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Spread-ing uncertainty, shrinking birth rates

Chiara L. Comolli, Daniele Vignoli

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Chiara L. Comolli*

Institute of Social Sciences and Life Course and Social Inequality Research Center
University of Lausanne
Geopolis, Quartier Mouline, Lausanne (CH)

chiara.comolli@unil.ch

Daniele Vignoli

University of Florence
Viale GB. Morgagni 59, 50134, Florence (IT)

daniele.vignoli@unifi.it

*Corresponding author

Abstract

Most studies document the pro-cyclicality of fertility to business cycles or labor market indicators. However, part of the recent fertility drop witnessed in Europe after the Great Recession is not explained by traditional measures. The present study advances that birth postponement might have accelerated in response to rising uncertainty, which fuelled negative expectations and declining confidence about the future. To provide empirical support for the causal effect of perceived uncertainty on births rate, we focus on the case of the sovereign debt crisis of 2011-2012 in Italy. Perceived uncertainty is measured using Google trends for the term “spread” – the thermometer of the crisis both in media and everyday conversations – to capture the degree of concern to the general public about the stability of Italian public finances. A regression discontinuity in time identifies the effect of perceived uncertainty on birth rates in Italy as a drop between 2.5% and 5%.

The business cycles pro-cyclicality of fertility rates, increasing during periods of economic growth and decreasing during recession, has been extensively investigated after the onset of the Great Recession (Goldstein et al. 2013; Lanzieri 2013; Sobotka et al. 2011). Rising unemployment rates are strongly and robustly correlated to Total Fertility Rate (TFR) drops during not only the most recent economic and financial crisis but in all the main economic downturns of the last centuries in advanced economies (Sobotka et al. 2011). However, the widespread and prolonged decline in birth rates that took place in Europe in the aftermath of the Great Recession remains a puzzle to solve. First, analyses that simultaneously include numerous indicators such as the unemployment rate, the economic policy uncertainty index, the cost of public debt and consumer confidence index, do well but do not entirely explain the decline in birth rates in Europe and the US in the period 2008-2013 (Comolli 2017). Second, a persistent drop in fertility has been registered after 2010 in the Nordic and other European countries where the Great Recession was comparatively mild; there, births decline is not explained by traditional macroeconomic indicators (Comolli 2018; Comolli et al. 2019). In Denmark, TFR dropped from 1.9 in 2010 to 1.7 in 2013 and for no apparent reason (Statistics Denmark 2014). Finland and Norway did even worse in 2018 reaching their historically lowest levels of fertility respectively to 1.4 and 1.56 children per woman (Statistics Finland 2019; Syse et al. 2018). These declines are no less radical than the drop in fertility rates seen in Greece after its economy collapsed. A recent study by Matysiak, Sobotka and Vignoli (2017), illustrates that the negative effects of GDP decline and of rising levels of unemployment and long-term unemployment were more pronounced during the recession period, in 2008–2014, than before. This intensification of the negative influence of economic conditions on fertility during the recession, however, did not result from the fact that Europeans adjust their fertility more strongly to the worsening rather than improvement of economic conditions (as it has been found for the US). In all, these studies indicate that there is something that drives contemporary European fertility decline that is not captured by traditional economic and labor market indicators. Part of this unexplained fertility decline in the aftermath of the Great Recession can be, we advance here, explained by the rise of fundamental uncertainty, a condition in which the future cannot be deducted by the present information (Dequech 2000).

In family demography, economic uncertainty is usually interpreted as an individual risk factor, mainly related to the labor market (e.g. unemployment, short-term contract jobs, underemployment, or a combination of these; Mills and Blossfeld 2003; Kreyenfeld et al. 2012; Alderotti et al. 2019). Clearly, most necessary information to evaluate uncertainty is directly associated with the job or the individual/employee's own characteristics. For example, a temporary labor contract usually implies higher job insecurity than a permanent one (Kreyenfeld et al. 2012: Kreyenfeld 2016; Vignoli et al. 2012). However, many information is unavailable in everyday life, such as policy-specific information that mainly emanates from state institutions, such as parliaments, governments, or courts (Garz 2012). For a majority of citizens, the media are an essential source of information on complex economic issues (Boomgaarden et al. 2011), which also evaluate, filter, and simplify information. The perception of economic uncertainty is thus strongly anchored in public images produced by the media and other powerful opinion formers. For instance, the media played a key role in shaping the general public's perception of the Euro crisis and by extension the European Union's institutional elite and its (in)ability to cope with the crisis (Joris et al. 2018a; Joris et al. 2018b). During the years of the Great Recession, media news contributed to the emergence of a European public sphere whose main characteristic has been a pessimistic view of a stagnant, underperforming continent (Cross and Ma 2013). The Great Recession became "pop", meaning popularized by a tsunami of news that favoured a simplified narrative of the crisis presented as the "evil" of contemporary European societies (Cepernich 2012). One of the pillars of the spectaculazation and simplification process is the use of a language based on earworms so that technical terms like *spread* become familiar and of everyday use (Cepernich 2012).

The aim of the present study is to frame and operationalize uncertainty going beyond empirical demographic and sociological tradition. We see economic uncertainty as a macro-level phenomenon, reflecting the fundamental uncertainty felt by people in times of economic turbulence (Sobotka et al. 2011). We posit that fertility postponement might have accelerated when economic uncertainty diffused across Europe, fuelled by negative expectations and declining confidence about the future driven by the narrative of the media; a process not captured in the studies published so far on the topic (Comolli 2018; Matysiak et al. 2017; Comolli et al. 2019). To provide first empirical support for the causal effect of perceived uncertainty on births rate, we focus on the case of the sovereign debt crisis of 2011-2012 in Italy. As a marker of the uncertainty produced by the crisis, and filtered by the media narrative, we refer to notion of *spread* – the interest rate differential between the Italian (risky) and the German (solid) long-term bond yields. The spread became in the media narrative the thermometer of the loss of credibility of the country in the financial markets, not just as a technical financial indicator of uncertainty but a crucial measure of how this uncertainty was perceived by the larger public (Ansa 2011). We expect that the popularization of the term spread in the media narrative produced a concern rise in the public, inducing people to search for additional information through internet. Based on this assumption, we use the Google searches for the term 'spread' as a proxy for when the interest in the topic peaked, isolate the uncertainty spike, and assess its impact on birth rates in Italy.

What is uncertainty?

Uncertainty is a widespread feature of contemporary societies. It represents a pervasive component of individual identities and social structures (Giddens 1991) and its consequences are vast (Halpern 2017; Keynes [1921] 1973; Knight 1921). In globalized societies, deregulation, internationalization and delocalization processes generate an intrinsic component of uncertainty (Mills et al. 2006; Blossfeld and Hofmeister 2006). In addition, uncertainty spikes when sudden shocks such as economic crisis, conflicts, natural disasters or social unrest produce unpredictability. The Great Recession that plagued advanced economies after 2008 represents a recent example of this surge in uncertainty affecting markets, institutions, and private individuals. In the aftermath of the economic and financial crisis, the notion of uncertainty, and in particular of economic uncertainty, has become central to the social science literature starting from economics and sociology but also family demography (Busetta et al. 2019). In general terms, a lack of predictability – of clarity – of future events, is what constitutes uncertainty (Johnson Hanks 2004).

The discourse around uncertainty largely focuses around the issues of its definition and measurement. The American economist Frank H. Knight (1921) coined the current definition of uncertainty as the condition under which, instead of taking decisions linked to a set of possible outcomes each one associated with a known probability (what is known as risk), actors are unable to assign a probability distribution to future outcomes. According to this definition, the main distinction between risk and uncertainty is thus that the former is quantifiable while the latter is not. This does not mean that the two concepts are not theoretically linked (Zinn 2006, Friedman et al. 1994; Dequech 2000) or empirically separable (Bloom 2014). Several works in sociology question a rigid distinction between uncertainty and risk (Beck 1992; Giddens 1991; Trinitapoli e Yeatman 2011). David Dequech (1999, 2000, 2003) maintains that uncertainties, or at least some types of uncertainties, are experienced by individuals and that they are measurable. Different kinds of uncertainties – some closer to the definition of risk (statistical uncertainty) some more distant (fundamental uncertainty) – have been identified. Uncertainty, for instance, can be real or socially constructed. The latter concerns a mental state of uncertainty or experiential uncertainty (uncertainty of means or of ends according to Johnson Hanks 2004). Overall, these definitions of uncertainty feature various degrees of ignorance of the actor in the decision-making process where failure is always a possibility, but the odds of failures are known to the actors with a different degree (Friedman et al. 1994).

In economics, measures of statistical uncertainty are mostly adopted to proxy aggregate economic uncertainty: volatility in GDP growth, stock market or professional forecasts. The more volatile the series is, the less it is predictable. A recent paper however shows that the number of relevant shocks is much lower than what stock market volatility would predict, but those few shocks are much stronger and have much more persistent effects on the real economy than volatility would predict (Jurado et al. 2015). In sociology and demography, economic uncertainty is measured differently. At the aggregate level, macroeconomic indicators are sometimes used to measure the uncertain climate individuals live in (Comolli 2017). Examples include consumer confidence, foreclosure rates or labor market indicators such as long-term unemployment rates or the share of temporary or fixed-term job contract in a given year. More exogenous measures of uncertainty include concerns generated by labor market reforms announcements (Hofmann and Hohmeyer 2013). At the individual level, uncertainty is measured through either direct questions to respondents about expectations or perceptions about the future situation (Kreyenfeld 2016), or about their knowledge about possible events (Trinitapoli and Yeatman 2011), or individual indexes of insecurity persistence (Busetta et al. 2019).

Uncertainty and the media

Through their coverage, the media tend to create images of society that strongly influence the public atmosphere. Not only the media select the topics they report on, they also define the way they cover them with respect to angles, tone, and so forth. A sample of studies in communication research suggest that media framing uses martial, aggressive language to describe the European public sphere. Bounegru and Forceville (2011) study the coverage of the Euro crisis in editorial cartoons and identify catastrophe/(natural) disaster, illness/death and begging as the most frequent metaphors. Horner (2011) studies public discourse on the 2008 US banking crisis and finds that the most dominant metaphors were illness, natural disaster, and mechanical failures. Esager (2011) analyses the global financial crisis in English and Danish newspapers, illustrating similarly aggressive metaphors to describe the public sphere in these two countries. Joris et al. (2018a) examine the metaphoric frames in the coverage of the Euro crisis in newspapers across Belgium, Finland, Germany, the Netherlands, Spain. In all five countries, the Euro crisis as *war* turned out to be the most prominent news frame. Relatedly, a review of Italian news illustrates that the more common narratives associated to the Great Recession are those juxtaposing the absolute categories of the “good” (before the crisis) and the “evil” (during the crisis) (Cepernich 2012). In sum, previous research has identified a media-induced pessimistic narrative of a troubled, failing European economic climate.

Media narratives and metaphorical frames might influence individuals’ opinions and attitudes (Robins and Mayer, 2000; Thibodeau and Boroditsky, 2011; Joris et al. 2018b). For the majority of citizens, in fact, the media are the major source of information regarding the economic sphere (Joris et al. 2018a; Joris et al. 2018b). Moreover, negative news has a stronger impact on perceptions than positive reports. For instance, asymmetric effects have been demonstrated on consumer confidence (Alsem et al. 2008) and inflation (Dräger 2015). This asymmetry can be explained by prospect theory (Kahneman and Tversky 1979): the argument based on the psychological phenomenon for which loss aversion causes negative news to have a stronger impact than positive information.

Several studies have evaluated how news coverage of labor market outcomes (e.g., the state or development of unemployment) affects perceptions (e.g., Mutz 1992). In a review of the effects of recession on fertility, Sobotka et al. (2011) emphasize the role of apprehension regarding future negative economic events that may result in feelings of anxiety and depression, in shaping fertility. They suggest that individuals' observations of the broader economic climate, including media coverage of the economy, might increase uncertainty and affect fertility. Along these lines, Morgan et al. (2011) find that the negative relationship between unemployment and fertility in the United States is stronger in states that voted less Democratic, which they interpreted as evidence that emotion and sentiment shape the effects of economic conditions on fertility. Schneider (2015) examines the effect of area-level economic conditions on state fertility in the years leading up to and including the Great Recession in the Unites States. He suggests that press coverage come closer to measuring the economic sentiments that shape economic uncertainty than the measures of unemployment and foreclosure. These examples are suggestive of a link between the perception of economic uncertainty and fertility channeled through the media coverage of the crisis, but no study of this kind actually exists for Europe. In addition, these studies fail in establishing a direct link between the media coverage and the individuals' receptivity of the media message. How do we know that the particular media framing of an event is known (and actually internalized) and it influences the behavior of the general public? The present study addresses this question.

In agreement with the studies mentioned above, we posit that in the era of uncertainty individuals take decisions while exposed to persistent media-channeled messages of the economic climate. The turbulence in the European economy not only increased actual hardship, but might have also generated feelings of economic uncertainty through media-oriented shared narratives. High news coverage of the economy is concentrated during recessions (Doms and Morin 2004). Typically, in crisis situations, people look for information about causes and consequences with more determination than usual (Coombs and Holladay, 2004). In addition, the fraction of people who update economic information increases in times of greater news coverage, because the costs for information procurement decrease (Carroll 2003; Doms and Morin 2004). At this premises, online search of critical recession-related information might represent a crucial marker of the fact that such general uncertainty perception seeped into private life as well. In the following, we explore the link between the individuals' reception of the narrative of the crisis proposed by the media and changes in the fertility realm.

Economic uncertainty and fertility

Due to the irreversibility of childbearing decisions and the possibility of postponing birth for a certain time, uncertainty may generate a re-evaluations of preferences, risk and opportunities that manifest through either a permanent decline or a temporary postponement of childbearing (Ranjan 1999). Caldwell (2006) argues that social upheaval, by creating uncertainty about the future, can accelerate fertility declines related to the demographic transition. Other studies demonstrate that adverse labor market conditions lead to delays in childbearing (Adsera 2011; Mills and Blossfeld 2003). This has been illustrated in general in relation to the current globalization processes (Blossfeld et al. 2006; Blossfeld and Hofmeister 2006; Blossfeld et al. 2009; Oppenheimer 2003) and employment insecurity (Hofmann and Hohmeyer 2013; Prifti and Vuri 2013). The effect of uncertainty on childbearing has also been shown in relation to more specific events. For instance, the drop of birth rates in the aftermath of the Great Depression (Ryder 1980), or in Eastern Europe after the collapse of the communist system and the transition to a market economy (Ranjan 1999; Billingsley 2011; Sobotka et al. 2011). Many authors relate the rise in economic uncertainty to childbearing postponement in the aftermath of the Great Recession (Busetta et al. 2019; Hofmann and Hohmeyer 2013; Kreyenfeld 2016; Prifti and Vuri 2013).

At the micro level, most studies measure the effects of economic uncertainty on fertility with labor market indicators such as job loss or unemployment (Adsera 2005, 2011; Ahn and Mira 2001; Da Rocha and Fuster 2006; De La Rica and Iza 2005), long-term unemployment (Matysiak et al. 2017), the share of precarious or temporary contracts in the economy (Vignoli et al. 2012, 2016, 2019) or indexes of joblessness persistence (Busetta et al. 2019). A few studies use exogenous labor market measures, and investigate the effect of the employment insecurity generated by labor market reforms on childbearing (Hofmann and Hohmeyer 2013; Pristi and Vuri 2013). Other studies, instead, look at income or earnings uncertainty in relation to a job loss and their impact on childbearing (Ranjan 1999; Santos and Weiss 2016; Sommer 2016). There is also evidence that, on top of the actual economic outlook or objective insecurity, the perception, or anticipation, of future downturns inhibit childbearing (Kreyenfeld et al. 2012; Kreyenfeld 2016; Trinitapoli and Yeatman 2011; Vignoli et al. 2018). Some studies use the direct question to respondents about how insecure they feel their own personal economic situation is (Bhumik and Nugent 2011; Kreyenfeld 2009, 2016) or their jobs are (Bernardi et al. 2008; Hanappi et al. 2017). Others use survey questions about respondents' knowledge about future possible events (Trinitapoli and Yeatman 2011).

In all, since the Great Recession hit advanced economies after 2007, economic uncertainty has often been cited as an explanation of the recent fertility rate decline in Europe and the US (Sobotka et al. 2011; Lanzieri 2013; Kreyenfeld 2016). Nonetheless, published studies on the topic suffer from two main limitations. First, the operationalization of economic uncertainty is in most cases limited to traditional indicators that do not capture the potential connection between the broader climate of uncertainty and fertility. Second, the causal nexus between the latter is usually not addressed (for an exception see Hofmann and Hohmeyer 2013 and Prifti and Vuri 2013). Taking the case of the sovereign debt crisis of 2011 in Italy, this study shows that part of the drop in the birth rate is causally generated by the perceived uncertainty channeled by the media.

Uncertainty and the sovereign debt crisis of 2011 in Italy

To provide a first empirical example of the causal effect of the media narrative of economic uncertainty on births rate, we focus on the case of the sovereign debt crisis of 2011-2012 in Italy. The crisis emerged because the costs of the Great Recession heavily weighted on public expenditure boosting government debts. Financial markets started doubting the capability of Italy to ever replay its large and increasing debt, and asked for a larger premium to buy Italian bonds. As a marker of the uncertainty produced by the sovereign debt crisis we refer to the interest rate differential between Italy (risky Bot) and Germany (solid Bund), or the spread. The record high level of Bot/Bund spread of 575 points of November 2011 elicited a high degree of political instability in the country, culminated in Silvio Berlusconi's resignation as Prime Minister (November 12). In the media narrative, the term spread became the thermometer of the crisis. Many TV-shows were interviewing people and politicians in the streets asking about the definition of spread (Ansa 2011). We use the Google searches for the term 'spread' to grasp the uncertainty spike and establish its impact on birth rates in Italy.

The Sovereign debt crisis

After the announcement by the European Central Bank that the Eurozone had entered into recession in the third quarter of 2008, the first months of 2009 were characterized by negative economic growth and fast-growing unemployment all over Europe, and by the countless public cash injections into the financial system and stimulus plans to sustain the economy. The massive public spending busted public deficits and endangered the ability of some countries to repay their fast-growing government debts. In June 2009, the European Central Bank (ECB) for the first time warned governments that had borrowed heavily to stop accumulating debt. In fact, later in 2009 a crisis of confidence emerged in European countries traditionally characterized by large public debt, and it materialized in widening bond yield spreads between them and the more virtuous ones. The interest rate to be paid on the public debt is a very sensitive measure of the risk associated with a country's ability to repay its debt, and of the uncertainty associated with credit worthiness. Public debates discussed repeatedly the chances of survival of the Eurozone (Joris et al. 2018a,b). Rumors about countries being in need of financial help were becoming more and more frequent at the time in the media. The financial speculative attack on public debts touched upon the very stability of those states in which a political, on top of the financial and economic, crisis exploded in the fall of 2011, with the premature end of national governments in Slovenia and Slovakia, Greece, and Italy.

Figure 1 (top panel) shows the trend in the spread between the Italian and the German bonds between January 2003 and mid-2014 (red line) and Italian birth rates in the same period (blue line). The graph shows that until early 2008 the differential between the cost of public debt in Italy and Germany is very close to zero. The spread starts increasing at the end of 2008 but the situation escalates only in mid-2011, with the spread peaking first at the end of that year to a 5% differential and again in mid-2012, though, to a lower value. This is a crucial step to understand the evolution of media representations of the crisis, because it is at this point that the spread becomes the major journalistic theme, invading the daily media arena, regardless of press and TV, information and infotainment (Cepernich 2012). The term spread become the main media earworm. On the other side, birth rates seem to start declining before the peak in the sovereign debt crisis at the end of 2011 but the decline seems also to accelerate after that. The time series, though, displays quite strong seasonality so more accurate analyses are needed to ascertain whether a drop in the aftermath of the surge of the spread took place and how large that has been.

[Figure 1 about here]

Google searches and issue salience

A small but growing body of research explores the socioeconomic and demographic implications of the growing internet diffusion and use. Part of this literature explores the meaning of web searches and their implications for individuals' decisions. The main mechanisms linking the two is information gathering: broadband availability and web searches reduce the cost of seeking information with respect to the more decentralized offline information markets (Guldi and Herbst 2017). Between 2007 and 2017 print newspapers read declined from 67% to 35.8% of Italians. In the same period households' expenses on print newspapers and book declined by 37% (CENSIS 2018). In 2014, the share of Italians reading online newspapers was 20.8% and reading news-related websites was 34.3% (CENSIS 2018).

The Google Trends (GT) tool was introduced by Google in the summer of 2008 to provide a public view into the relative internet search volumes. GT provides a time series index of the volume of the queries into Google in a specific geographic area (Choi and Varian 2012). The advantage of Google search activity data is that they express the demand for a wide range of information. They allow to investigate combinations of space, time and context related to many dimensions of human behavior. Finally, the data are high in frequency and are available almost in real time. The drawbacks of Google search activity data are that they are available only in aggregate form and the methodology of collection and reporting of the data is not very transparent. Moreover, the geographical distribution of the searches is not always precisely estimated since the IPs cannot always be properly located and the meaning of some terms may change over time and places (Askitas 2015).

The use of search behavior as a proxy was popularized by Ginsberg et al. (2009) with Google Flu article. GTs are mostly recognized as useful to measure the issue salience of a topic among the general public (Mellon 2013; 2014) and for the "tracking of real-life quantities" (Ojala et al. 2017). GTs have been used to track economic indicators, such as 'job search' for unemployment in various countries (Germany, Italy, Spain) (Choi and Varian 2012; Simionescu and Zimmermann 2017 for a review). Mellon (2013) shows that for Spain, even with low internet penetration levels, GT searches generate search data that closely match survey measures, especially for economic terms (Mellon 2013: 289). In Italy internet coverage of households is very similar to Spain (Eurostat 2017). In relation to fertility, searches for the term 'maternity' have been shown useful to forecast fertility and in tracking temporal and spatial variation in fertility and the meaning of fertility in different context (Billari et al. 2019; Ojala et al. 2017). In relation to the consequences of the Great Recession, Google queries for "malaise" and "symptoms" have been used to track the effects on health (Askitas and Zimmermann 2015) and searches for "hardship letter" in the US have been used as an indicator of mortgage delinquency to track the effects of the crisis on the housing market (Askitas and Zimmermann 2011).

Figure 1 (bottom panel) shows that google searches for the term spread peaked in Italy in November 2011. They were almost zero before that date and gradually returned to close to zero today. The date of the maximum searches can identify when the sovereign debt crisis in Italy was perceived as most salient among the population. The latter can be used to investigate the effects of the media narrative of uncertainty on birth rates by looking at what happened 9 months after that peak.

Data and measures

National and regional crude birth rates are calculated from ISTAT (Istituto Nazionale di Statistica Italiano) as the ratio between live births per month and the number of women 15-44 resident in Italy at January 1st each year. Monthly data are derived from national vital statistics on births, which is complete. At the regional level (N=20), monthly live births in each region are divided by the number of women 15-44 resident in the region at January 1st each year. Birth rates (per 1000 women) are de-seasonalized using a centered 12-months moving average (each point in time is the average of the preceding 6 months and the following 6 months). In this way the expected birth rate captures long-term trends but not seasonal trends, without imposing a specific shape of the seasonal pattern across calendar months (Seiver 1985; Bernal et al. 2017). Finally, birth rates are led 9 months.

GT data (for a description of how data are collected and released see Askitas 2015) represent the searches for the word 'spread' in www.google.it. The values represent search interest *relative* to the highest point in a given region and time [$\frac{\#Searches}{Maximum\#} * 100$]. A value of 100 is the peak popularity for the term. A value of 50 means that the term is half as popular. A score of 0 means that there was not enough data for this term. To roughly assess the *absolute* magnitude of the searches, we can consider the change in popularity of the term spread over the period 2006-2016 in Italy relative to searches regarding very common terms used in Italy to inquire about football: "Serie A" (A league), "Campionato" (Championship) and "UEFA Champions League". Until 2010 the queries for spread were null compared to any of the other three terms. In 2012 the queries for spread become almost 100 times those of UEFA Champions League, 60 times that of Campionato and 15 times that of Serie A, and gradually decline in the following years.

The system eliminates repeated queries from a single user over a short period of time, so that the level of interest is not artificially affected by these type of queries (for instance, by typing errors). Complements, namely searches for the term 'spread' in non-related words (*Spread Eagle*, US band; *Spreadsheet*, Excel; *Spread shirt*, clothes printing online shop) have been removed. GT at national level used in this analysis are robust to related search category: All categories, Finance, People and Society; while, as expected, the trend values are different in non-related categories (e.g. Food and Drinks). Estimates are also robust depending on whether the search is done in Web search or News search. A related event to the burst of the sovereign debt crisis in Italy was the resignation of the

Prime Minister Berlusconi, which also took place in November 2011. Predictably, the search for the term “dimissioni Berlusconi” (resignation Berlusconi) peaked at the same time in the News category search on Google, however, the query was not so prevalent as that of ‘spread’ when we consider the general category.

Geo-localization allows to see how popular the query for ‘spread’ is in more specific locations during the specified time frame. As in case of country-level data, a higher GT value means a higher proportion of all queries, not a higher absolute query count. A key limitation with GT at regional level is data sparsity, in fact, zeroes indicate a location where there was not enough data for queries on this term. When modelling temporal variation at the regional level, GT fails to provide any data in 926/2640 (35.1% of cases) because there were not enough queries on those region/month combinations (reported as missing data in the GT variable). For this reason, both national and regional estimates are presented here.

The treatment variable is a dummy for the months after the peak in searches (1 after GT=100). The search index itself is included as a control in some models as a robustness check. It is worth noting that, although the treatment dummy in the model is allowed to differ by region, for the period 2004-2018 in almost all regions the peak in GT was registered in November 2011. The only two exceptions are Val d’Aosta, where the peak in GT queries for spread took place in December 2011, and Molise that registered the peak in March 2012.

Research design

Non-experimental data pose many challenges to the distinction of correlation from causality (Angrist and Krueger 2000). Regression discontinuity (RD) represents one strategy to identify the causal effect of a treatment using observational data in which the treatment is based on being below or above a certain threshold of a ‘forcing’ variable, such as a location, birthdate or time. The identifying assumption is that the characteristics of individuals just below or above the threshold for treatment assignment do not change. Units around the cutoff do not systematically differ in their unobservable characteristics, thus offering a valuable counterfactual comparison between control and treatment group (Calonico et al. 2017).

When as in the present case, time is the forcing variable, the design is a particular case of RD called Regression Discontinuity in Time (RDiT). RDiT design is often used in similar contexts, but it is not identical to cross-sectional RD (Shadish et al. 2002) and to event study or interrupted time series regression methods (Bernal et al. 2017). One advantage of using RDiT in contrast to event studies is that it is not necessary to assume that there are no unobservable variables correlated with time; it is enough to assume – with the caveats expressed below – that the latter do not change discontinuously at the threshold (Davis 2008; Hausman and Rapson 2018).

The cross-sectional vs time-series type of data represents the first difference between RD and RDiT. In cross-sectional RD one needs to have a large-enough sample (N) in the neighborhood of the cut-off to approximate the limit of the conditional expectation of the outcome variable just-below and just-above; however, in an RDiT there is little or no cross-sectional variation. This could be problematic in light of a bias/precision trade-off as the sample size increases away from the cut-off by increasing T instead of N (as in standard RD analyses). Researchers must rely on observations away from the threshold in order to obtain sufficient power to precisely estimate the coefficient, but using observation remote in time from the cut-off "represents a substantial conceptual departure from the identifying assumption used a cross-sectional RD" (Hausman and Rapson 2018: 535). Therefore, if unobservable confounders (for instance: self-selection into treatment, anticipation behavior) or time-series properties are not correctly addressed, estimates could be biased. Assuming continuity of unobservables at the threshold, normally enough to ensure identification in standard RD, is not enough in the case of RDiT. With the latter, in fact, three additional issues arise: anticipation close to the threshold, time-series auto-regression, and short- vs long-term effects of the treatment. While the last two issues are addressed later, regarding anticipation, Figure 2 shows that from July 2011 the GT for spread slowly increases with a blip in October 2011, just before the jump in November. Searches, though, remain between 1/10 and 1/5 of the peak in November, suggesting that the anticipation would not affect the estimates.

The identification assumption at the basis of this paper is that births that take place around 9 months after the peak in spread do not differ on parents' unobservable characteristics, the only unsmooth change at the cutoff is due to the sudden surge in the spread salience, namely in uncertainty. Figure 2 shows that on the treatment date, in November 2011, the jump is observed in the treatment only while other determinants of fertility – Google Trends for spread, the unemployment rate and the consumer confidence index – are smooth on the threshold.

[Figure 2 about here]

As mentioned, RDiT is affected by a tradeoff between precision and bias. The researcher wants to stay as close as possible to the cutoff (where observations are more similar), but also wants to have enough data points to get precise estimates. The assumed functional form of the relation also determines how close one can stay to the cutoff: the closer to the cutoff the more linear the relationship gets. If the underlying regression function of Y is fairly linear, the bandwidth can be enlarged to get more precise estimates without loss in terms of bias; however, if the regression line of Y is non-linear, the bandwidth should be restricted to get unbiased estimates. Since there is no prior knowledge to assume that the functional form of the births rates might be linear (as predicted by a Local linear regression, Equation 1) rather than polynomial of any degree (as in a Global Polynomial estimation, Equation 2), the underlying regression function is estimated using both approaches[1].

$$MA(\,Birth\,rate_{t+9}) = \gamma_0 + \gamma_1 D + \gamma_2 t + \gamma_3 D * t + \varepsilon_t \qquad \text{with } -h < t \leq +h \tag{1}$$

$$MA(\,Birth\,rate_{t+9}) = \gamma_0 + \gamma_1 D + \gamma_2 t + \gamma_3 D * t + \sum_{k=2}^{P} \delta_k\, t^k + \sum_{k=2}^{P} \beta_k D * t^k + \varepsilon_t \tag{2}$$

On the left-hand-side we have the 12 months moving average birth rate at time *t* (leaded 9 months), and on the right-hand-side we have the continuous time variable *t (year-month)*, centered around the cutoff date (0 in November 2011). *D* is the treatment dummy variable for after November 2011 (D=1 if t ≥ November 2011 and D=0 if t < November 2011), indicating the eventual departure from the trend occurring after the peak in Google searches for spread. Parameters are allowed to differ on the left (γ_2) and on the right (γ_3) of the cutoff (November 2011). If we allow the slope to be identical on both sides of the cutoff, we would be using data on the right-hand-side of the cutoff to estimate the effect, which is inconsistent with the spirit of RD (on the right-hand-side are treated units while on the left-hand-side are control units). The main coefficient of interest, the jump at the cutoff, is γ_1. The last polynomial term in Equation 2 is added for the time trend for global polynomial estimation. Time series are autoregressive, as mentioned earlier, so to account for the dependence in the residuals, we clustered standard errors for years[2]. Local linear regression results are presented using different bandwidths and global polynomial are presented for different polynomial orders. If the underlying regression function of Y is fairly linear, the optimal bandwidth would be larger to get more precise estimates without loss in terms of bias; but if the regression line of Y is non-linear, the optimal bandwidth would be restricted to get unbiased estimates. A rectangular kernel – where observations are not weighted depending on their distance from the cutoff – is preferred to a triangular kernel function as the latter approach is more arbitrary regarding the choice of the weights (Lee and Lemieux 2010).

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[1] Lee and Lemieux (2010) mention polynomial functions as a simple way to relax the linearity assumption. However, others recommend not to use third or higher order polynomials in regression discontinuity. Gelman and Imbens (2018) argue that higher order polynomials lead to noisy estimates sensitive to the degree of the polynomial and poor confidence intervals and that local linear or local quadratic estimates should be preferred (Gelman and Imbens 2018: 448).

[2] Additional checks have been conducted using a AR(1) process.

Results

Table A.1 in the Appendix A reports summary statistics of the variables used in the analyses before and after the cutoff at the national and regional level. It shows that after the peak in uncertainty in November 2011, the financial and economic outlook of the country worsen together with the perception of economic conditions by consumers and the socio-demographic indicators. Both average crude birth and marriage rates decline, all the consumer confidence indicators worsen, the actual spread on Italian bonds quadruple and the unemployment rate significantly increases. Figure 3 illustrates the RDiT plot of monthly birth rates for Italy (national estimates). The top-left panel shows the scatterplot of the raw data where each dot represents the birth rate of one month (N=144). The cutoff (leaded 9 months) point is in August 2012 and the vertical dotted line indicate an example of a 6 months' bandwidth. The other three panels report the same plot varying the width in which each bin is calculated averaging the birth rate over a given number of months (2 in the top-right, 5 in the bottom-left and 7 in the bottom-right panel). The figure illustrates the trade-off between precision and unbiasedness of the estimate of the jump at the threshold.

[Figure 3 about here]

Figure 4 reports results of national (top panels) and regional (bottom panels) estimates for the local linear (left panels) and the global polynomial (right panels) RDiT estimates. Full models' estimates are reported in Tables A.2-5 in the Appendix. For the local linear, different estimates are reported varying the bandwidth: using the whole sample or a symmetric bandwidth between 3 years and 3 months around the cutoff. For the global polynomial different estimates are presented varying the degree of the polynomial between the linear and an 8th order polynomial. It is important to notice that the magnitude of the effect is sensitive to the specific bandwidth. However, all estimates range between -0.20 and -0.10 with more precise estimates coming from the models using regional data as more observations are available. Additional results (available upon request) simultaneously varying the order of the polynomial and reducing the bandwidth display similar coefficients. Taking the conservative estimate from the models, a drop of -0.10 in birth rate 9 months after the peak in GI for spread, considering an average rate of 4 births per 1000 women age 15-44 per month before the uncertainty burst, translates into a 2.5% drop in births due to the sovereign debt crisis. Importantly, the RDiT results are stronger than the associational evidence in a regions fixed effect OLS model of GT searches for spread and monthly birth rates per 1000 women (-0.0034 with 95% confidence interval -0.004 – -0.003, and intercept 4 births per 1000 women).

[Figure 4 about here]

Together with using different data (national and regional) and the RD alternative specifications (varying the bandwidth and using both local linear and global polynomial estimates, with various polynomial order), an extensive number of robustness checks is included in Appendix B of the present study. They all corroborate our results. First, we re-estimated the models using several additional control variables (Table B.1): the women's age structure index; the actual spread between Italian and German sovereign bonds; the GT index; the unemployment rate; and the consumer confidence index and some of the more detailed indicators used to construct it (confidence in own and general economic situation, confidence in current and future economic situation). Second, we re-estimated the discontinuity in a regions' fixed effect model which controls for time invariant regional characteristics that might affect both regional birth rates and GT searches (Figure B.1). Third, to account for the diversity across the Italian territory in internet access, we added a correction factor to the GT variable that weights the queries on the basis of households' internet access in the region (Table B.1). Finally, the Appendix also includes a placebo tests using a variable (monthly crude marriage rates) not affected by the treatment. While marriage rates are likely to be negatively influenced by economic uncertainty, in fact, there is no reason to expect that this negative effect of uncertainty materializes nine months after the uncertainty shock, as it is the case for childbearing (Figure B.2).

Concluding discussion

The emergence of new forms of risk is a consequence of the rising levels of complexity in modern industrial societies (Beck 1992). With the globalization process, liberalizations and labor market deregulation, the probability of experiencing recessions or negative outcomes such as income drops, financial losses, unemployment or job precariousness, and downward mobility have increased. As these new forms of risk emerged in contemporary societies, some authors have argued that the risk framework is not enough to capture the degree of unpredictability of events in contemporary society. The concept of uncertainty, differentiated from risk, highlights the condition of ignorance in which actors cannot predict the likelihood of the outcome produced by their actions (Knight 1921). Olivier Blanchard refers to this *Knightian* definition of uncertainty in his foreword to the International Monetary Fund (IMF) Outlook in 2012, talking about the Great Recession and its consequences. The diffusion of fundamental uncertainty produced consequences way outside the public finance realm and individuals were affected by the insecurity produced. As Nau et al. (2015) argue: "there are many implications of having moved to a debt society that we are only beginning to understand […] young adults today must borrow against future in the hope that his investment pays off" (Nau et al. 2015: 121). The rise of fundamental uncertainty has been facilitated by the media, which served as amplifiers of uncertainty (Joris et al. 2018a; Joris et al. 2018b). In this article, we posit that the rising perception of fundamental uncertainty, channeled via the media framing of the economic crisis, might have contributed to the unexpected loss of births experienced by contemporary European societies.

To provide first evidence about the causal nexus between birth rates and perceived economic uncertainty, we focus on the case of Italy in the aftermath of the sovereign debt crisis of 2011. In a later phase of the Great Recession, some countries like Italy suffered a loss of credibility in the financial market due to their skyrocketing public debts. The speculation on the inability of the country to repay its debt and the subsequent rise in the cost of the Italian debt was so brutal that the financial crisis rapidly escalated into a political crisis in which the very permanence of Italy and other countries in the EU was doubted. Sovereign debt is everyone's debt and as such its cost weights on everyone's future. Moreover, the spread between the cost of the risky Italian and the safe German bonds became a thermometer of the country's financial uncertainty in the media narrative and in everyday conversations (Ansa 2011; Cepernich 2012). In the media simplified narrative of the sovereign debt crisis, the term spread became popularized as the earworm of the time. Its widespread use in the media discourse expanded public concern with the Italian situation within the global crisis and raised the general interest in the definition of spread and the consequences its increase would produce. In a situation of ignorance, people start looking for information about causes and effects more than they usually do (Coombs and Holladay, 2004). They seek information where they can, and Google is one of these sources. The search queries for the term 'spread', in fact, suddenly spiked in November 2011 when, we argue, the salience of the specific issue, as an indicator of perceived uncertainty, also peaked. We use this discontinuity to assess what have been the consequences on birth rates in Italy nine months after the peak.

Using monthly birth data from the ISTAT at the national and regional level, the study shows that around 2.5% of the drop in crude births nine months after the uncertainty shock in November 2011 was due to the sovereign debt crisis. In size, this is similar to the associational evidence found between unemployment rates and total fertility rates (-3%) and it is higher than the association between the decline in consumer confidence and total fertility rates (1%) for Europe and the US (Comolli 2017). This result comes from the most conservative estimate from the models, but considering the average rate of 4 births per 1000 women age 15-44 per month before the uncertainty burst, some point estimates suggest a drop in birth rate around -0.2 which translates into around a 5%

drop in births due to the sovereign debt crisis. Results are corroborated by robustness checks including a placebo on marriage rates nine months after the shock, which, as expected, are not affected by the uncertainty spike. In 2011-12, the term “spread” was popularized by Italian media as the slogan of the time, serving as a multiplier of uncertainty and, we prove here, also contributed to shrink the number of births.

Despite the novelty of the study and its contribution to the literature on the pro-cyclicality of childbearing, the present study has its own limitations. First, as many research designs aimed at identifying the causal effect of events, RDiT favors internal validity at the expenses of external validity. In this case the question is how much the effect identified here is limited to the specific case of the sovereign debt crisis in Italy. Second, the estimates of a -2.5/5% drop in birth rates represent a short-term impact as the largest bandwidth here includes time points within three years after the shock (fall 2014). What we observe is thus a postponement of childbearing. Whether the latter produced long term or even permanent effects remains to be seen. A third limitation concerns the separation between the strictly monetary component of debt and its value as an indicator of perceived uncertainty. A decline in the share of public debt owned by Italian private citizens was indeed registered in the aftermath of the crisis (21% in 2011 and 6% in 2018). However, previous studies have shown that the meaning of debt goes beyond its monetary component with an excess of debt being problematic and stressful (Nau et al. 2015). A final concern is that, despite the growing evidence of the usefulness of internet search data and the considerable amount of studies confident in the use of internet search data – at least to predict macroeconomic indicators – their use as a measure of the economic uncertainty channeled via the media coverage of the crisis is a novelty and further research along this line is needed.

Despite these limitations, the current study proposes an innovative framework to investigate the mechanisms that link economic uncertainty to childbearing through the particular media coverage of the event. Existing studies hint to a causal effect of perceived economic uncertainty channeled by the media and fertility, but especially the link between the media coverage and the individuals' response has never been proved. Here, instead, we are able to show that the general public respond to the framing of uncertainty offered by the media, in our case by suddenly searching on Google.it information regarding the source of economic uncertainty identified by the media. Finally, we show that this general concern produces a postponement of births difficult to attribute to something different from the surge in the concern for economic uncertainty.

Appendix A

Table A.1: Summary statistics

	BEFORE November 2011					AFTER November 2011				
NATIONAL ESTIMATES	**N**	**Mean**	**Std. Dev.**	**Min**	**Max**	**N**	**Mean**	**Std. Dev.**	**Min**	**Max**
Birth rate*1000	106	*4.03*	0.30	3.33	4.70	29	*3.90*	0.30	3.36	4.61
Marriage rate*1000	106	*0.33*	0.22	0.06	0.79	29	*0.27*	0.19	0.06	0.67
GT	94	*4.20*	1.81	3	16	38	*27.95*	16.13	14	100
Spread	106	*0.70*	0.75	0.14	3.97	32	*3.20*	1.02	1.66	5.19
Unemployment rate	106	*7.55*	0.82	5.80	8.80	26	*11.23*	1.02	9.20	12.50
Consumer confidence	94	*100.94*	3.81	92.20	108.90	38	*94.39*	7.16	84.60	105.90
Confidence on own situation (2005=100)	94	*101.47*	4.08	92.10	110.30	38	*96.85*	4.06	89.30	102.40
Confidence on general situation (2005=100)	94	*99.48*	10.25	73.00	121.80	38	*87.86*	16.73	58.10	116.90
Confidence on current situation (2005=100)	94	*103.60*	5.22	91.30	112.60	38	*97.10*	4.55	89.20	104.60
Confidence on future situation (2005=100)	94	*97.42*	5.32	82.10	107.20	38	*90.81*	12.22	69.60	108.90
	BEFORE November 2011					AFTER November 2011				
REGIONAL ESTIMATES	**N**	**Mean**	**Std. Dev.**	**Min**	**Max**	**N**	**Mean**	**Std. Dev.**	**Min**	**Max**
Birth rate*1000	1,880	*3.94*	0.47	2.65	6.09	751	*3.82*	0.51	2.54	5.94
GT	981	*6.87*	6.07	1	67	733	*28.90*	17.83	3	100
Unemployment rate	1,880	*9.77*	4.94	1.91	25.15	760	*9.68*	4.94	2.25	24.60

Source: Istat and Google data (2017).

Table A.2: National-level LLR RDiT estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	Whole sample	Symmetric 3 years	Symmetric 1 years	Symmetric 1 year	Symmetric 6 months	Symmetric 3 months
RDiT	-0.213***	-0.115***	-0.097***	-0.128**	-0.071	-0.042
	(-0.312 - -0.114)	(-0.155 - -0.074)	(-0.112 - -0.083)	(-0.211 - -0.045)	(-0.565 - 0.423)	(-0.136 - 0.051)
Date (mean cent.)	0.002**	-0.002***	-0.002**	0.002	-0.017	-0.013
	(0.000 - 0.003)	(-0.003 - -0.001)	(-0.004 - -0.001)	(-0.009 - 0.013)	(-0.017 - -0.017)	(-0.013 - -0.013)
RDiT *Date	-0.005***	-0.001	-0.002**	-0.003	0.014	-0.030
	(-0.009 - -0.002)	(-0.005 - 0.003)	(-0.004 - -0.000)	(-0.013 - 0.006)	(-0.110 - 0.139)	(-0.312 - 0.251)
Constant	4.139***	4.041***	4.034***	4.053***	3.989***	3.992
	(4.049 - 4.229)	(4.022 - 4.059)	(4.020 - 4.048)	(4.007 - 4.099)	(3.989 - 3.989)	(3.992 - 3.992)
N	135	65	48	24	12	6
R-squared	0.609	0.850	0.840	0.750	0.888	0.935

Source: Istat and Google data (2017). Note: *** p<0.01, ** p<0.05, * p<0.1.

Table A.3: Regional-level LLR RDiT estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	Whole sample	Symmetric 3 years	Symmetric 1 years	Symmetric 1 year	Symmetric 6 months	Symmetric 3 months
RDiT	-0.232***	-0.138***	-0.078***	-0.083***	-0.026	-0.106**
	(-0.338 - -0.126)	(-0.214 - -0.063)	(-0.120 - -0.035)	(-0.118 - -0.049)	(-0.073 - 0.021)	(-0.194 - -0.017)
Date (mean cent.)	-0.000	-0.005***	-0.007**	-0.004	-0.024***	0.028
	(-0.001 - 0.001)	(-0.009 - -0.002)	(-0.013 - -0.002)	(-0.014 - 0.005)	(-0.041 - -0.007)	(-0.012 - 0.068)
RDiT *Date	-0.001	0.004	0.002	0.000	0.017*	-0.061***
	(-0.008 - 0.006)	(-0.004 - 0.012)	(-0.004 - 0.008)	(-0.009 - 0.009)	(-0.001 - 0.035)	(-0.099 - -0.023)
Constant	4.054***	3.959***	3.937***	3.944***	3.885***	3.982***
	(3.905 - 4.202)	(3.808 - 4.110)	(3.778 - 4.096)	(3.790 - 4.098)	(3.717 - 4.054)	(3.830 - 4.135)
N	1,732	1,202	828	440	228	117
R-squared	0.154	0.144	0.129	0.046	0.048	0.023

Source: Istat and Google data (2017). Note: *** p<0.01, ** p<0.05, * p<0.1.

Table A.4: National-level Polynomial RDiT estimates

	(1) Model	(2) Model	(3) Model	(4) Model	(5) Model	(6) Model	(7) Model	(8) Model
RDiT	-0.213***	-0.083***	-0.109***	-0.074*	-0.181**	-0.048**	-0.047	-0.104***
	(-0.312 - -0.114)	(-0.119 - -0.047)	(-0.170 - -0.048)	(-0.155 - 0.007)	(-0.323 - -0.040)	(-0.088 - -0.007)	(-0.106 - 0.012)	(-0.178 - -0.031)
Date (mean cent.)	0.002**	-0.004***	-0.006**	-0.008	0.012	-0.021**	-0.010	0.024
	(0.000 - 0.003)	(-0.006 - -0.003)	(-0.011 - -0.001)	(-0.019 - 0.002)	(-0.004 - 0.028)	(-0.038 - -0.005)	(-0.030 - 0.011)	(-0.030 - 0.077)
RDiT*Date	-0.005***	-0.003	0.016*	0.002	0.024	-0.035	-0.142**	-0.175**
	(-0.009 - -0.002)	(-0.012 - 0.005)	(-0.001 - 0.033)	(-0.050 - 0.054)	(-0.035 - 0.084)	(-0.111 - 0.042)	(-0.260 - -0.023)	(-0.339 - -0.011)
Date squared		-0.000***	-0.000	-0.000	0.001**	-0.002**	-0.000	0.005
		(-0.000 - -0.000)	(-0.000 - 0.000)	(-0.001 - 0.000)	(0.000 - 0.002)	(-0.003 - -0.000)	(-0.003 - 0.002)	(-0.003 - 0.012)
Date cubic			-0.000	-0.000	0.000**	-0.000***	-0.000	0.000
			(-0.000 - 0.000)	(-0.000 - 0.000)	(0.000 - 0.000)	(-0.000 - -0.000)	(-0.000 - 0.000)	(-0.000 - 0.001)
Date order 4				-0.000	0.000**	-0.000***	0.000	0.000
				(-0.000 - 0.000)	(0.000 - 0.000)	(-0.000 - -0.000)	(-0.000 - 0.000)	(-0.000 - 0.000)
Date order 5					0.000**	-0.000***	0.000	0.000
					(0.000 - 0.000)	(-0.000 - -0.000)	(-0.000 - 0.000)	(-0.000 - 0.000)
Date order 6						-0.000***	0.000	0.000*
						(-0.000 - -0.000)	(-0.000 - 0.000)	(-0.000 - 0.000)
Date order 7							0.000	0.000*
							(-0.000 - 0.000)	(-0.000 - 0.000)
Date order 8								0.000
								(-0.000 - 0.000)
RDiT*Date squared		0.000	-0.001*	0.002	-0.011	0.028*	0.079***	0.074***
		(-0.000 - 0.001)	(-0.003 - 0.000)	(-0.006 - 0.009)	(-0.028 - 0.005)	(-0.005 - 0.062)	(0.024 - 0.134)	(0.024 - 0.124)
RDiT*Date cubic			0.000*	-0.000	0.001	-0.004*	-0.015***	-0.016***
			(-0.000 - 0.000)	(-0.001 - 0.000)	(-0.001 - 0.003)	(-0.009 - 0.001)	(-0.025 - -0.005)	(-0.026 - -0.005)
RDiT*Date order 4				0.000	-0.000	0.000*	0.001***	0.001***
				(-0.000 - 0.000)	(-0.000 - 0.000)	(-0.000 - 0.001)	(0.000 - 0.002)	(0.000 - 0.002)
RDiT*Date order 5					0.000	-0.000*	-0.000***	-0.000***
					(-0.000 - 0.000)	(-0.000 - 0.000)	(-0.000 - -0.000)	(-0.000 - -0.000)
RDiT*Date order 6						0.000**	0.000**	0.000**
						(0.000 - 0.000)	(0.000 - 0.000)	(0.000 - 0.000)
RDiT*Date order 7							-0.000**	-0.000**
							(-0.000 - -0.000)	(-0.000 - -0.000)
RDiT*Date order 8								0.000
								(0.000 - 0.000)
Constant	4.139***	4.027***	4.015***	4.000***	4.077***	3.984***	4.010***	4.068***
	(4.049 - 4.229)	(4.001 - 4.053)	(3.977 - 4.054)	(3.942 - 4.058)	(4.016 - 4.139)	(3.932 - 4.036)	(3.969 - 4.051)	(3.975 - 4.160)
N	135	135	135	135	135	135	135	135
R-squared	0.609	0.769	0.776	0.780	0.811	0.851	0.859	0.866

Source: Istat and Google data (2017). Note: *** p<0.01, ** p<0.05, * p<0.1.

Table A.5: Regional-level Polynomial RDiT estimates

	(1) Model	(2) Model	(3) Model	(4) Model	(5) Model	(6) Model	(7) Model	(8) Model
RDiT	-0.232***	-0.077***	-0.024	-0.092***	-0.037*	-0.071**	-0.097***	-0.064**
	(-0.338 - -0.126)	(-0.132 - -0.023)	(-0.080 - 0.032)	(-0.132 - -0.051)	(-0.078 - 0.004)	(-0.137 - -0.005)	(-0.141 - -0.053)	(-0.122 - -0.007)
Date (mean cent.)	-0.000	-0.008***	-0.014***	-0.008	-0.021**	-0.011	0.012	-0.011
	(-0.001 - 0.001)	(-0.011 - -0.005)	(-0.023 - -0.005)	(-0.020 - 0.004)	(-0.036 - -0.005)	(-0.041 - 0.019)	(-0.012 - 0.035)	(-0.051 - 0.029)
RDiT*Date	-0.001	-0.002	0.002	0.019	0.018	0.024	-0.031	-0.009
	(-0.008 - 0.006)	(-0.010 - 0.006)	(-0.009 - 0.013)	(-0.008 - 0.046)	(-0.010 - 0.045)	(-0.005 - 0.054)	(-0.084 - 0.022)	(-0.072 - 0.054)
Date squared		-0.000***	-0.000**	0.000	-0.001**	0.000	0.003***	-0.001
		(-0.000 - -0.000)	(-0.000 - -0.000)	(-0.000 - 0.000)	(-0.002 - -0.000)	(-0.003 - 0.003)	(0.001 - 0.006)	(-0.008 - 0.007)
Date cubic			-0.000**	0.000	-0.000**	0.000	0.000***	-0.000
			(-0.000 - -0.000)	(-0.000 - 0.000)	(-0.000 - -0.000)	(-0.000 - 0.000)	(0.000 - 0.000)	(-0.001 - 0.001)
Date order 4				0.000**	-0.000***	0.000	0.000***	-0.000
				(0.000 - 0.000)	(-0.000 - -0.000)	(-0.000 - 0.000)	(0.000 - 0.000)	(-0.000 - 0.000)
Date order 5					-0.000***	0.000	0.000**	-0.000
					(-0.000 - -0.000)	(-0.000 - 0.000)	(0.000 - 0.000)	(-0.000 - 0.000)
Date order 6						0.000	0.000**	-0.000
						(-0.000 - 0.000)	(0.000 - 0.000)	(-0.000 - 0.000)
Date order 7							0.000**	-0.000
							(0.000 - 0.000)	(-0.000 - 0.000)
Date order 8								-0.000
								(-0.000 - 0.000)
RDiT*Date squared		0.000*	0.001	-0.003*	0.001	-0.005	0.006	0.010
		(-0.000 - 0.001)	(-0.000 - 0.002)	(-0.005 - 0.000)	(-0.004 - 0.006)	(-0.014 - 0.004)	(-0.014 - 0.025)	(-0.011 - 0.030)
RDiT*Date cubic			-0.000	0.000*	-0.000	0.000	-0.002	-0.002
			(-0.000 - 0.000)	(-0.000 - 0.000)	(-0.001 - 0.000)	(-0.001 - 0.001)	(-0.005 - 0.001)	(-0.005 - 0.002)
RDiT*Date order 4				-0.000*	0.000	-0.000	0.000	0.000
				(-0.000 - 0.000)	(-0.000 - 0.000)	(-0.000 - 0.000)	(-0.000 - 0.000)	(-0.000 - 0.000)
RDiT*Date order 5					-0.000	0.000	-0.000	-0.000
					(-0.000 - 0.000)	(-0.000 - 0.000)	(-0.000 - 0.000)	(-0.000 - 0.000)
RDiT*Date order 6						-0.000	0.000	0.000
						(-0.000 - 0.000)	(-0.000 - 0.000)	(-0.000 - 0.000)
RDiT*Date order 7							-0.000	-0.000
							(-0.000 - 0.000)	(-0.000 - 0.000)
RDiT*Date order 8								0.000
								(0.000 - 0.000)
Constant	4.054***	3.950***	3.904***	3.933***	3.893***	3.916***	3.957***	3.924***
	(3.905 - 4.202)	(3.801 - 4.098)	(3.745 - 4.063)	(3.766 - 4.101)	(3.726 - 4.061)	(3.761 - 4.071)	(3.793 - 4.120)	(3.766 - 4.081)
N	1,732	1,732	1,732	1,732	1,732	1,732	1,732	1,732
R-squared	0.154	0.174	0.177	0.179	0.180	0.180	0.181	0.181

Source: Istat and Google data (2017). Note: *** p<0.01, ** p<0.05, * p<0.1.

Appendix B: Robustness checks

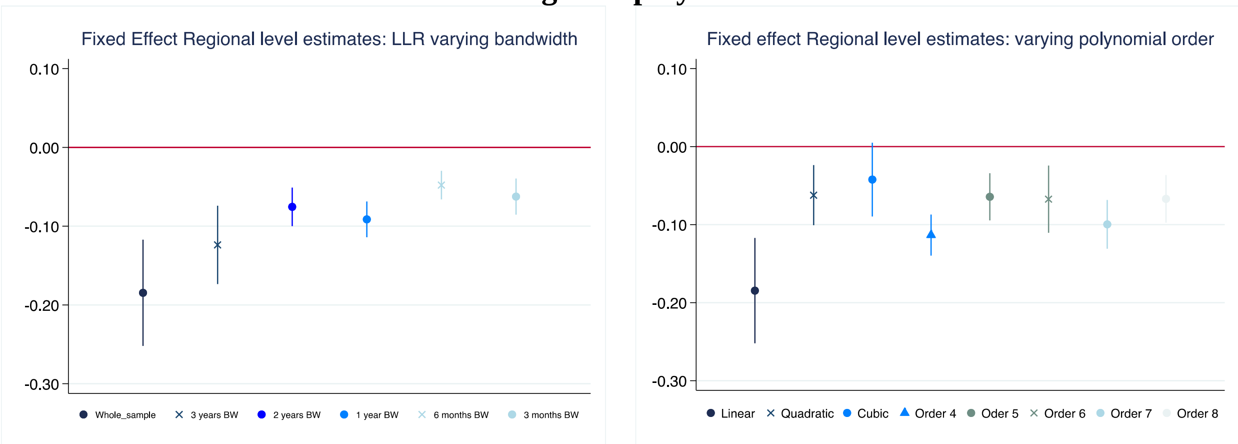
Table B.1 (Models 1-5) reports estimates obtained from the national sample, second order polynomial RDiT model using the entire period, controlling in the models for potential confounding factors, such as GT searches for the term spread, the spread itself, unemployment rate and Consumer Confidence Index (CCI). The table shows that the treatment effect remains substantially around -0.10. Figure B.1 instead shows the RDiT estimates from a regional fixed effect model which controls for time invariant regional characteristics that might affect both regional birth rates and GT searches. As in Fig. 4 both local linear regression results obtained varying the bandwidth and global polynomial estimates varying the polynomial order are shown respectively in the left and with panel of the figure. Results are essentially identical to the simple OLS estimates presented earlier.

Table B.1: National-level 2nd order polynomial RDiT controlling for confounding variables

	Model (1) National estimates	Model (2) National estimates	Model (3) National estimates	Model (4) National estimates	Model (5) National estimates	Model (6) Regional estimates	Model (7) Regional estimates
RDiT	-0.109***	-0.082***	-0.132***	-0.133***	-0.107***	-0.151***	-0.309***
	(-0.150 - -0.068)	(-0.109 - -0.055)	(-0.203 - -0.060)	(-0.224 - -0.042)	(-0.169 - -0.045)	(-0.254 - -0.048)	(-0.447 - -0.171)
Date (mean cent.)	-0.004***	-0.003	-0.004**	-0.004**	-0.004***	-0.007***	-0.010***
	(-0.006 - -0.002)	(-0.007 - 0.001)	(-0.007 - -0.001)	(-0.007 - -0.001)	(-0.007 - -0.002)	(-0.010 - -0.005)	(-0.012 - -0.009)
RDiT *Date	0.002	0.001	0.002	0.002	0.002	0.008***	0.017***
	(-0.002 - 0.007)	(-0.001 - 0.003)	(-0.002 - 0.007)	(-0.004 - 0.009)	(-0.003 - 0.008)	(0.004 - 0.013)	(0.015 - 0.020)
Date squared	-0.000***	-0.000**	-0.000***	-0.000**	-0.000***	-0.000***	-0.000***
	(-0.000 - -0.000)	(-0.000 - -0.000)	(-0.000 - -0.000)	(-0.000 - -0.000)	(-0.000 - -0.000)	(-0.000 - -0.000)	(-0.000 - -0.000)
Unemployment rate		-0.015					
		(-0.048 - 0.018)					
CCI			-0.001				
			(-0.004 - 0.001)				
GT spread				0.000			
				(-0.001 - 0.002)			
Spread					-0.001		
					(-0.025 - 0.023)		
GT*Internet Access							0.007***
							(0.003 - 0.010)
Constant	4.028***	4.163***	4.157***	4.034***	4.030***	3.958***	3.894***
	(4.002 - 4.054)	(3.851 - 4.476)	(3.888 - 4.427)	(3.993 - 4.074)	(3.961 - 4.099)	(3.913 - 4.004)	(3.852 - 3.936)
N	135	132	123	123	135	1,705	1,646
R-squared	0.766	0.781	0.745	0.743	0.766	0.178	0.205

Source: Istat and Google data (2017). Note: *** p<0.01, ** p<0.05, * p<0.1.

Figure B.1: RDiT coefficients plot. Regional fixed effect local linear regression and varying order global polynomial



Source: Elaboration of the author based on Istat data.

The crude birth rate is the only available indicator of fertility for Italy at the regional level and on a monthly basis, however, it is affected by the population structure and in particular by the age structure of women in reproductive age (Kent and Haub 1984). To partially account for this, we constructed an index of ageing structure of women in reproductive age to account for the turnover between older and younger women (calculated as $[\frac{\#Women\ 35-44}{\#Women\ 15-34} * 100]$). When the turnover is added as a control variable the estimates of the discontinuity remain identical and the association between a younger age structure of women and the crude birth rate is positive and, as expected, very large (results available upon request to the authors). To give an example: for every 10 young women more that replace 100 older women leaving the reproductive age, the crude birth rate increases around 0.13-0.19 (depending on the model) per 1000 women.

An additional factor to consider when using regional data is the diversity across the Italian territory in internet access which might introduce relevant biases to the representativeness of the data. In 2005, households' access to internet varied from only 23% in Sicily to 40% in Lazio (Istat). Ten years later, 71% in Trentino but still only 54% of households in Basilicata had internet access at home (Istat). To account for this, we added a correction factor to the GT variable that weights the queries on the basis of households' internet access in the region. The correction proposed in Equation (B.1) equals 1 in the region-year with the highest proportion of Internet users and moves towards 0 as the percentage of Internet users declines. This means that the maximum searches now do not reach 100 (but 78.8), however, the date of the peak in searches do not vary. What is interesting is the simple second order polynomial RDiT model using the entire period, in which the GT searches corrected for

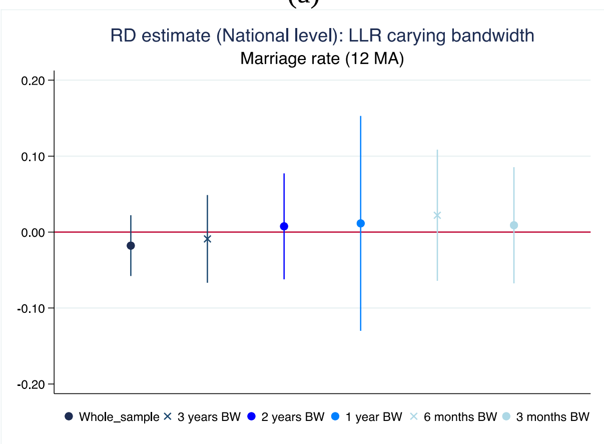
Internet access is used as a potential confounding factor of the discontinuity. As shown in Models 6-7 in Table B.1, the amount of queries weighted for internet access is actually positively associated to the crude birth rate, however, the confounder is negatively associated to the discontinuity, that now – net of internet access – has a doubled negative effect on births.

$$GT * \frac{\%InternetUsers_{jt} - min(\%InternetUsers)}{max(\%InternetUsers) - min(\%InternetUsers)} \qquad \text{(B.1)}$$

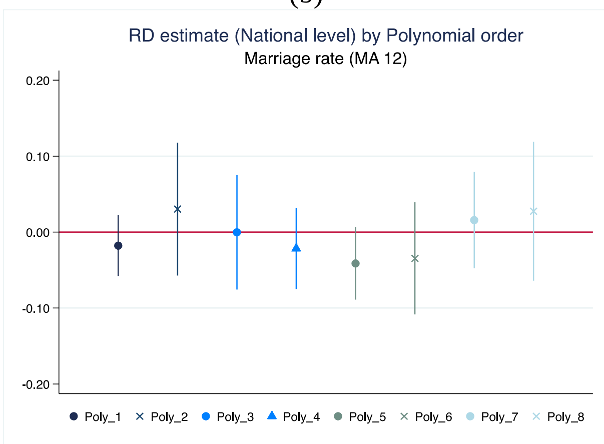
Finally, a placebo treatment on monthly crude marriage rate nine months after the peak in uncertainty is tested. While marriage rates are likely to be negatively influenced by economic uncertainty, due to a similar argument to childbearing (although marriages are reversible, at a certain cost) there is no reason to expect that this negative effect of uncertainty materializes nine months after the uncertainty shock, as it is the case for childbearing. Figure B.2 illustrates both LLR and Polynomial RDiT estimates on marriage rates in Italy using national level data, varying respectively the bandwidth and the polynomial order (monthly marriage rates at the regional level were not available at the time of writing). The figure shows that, as expected, the uncertainty shock had no effect on the national marriage rate.

Figure B.2: RDiT LLP and polynomial coefficients plot. National-level data

(a)



(b)



Source: Elaboration of the author based on Istat data.

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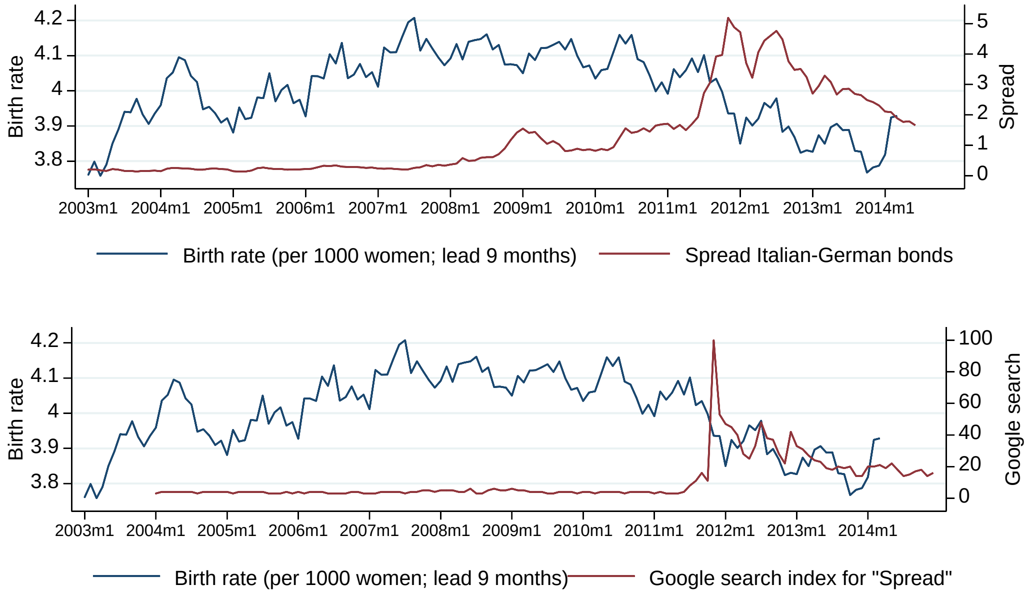
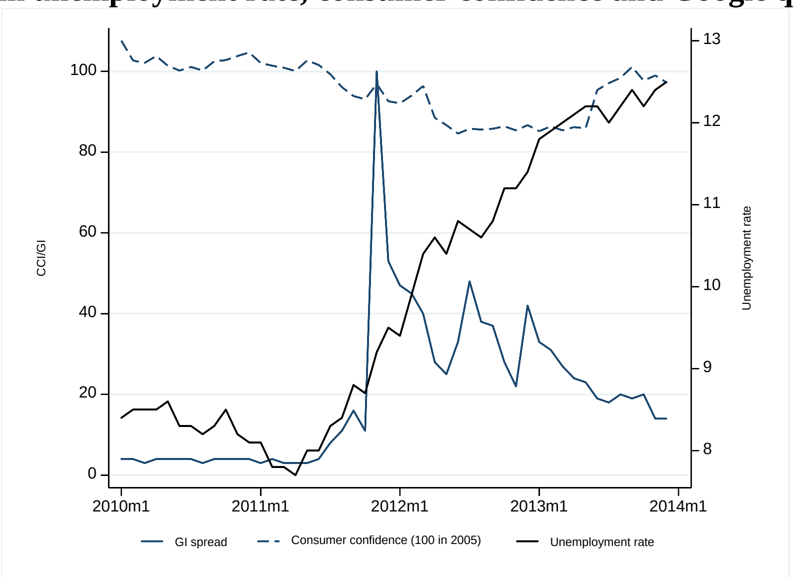
Figures

Figure 1: Birth rates, Spread and Google queries for the term "spread"



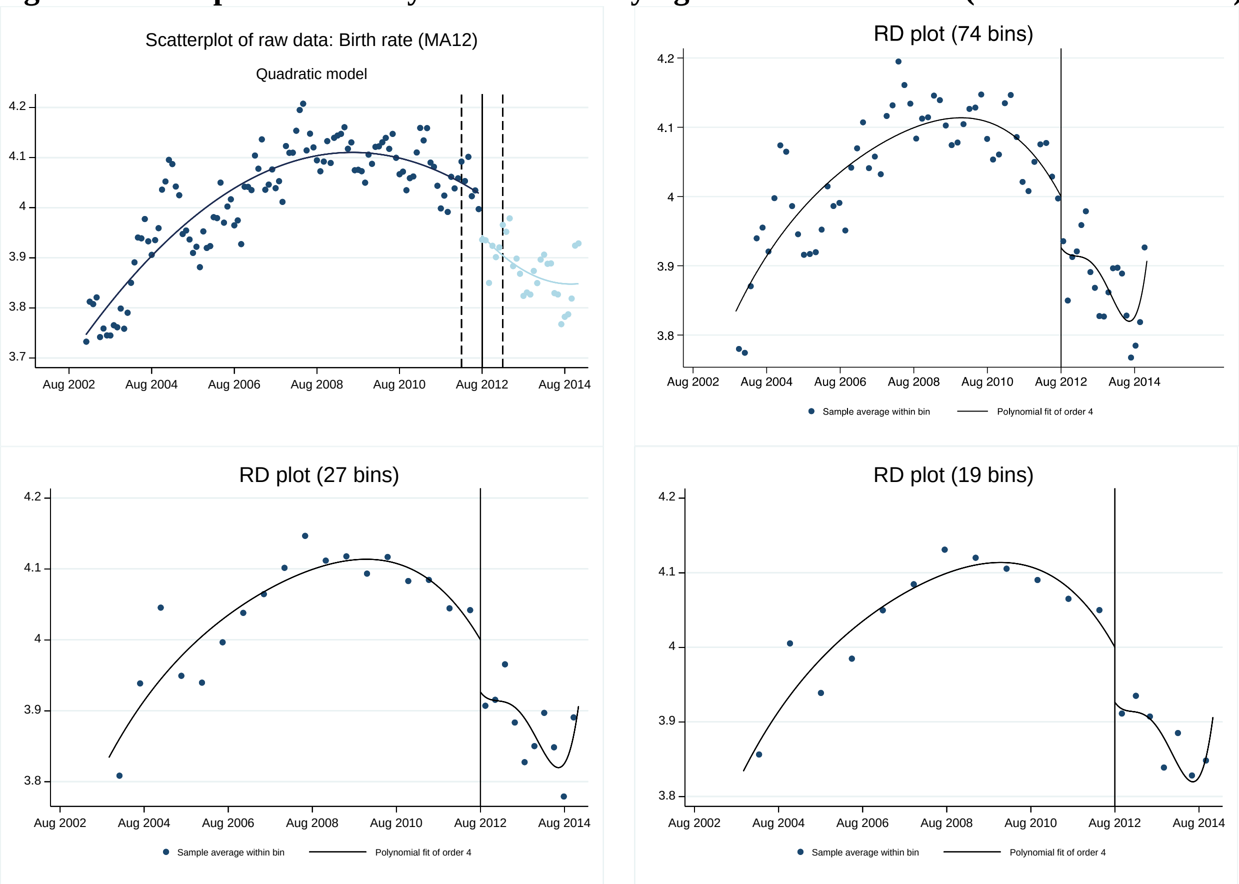
Source: Elaboration based on Eurostat, ECB and Google data (2018).

Figure 2: Trends in unemployment rate, consumer confidence and Google queries for spread.



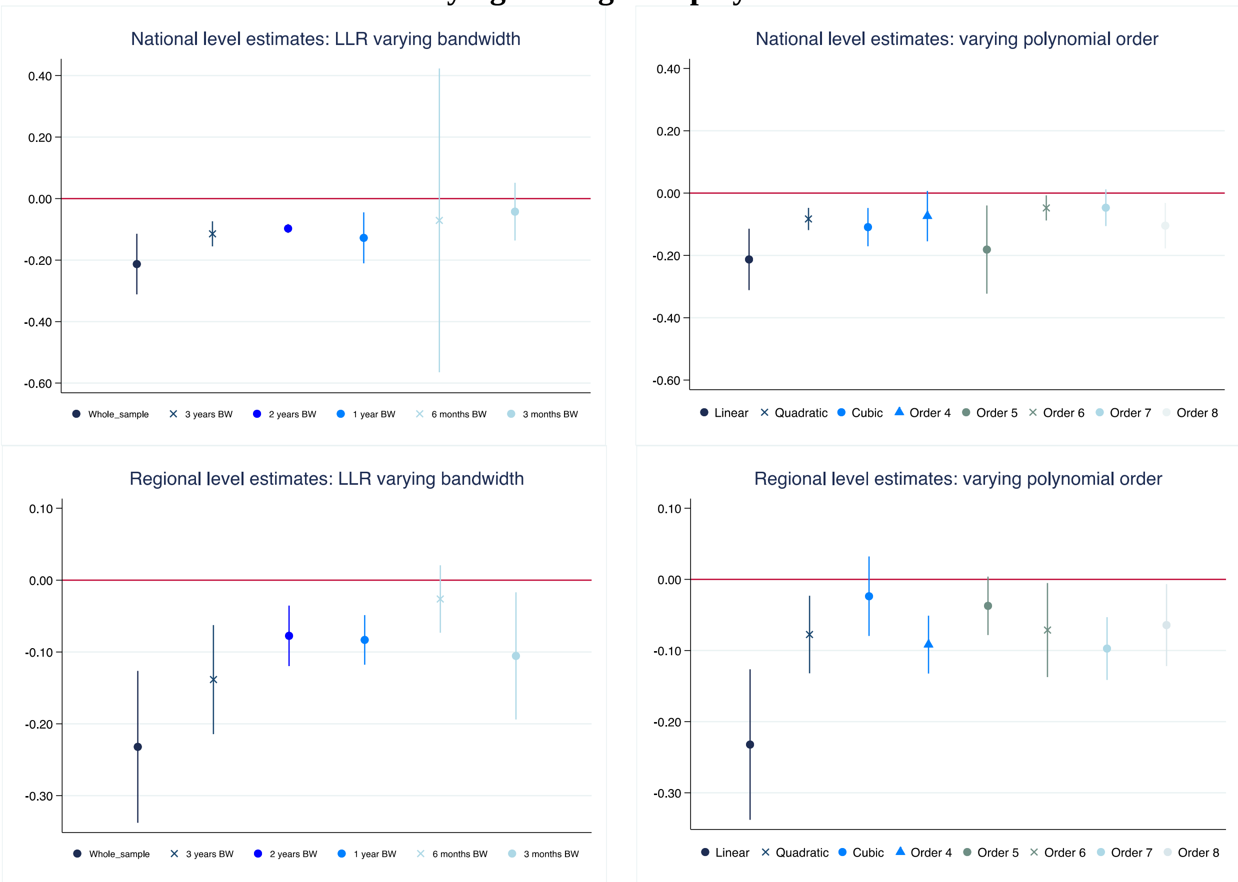
Source: Elaboration based on Google Trends, Eurostat and Istat data (2018).

Figure 3: RDiT plot of monthly birth rates varying the number of bins (National-level data)



Source: Elaboration based on Istat data.

Figure 4: RDiT coefficients plot. National and regional data. Local linear regression and varying order global polynomial



Source: Elaboration based on Istat data.