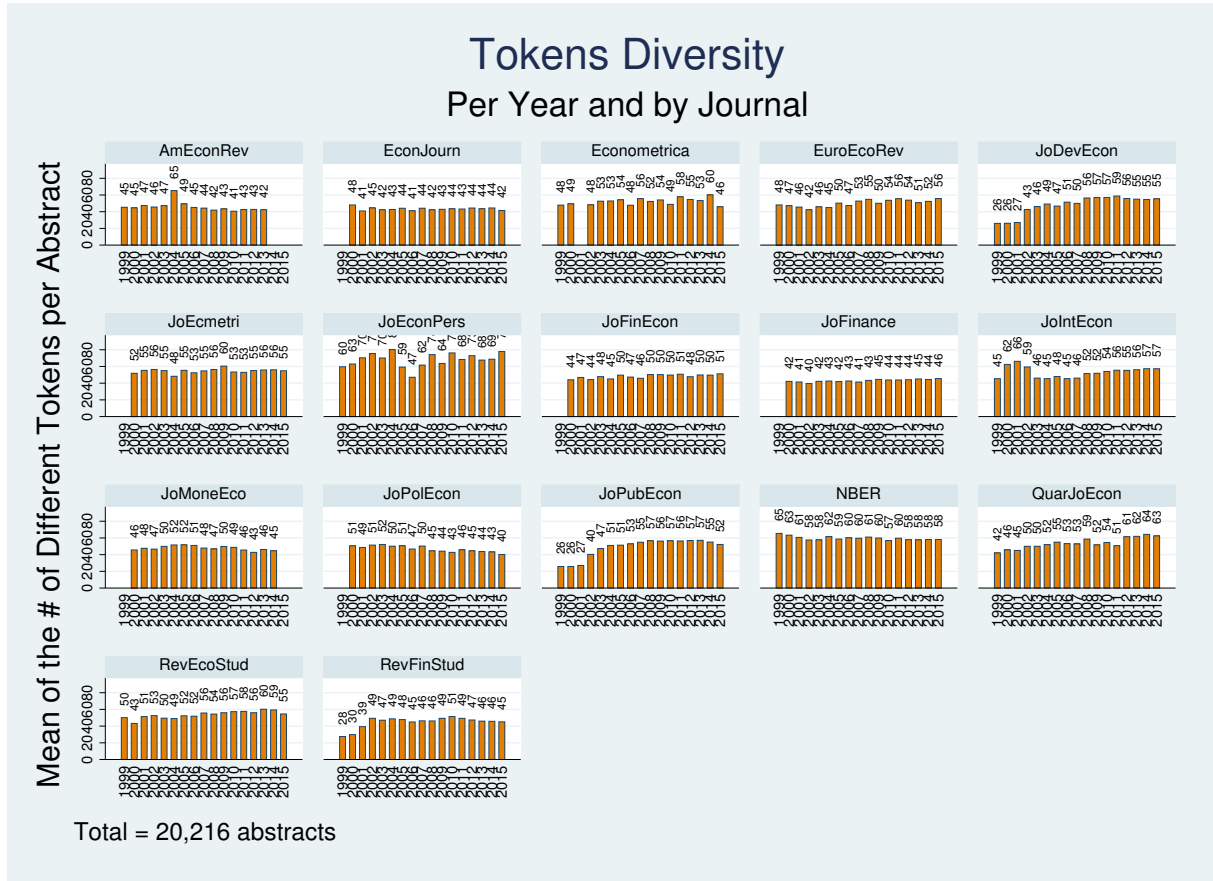
## E Token Diversity

Figure 20: Yearly evolution of the number of different words per abstract



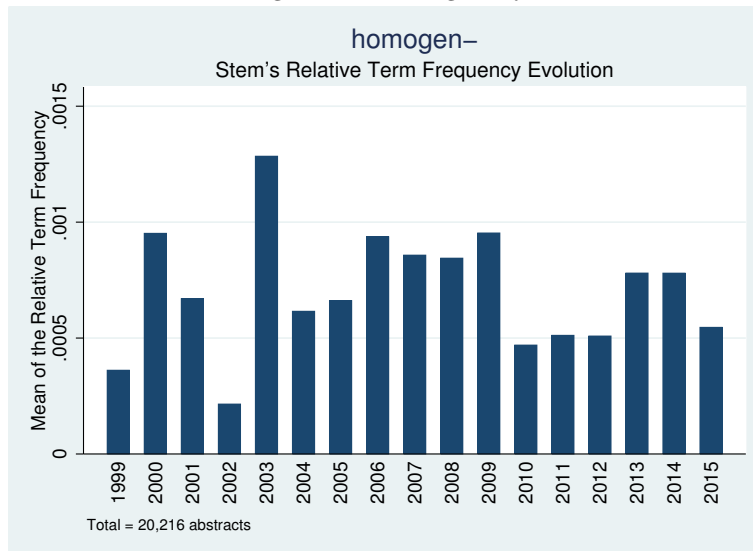
## F Token Diversity by Journal

Figure 21: Token Diversity yearly evolution by journal



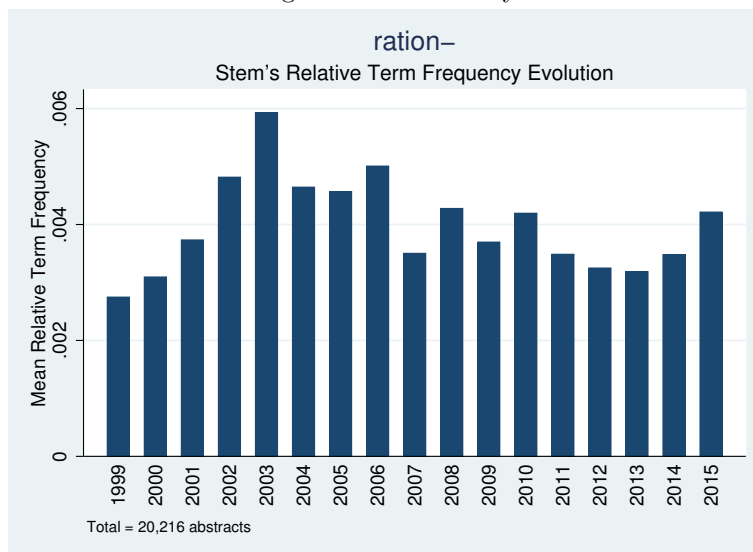
## G Rationality and Homogeneity

Figure 22: Homogeneity



Abstracts coming from 16 Journals and NBER. The mean of the relative term frequency is calculated per year

Figure 23: Rationality



Abstracts coming from 16 Journals and NBER. The mean of the relative term frequency is calculated per year

## H Other Findings

This section present a few findings that were not related to my hypothesis but which are worth noting as they reveal important trend in economics.

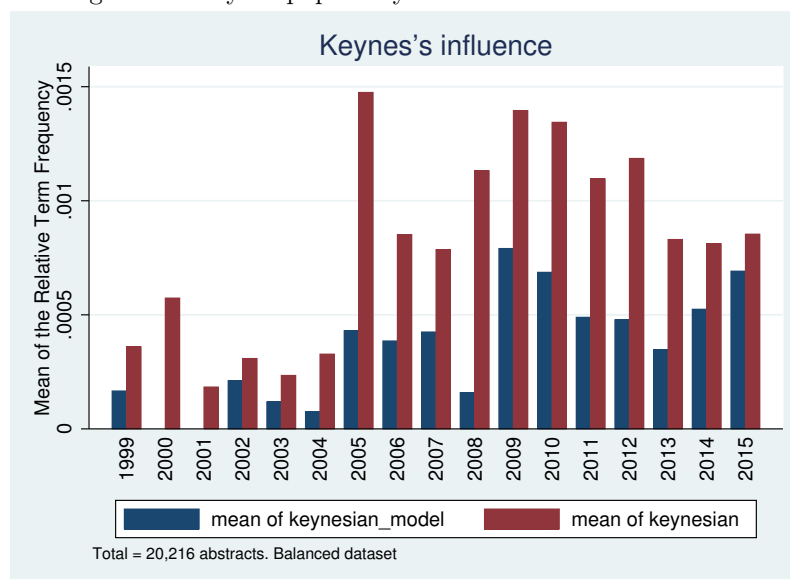
Looking at the evolution of the adjective keynesian in figure 24, one see a strengthening of its presence in abstracts after the crisis as could be expected given the strong keynesian policies used in the USA to fight the crisis

Given the historical significance of the 2008 crisis, reference to the great depression of the 30's was expected to rise. Figure 25 tend to confirm this with a sharp rise in the usage of the word 'Great Depression' in 2009 but no clear trends is visible given the sizeable variation between each year. This problem comes from the very low frequency of these terms. Appearing only a handful of time per year makes them subject to greater variation. The coining of the term "*great recession*" appears to happen in 2008 for the first time, and grew quickly in significance to reach a maximum in 2012. In 2008 the stem great recession appeared only once (see table 4 for confirmation) in the abstract of a NBER working paper<sup>49</sup>. This is very early for a scientific text since even in the non-scientific literature the usage of the phrase 'Great Recession' started to rise sharply only in the second half of 2008 according to a New York Times article from Rampell (2009).

Figure 26 reveals with more precision the trend identified in figure 14 about the rise of climate change words.

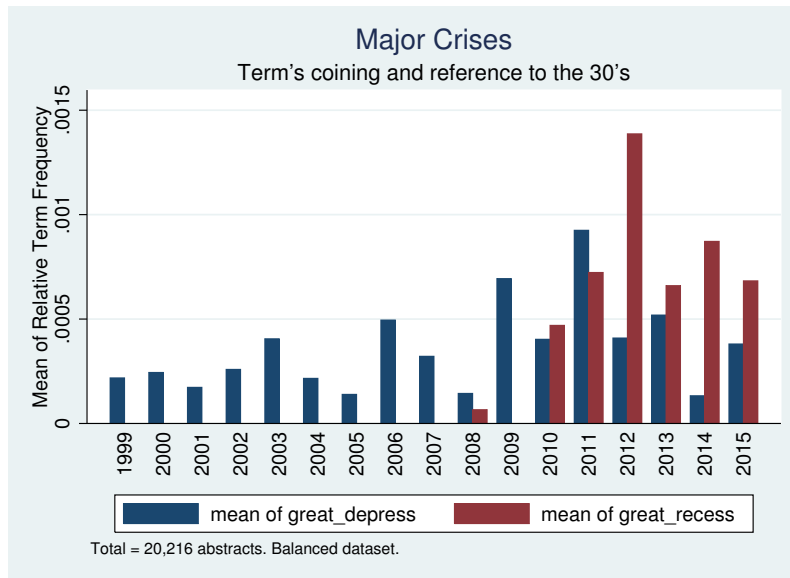
<sup>49</sup>NBER working paper number14092 accessible online here: <http://www.nber.org/papers/w14092>

Figure 24: Keynes popularity in the aftermath of the crisis



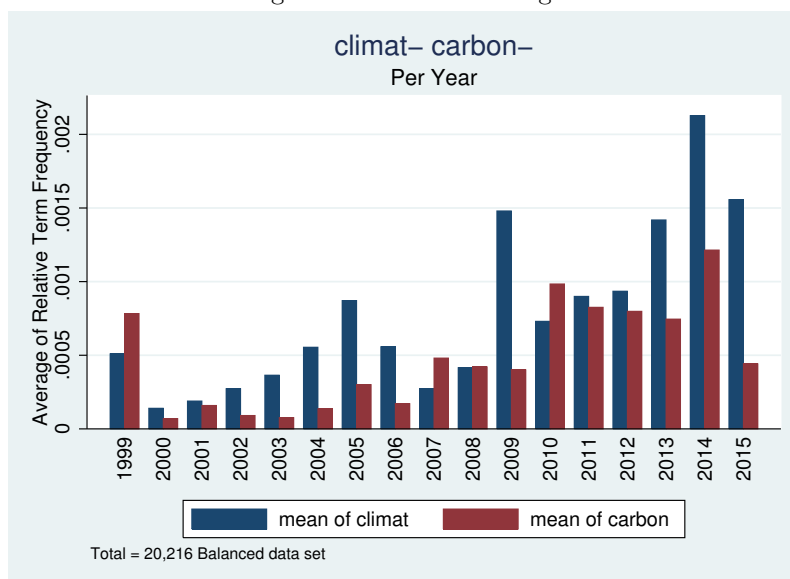
Notes : Abstracts coming from 16 Journals and NBER. The mean of the relative term frequency is calculated per year

Figure 25: Great Depression and Great Recession



Notes: Abstracts coming from 16 Journals and NBER. The mean of the relative term frequency is calculated per year

Figure 26: Climate Change



Notes: Abstracts coming from 16 Journals and NBER. The mean of the relative term frequency is calculated per year