Effects of Unemployment News on Economic Perceptions – Evidence from German Federal States

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September 2017

I thank Jan Bakker, Osea Giuntella, Laszlo Goerke, Dirk Krueger, Elena Lucchese, Sabrina Maaß, Andrea Prat, Armin Rott, Jil Sörensen, participants at the Regional Economics Workshop at ifo Dresden, the Workshop on Subjective Survey Data at IAAEU Trier, the 15th Brucchi Luchino Workshop in Bologna, the media economics seminar in Hamburg, and members of the Economics of Media Bias Network for helpful comments and suggestions. Moreover, I am grateful to Spiegel Publishing for providing access to their newspaper archives. A previous version of this paper circulated under the title "Effects of Unemployment News on Consumers".
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Abstract

This study investigates whether news coverage about unemployment affects people's perceptions of the state of the economy. I compile a German state-level data set, based on household surveys and information obtained from analyzing 35 newspapers. The data are used to separate media effects from real economic consequences, taking advantage of two sources of exogenous variation. First, I exploit the salience of "milestones" in the number of unemployed. The news value of these milestones, which is not based on economic fundamentals, causes the media to report more about unemployment than usually. Second, I show that the amount of reports decreases when competing newsworthy events occur at the time of the release of the monthly unemployment statistics. Instrumental variable estimates indicate that a one standard deviation increase in coverage accounts for about a quarter of the average monthly change in the index of economic perceptions.

Keywords: left-digit bias; media; news competition; regional differences; sentiment

JEL classification: D12; L82; R10; R20

1. Introduction

Household perceptions of the state of the economy are of great economic and political interest. As a main component of consumer confidence, these perceptions likely affect decisions to save, invest, and consume.[1] For instance, pessimistic households might have lower consumption expenditures than optimistic ones. Subjective evaluations of the economy are also known for their potential effects on voting. If people believe that the economy is in a bad shape, incumbents usually have smaller chances of re-election than when voters' economic perceptions are positive.[2]

Does economic news coverage affect these perceptions? On the one hand, most of the information necessary to assess the state of the economy can only be obtained from the news media. On the other hand, time series of economic news coverage and consumer sentiment usually correlate with each other.[3] However, causal interpretations based on the timing of changes in the variables remain doubtful because they do not account for the possibility that the time series are contaminated with the expectations of the actors involved. Even if the time series indicate that past news coverage can predict future changes in economic perceptions or behavior, this does not necessarily imply causality running from the media to the recipients. There might be reverse causality if the media are able to anticipate the views of their audiences.

The goal of this paper is to examine the effect of unemployment news coverage on people's perceptions of the state of the economy. To address the endogeneity problem, I use exogenous variation in the news output. First, I exploit the increased news value that is associated with macroeconomic variables reaching important milestones. For instance, when the official number of unemployed reached the five-million threshold for the first time in Germany since World War II, this incident caught much more media attention than counting 4,464,416 unemployed in the month before, or 5,288,245 in the month after. In this study, I consider it a milestone if the state or national number of unemployed exceeded or fell below a round number – i.e., any value that

[1] For example, see Carroll, Fuhrer, and Wilcox (1994), Ludvigson (2004), and Bryant and Macri (2005).
[2] The phenomenon of "economic voting" has been widely studied in the political science literature; see Vavreck (2009) for a review.
[3] Examples for these correlations relate to the Netherlands (Hollanders and Vliegenthart, 2011), the UK (Sanders and Gavin, 2004; Soroka, 2006), and the US (De Boef and Kellstedt, 2004; Doms and Morin, 2004; Starr, 2012; Nguyen and Claus, 2013; Lachowska, 2016).

contains only zeros after the first digit – for the first time in at least two years. Round numbers are particularly salient because they serve as cognitive reference points (Rosch, 1975), whereas the two-year period guarantees to only include rare cases. In combination, both characteristics – the salience of round numbers and the rarity of milestones – cause news media to increase their unemployment coverage above the usual level. The additional news coverage, which is not based on economic fundamentals, increases the chances that people update their views about the economy.

Competing newsworthy events serve as a second source of exogenous variation. In particular, I determine whether the monthly press conference of the Federal Employment Agency (FEA – Bundesagentur für Arbeit) coincides with natural disasters or terrorist attacks. The FEA uses this press conference to release the latest national and regional unemployment figures. News media regularly report about the release of these statistics, often in the form of front-page newspaper coverage. However, if the release coincides with a severe disaster or terrorist attack, a crowding out of the unemployment coverage can be observed. Competing newsworthy events thus cause variation in the amount of reports about unemployment, which in turn affects the degree of attention households pay to the state of the economy. This mechanism often has a regional dimension, because of the state-level variation in the news value of (local) disasters and attacks.

I collect information about reporting on unemployment in seven national and 28 regional newspapers. Matching the (local) news output with regionally aggregated survey data from over 180,000 interviews about people's perceptions of the economy allows for addressing the research question at the state-month level. The data cover the time from 2005 to 2014, a period including economically stable years and the global economic crisis.[4] The investigation benefits from the resulting variation in sentiment, unemployment, and corresponding news coverage.

In the baseline specification, instrumental variable (IV) estimates indicate that a one standard deviation increase in front-page unemployment news (= 496 words or 1.8 articles) accounts for 18.8% of the average monthly change in people's economic perceptions. When the news output is weighted by the newspapers' circulation shares, the effect accounts for 29.8%. Similar results are obtained when using alternative measures of news coverage, including each instrument

[4] The period of investigation is determined by data availability. The content of most regional outlets in the sample is not archived before 2005; and the latest edition of the survey data refers to 2014.

individually, modifying the timing of the control variables, as well as adding month, year, and state fixed effects and interactions of these fixed effects. Distinguishing between good and bad unemployment news suggests that the results are driven by negative reporting.

The findings contribute to the literature on the role of subjective assessments for regional differences in economic variables. For example, Conroy, Deller, and Tsvetkova (2016) show that local variation in business climate explains cross-border company relocations. Pereira Lopes, Jardim da Palma, and Pina e Cunha (2011) investigate the implications of subjective well-being for regional development. Several studies emphasize potential effects of risk perceptions on real estate prices and housing rents (Naoi, Seko, and Sumita, 2009; Zhu et al., 2016; Zhang, 2016) or vegetable prices (Tajima, Yamamoto, and Ichinose, 2016). These studies investigate how newsworthy events (e.g., earthquakes, floods, or the Fukushima nuclear disaster) affect perceptions of households, all implying potential effects of mass media. In contrast to these studies, I explicitly investigate the role of media for regional differences in subjective assessments of economic variables. In particular, I use exogenous variation in regional unemployment news to show that newspapers affect state-level perceptions of the economy.

Moreover, the findings contribute to research that investigates causal links between media and consumers. Baker and George (2010) use random differences in the regionally staggered introduction of television in the US to show that advertising increases household debt. Bursztyn and Cantoni (2016) provide evidence of media affecting consumption baskets of East Germans by exploiting differences in the access to Western television. Similar to these studies, I investigate regional variation in news coverage. However, I provide strong evidence of effects on household perceptions instead of actual consumer behavior.

Using milestones in the number of unemployed to identify these effects also relates to research on the economic implications of round numbers and left-digit bias. For example, Lacetera, Pope, and Sydnor (2012) show that sales prices of used cars disproportionately decrease at 10,000-mile odometers values. Keefer and Rustamov (2017) find sharp discontinuities in energy consumption after households' electricity bills cross the $50 threshold. Other studies highlight the role of round numbers for the identification of optimization frictions in the context of tax filings (Kleven and Waseem, 2013; Best and Kleven, 2017), investment behavior (Begley, 2015), and risk taking (Foellmi, Legge, and Schmid, 2016). My identification strategy emphasizes the salience of round numbers too, but I apply the idea in the context of news coverage and people's economic perceptions. It is conceivable that milestones also affect the salience of other macroeconomic variables, such as stock indices, inflation, or growth. Thus, the identification strategy can likely be applied to other contexts as well.

The next section describes the data and the identification strategy. Afterwards, I present and discuss the estimation results and various robustness checks. The last section concludes.

2. Data and identification strategy

2.1 News coverage

To verify whether media affect household perceptions, I focus on unemployment news. Unemployment is one of the most important macroeconomic variables. It is of great interest to large parts of the population because unemployment figures are main indicators of the economic situation of the country. In addition, the publication procedure of unemployment statistics in Germany helps to retrieve the corresponding press coverage. The FEA hosts a press conference at the beginning of each month, in which it releases the latest national and state-specific unemployment figures. The press usually publishes most of the corresponding reports the day after this press conference. It is therefore possible to conduct keyword-based searches in newspaper archives in combination with the date of the press conference to identify the reports in question without human coding.

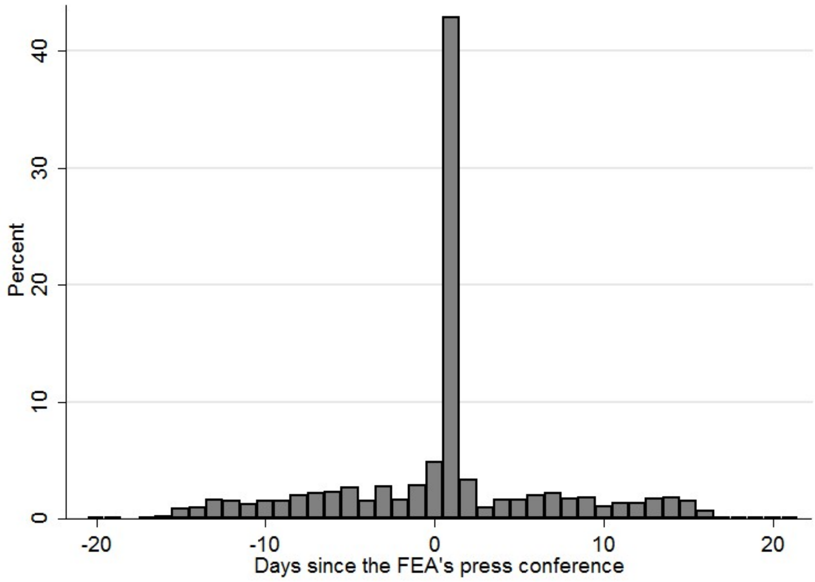
It would be optimal to not only use newspapers here, but also television, radio, and online news. In the case of newscasts and radio, the lack of data prevents the inclusion of these news sources. Regarding online outlets, news data are hardly comparable over time, as the online market has still been evolving in recent years. However, assuming that the press continues to have an agenda-setting role, it does not pose a severe problem to neglect newscasts, radio news, and online outlets. While many other media barely produce content themselves, most newspapers still rely on own editorial and journalistic input. In addition, surveys suggest that editors and journalists often use newspapers for guidance in topic selection and preparation (e.g., Reinemann, 2003; Reinemann and Huismann, 2007; Jandura and Brosius, 2011). German media markets are fairly concentrated, which likely contributes to a homogeneous news coverage as well (Van der Wurff, 2005; Roessler, 2007; KEK, 2015). For example, the broadcasting market is dominated by the public service providers and two media conglomerates; and these conglomerates hold shares in many important print, radio, and online outlets.

The newspaper archives DIGAS, Nexis, and Genios allow to consistently search for articles in the national newspapers Bild, Frankfurter Allgemeine Zeitung, Frankfurter Rundschau, Handelsblatt, Süddeutsche Zeitung, TAZ, and Welt, as well as in 28 regional newspapers (see Table A1 for details). This selection comprises all daily newspapers of national significance. The regional newspapers include most of the largest ones in Germany; they represent seven of the ten largest publishing companies in the market; and they are reasonably distributed across the West German federal states considered in this study. According to the Commission on Concentration in the Media (KEK – Kommission zur Ermittlung der Konzentration im Medienbereich), German regional newspapers had a combined circulation of about 13.4 million copies in the second quarter of 2014 (KEK, 2015). At this time, the circulation of my sample amounted to 3.7 million copies.

The search query < “Bundesagentur für Arbeit” AND HEADLINE[arbeitslos*] > (“Federal Employment Agency” AND HEADLINE[unemploy*]) retrieves 7,359 articles between 2005 and 2014. Figure 1 displays the time-wise distribution of these articles. The publication pattern suggests that the search query produces meaningful results, especially when only considering articles that are published the day after the press conference (= 3,157).

Furthermore, I only include front-page articles (=943) to construct the news variables. First, when thinking about media effects, it is reasonable to assume that reports on the cover page have more persuasion potential than other articles. By placing reports on the front page, editors signal to their readers that these articles contain the most important news of the day. At the newsstand, the cover page and the headlines it carries are visible to people who do not even buy the newspaper. Readers who do buy the newspaper, but do not actually read all articles, likely receive the messages of the front page at least. Second, it is more likely for a displacement of unemployment reports by competing stories to take place on the front page. There are limitations to the number of articles that can be placed on the cover page; however, there is some flexibility allowing to move articles to other pages in the newspaper.

Figure 1: Timing of publication of unemployment news



Notes: N = 7,359 articles.

For each newspaper and month, I calculate the sum of words w of front-page articles related to unemployment that were published the day after the press conference of the FEA.[5] I use these newspaper-specific amounts of coverage to determine the state-specific quantities as follows: Unemployment reports of national newspapers n can potentially affect people's perceptions everywhere in Germany; for each state s, the sum words of these articles is equal. Coverage of regional newspapers r is included in the state-specific amount for those states in which the

[5] It could be argued that a relative measure (e.g., the number of words of front-page unemployment reports divided by the number of words of all page-one articles) is more appropriate to capture the amount of the news coverage than the absolute number of words, because there might be variation in the density of the front page within and across outlets. Unfortunately, the data necessary to construct this kind of measure are not available. The lack of a relative measure of news coverage is unlikely to pose a problem though. First, as Garz and Sörensen (2017) point out, there is little variation in the volume of newspapers, so that relative and absolute measures tend to be similar. Although they investigate a different context and only a subset of the outlets considered here, they find a bivariate correlation of 0.99 between both measures. Second, I conduct a robustness check in which I use the share of newspapers per state and month that report about unemployment on their front-page, resulting in estimates that are very similar to those obtained when using the absolute measure of news coverage.

newspapers circulate. That is, the state-specific amount of unemployment news for press conference t is the sum of words of articles in national newspapers and relevant regional outlets:

$$w_{s,t} = \sum_{n=1}^{N} w_{n,t} + \sum_{r_s=1}^{R_s} w_{r_s,t} \tag{1}$$

It is possible that the newspapers vary in their effect on household perceptions, due to differences in circulation. Based on data from the German audit bureau of circulation (Informationsgemeinschaft zur Feststellung der Verbreitung von Werbeträgern, IVW), I calculate each newspaper's annual, within-sample circulation share c. This share is used to weight the newspapers' monthly sum of words of unemployment articles:

$$w_{s,t}^{*} = \sum_{n=1}^{N} w_{n,t}c_{n,t} + \sum_{r_s=1}^{R_s} w_{r_s,t}c_{r_s,t} \tag{2}$$

To ease the interpretation of the regression coefficients, the weighted sum of words is normalized, so that this variable has the same sample mean as its unweighted counterpart:

$$w_{s,t}^{n} = w_{s,t}^{*}(\overline{w}/\overline{w}^{*}) \tag{3}$$

Table A4 provides summary statistics of the resulting news variables. Accordingly, the average number of front-page unemployment reports per state and press conference is 2.2 (or 415 words), with a maximum of 9.0 articles (or 3,123 words).

Unemployment news could affect household perceptions in two directions. Good unemployment news might make people perceive the economy in a more favorable way; bad unemployment reports can have the opposite effect. The distinction between good and bad news may seem straightforward in the case of unemployment because people usually agree that increases in unemployment are bad, whereas decreases are good. Unfortunately, reports on unemployment are more complex, as there are different indicators to describe different aspects of the phenomenon. For instance, articles often simultaneously report seasonally adjusted and raw numbers; the change from the previous month and the change from the same month of the previous year; the unemployment rate and the number of unemployed; or the development at the national and at the state level. From a good news-bad news perspective, it is quite possible that the different indicators contradict each other at the same point of time, which often causes unemployment coverage to be ambiguous. In addition, expectations often prevent articles from having a clear message; for instance, when a report states that the unemployment rate decreased less than expected, or when there is a positive outlook while the current development is negative. It is not clear how people interpret such ambiguous information. For these reasons, I do not distinguish between good and bad news in the baseline specifications but merely consider how the amount of unemployment reports affects *absolute changes* in household perceptions. However, I conduct robustness checks including directional estimates, using simple dictionary-based classifications of good and bad reports.

2.2 Household perceptions of the state of the economy

Data on people's evaluations of the economic situation come from the Politbarometer surveys, as provided by GESIS – Leibnitz-Institute for the Social Sciences. Among other things, the participants are asked to evaluate the state of the economy on a scale from 1 (= good) to 3 (= bad).[6] Although the surveys are otherwise representative of the German electorate, the perceptions data are only consistently available for the eleven West German states, including West Berlin. Between 2005 and 2014, the surveys include 180,037 interviews, which corresponds to a monthly average of about 1,500 responses. For each state s and month t, I calculate the mean of this variable by averaging over perceptions p of individuals i:

$$\bar{p}_{s,t} = \sum_{i=1}^{I} p_{i,s,t} \tag{4}$$

As Table A4 indicates, this index of perceptions ranges from 1.185 (most positive assessment; Bremen, September 2014) to 2.765 (most negative assessment; also Bremen, June 2009). The sample average of 1.945 suggests that the perceptions were slightly tilted towards a positive evaluation of the economy in the period under investigation. For the regressions, I compute the state-specific, absolute monthly change in the average perception score (i.e., the modulus):

[6] The exact wording is: "In general, how would you assess the current state of the German economy? Is it good, partly good/partly bad, or bad?"

$$\left|\Delta\bar{p}_{s,t}\right| = \left|\bar{p}_{s,t} - \bar{p}_{s,t-1}\right| \quad (5)$$

Using the monthly change in people's perceptions ascertains that the estimates refer to immediate rather than long-term effects. Taking the modulus results in an equal treatment of increases and decreases in the index of perceptions, so that it is not necessary to make assumptions about good and bad unemployment news.[7]

2.3 Controls

To account for economic fundamentals, the control variables include the official state and national unemployment rates[8], the national index of industrial production, and the national inflation rate. I use the index of industrial production as a proxy for GDP because data on the latter are not available on a quarterly basis in Germany. The monthly production index accounts for the general performance of the economy, which is particularly important in light of the global financial crisis in 2008 and 2009. The inflation rate captures possible changes in sentiment due to losses in purchasing power. All variables are included in levels and as the absolute monthly change because households might react to short-term developments and long-run trends when making their assessments. Table A4 provides details on the definition, measurement, and sources of the control variables.

The following timing is assumed: The press conference takes place at the beginning of each month, while the surveys on people's evaluations are conducted over the course of the same month. That is, news coverage in t possibly affects households in t. The press conference in t provides the unemployment figures for $t-1$, and unemployment news coverage in t refers to the unemployment figures in $t-1$ too. In the baseline specifications, I thus include the values of the control variables of the previous month. However, robustness checks show that the findings remain the same when using current-month values.

[7] I use the simple monthly change in the index of perceptions ($\Delta\bar{p}_{s,t} = \bar{p}_{s,t} - \bar{p}_{s,t-1}$) for the robustness checks with good and bad unemployment news.

[8] The state and national unemployment rates correlate with each other (bivariate correlation coefficient = 0.465). However, this correlation does not bias the results. Removing either variable from the models leads to very similar estimates of the coefficients of interest.

In addition, all models control for the state and national election cycles, measured as the number of months until the next election. The baseline specifications also include year and state fixed effects, to account for unobserved differences over time and across states. I do not initially include calendar month fixed effects because these are highly collinear with the seasonal patterns in the unemployment, inflation, and industrial production variables. Again, robustness checks confirm that including richer sets of fixed effects does not alter the results though.

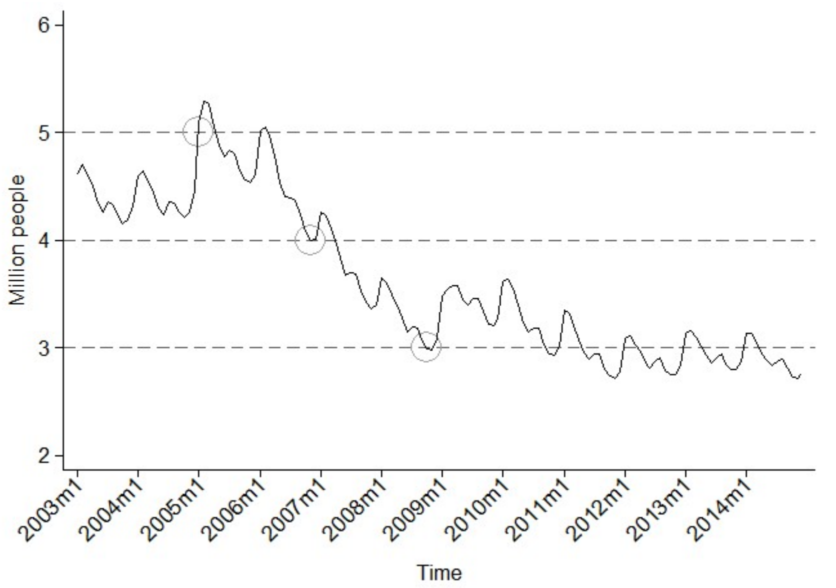
2.4 Exogenous variation

2.4.1 Milestones in the number of unemployed

Research in psychology suggests that people often condense multiple-digit numbers to multiples of ten because it is easier to process and memorize these values. Round numbers thus serve as cognitive references points and heuristic shortcuts (Rosch, 1975). The salience of round numbers can lead to left-digit bias in human behavior. For example, people are more likely to make life-changing decisions at round ages (e.g., Alter and Hershfield, 2014; Miron-Shatz, Bhargave, and Doniger, 2015) and they tend to underestimate prices that are set just below a round number (e.g., Anderson and Simester, 2003; Thomas, Simon, and Kadiyali, 2010). Lacetera, Pope, and Sydnor (2012) show that the value of used cars discontinuously drops at 10,000-mile odometers thresholds. According to Keefer and Rustamov (2017), households disproportionately decrease their energy consumption if their last electricity bill just crossed the $50 threshold. Other examples include the clustering of stock prices (e.g., Sonnemans, 2006; Schwartz, Van Ness, and Van Ness, 2007) and dividends at salient values (e.g., Aerts, Van Campenhout, and Van Caneghem, 2008).

I argue that left-digit bias also affects the salience of unemployment statistics. For example, when the official number of unemployed reached the value of five million for the first time since World War II, the event became an agenda-setting topic. I use two criteria to define a milestone, based on examining the retrieved unemployment reports: First, the number of unemployed exceeds or falls below a round number; i.e., any value that contains only zeros after the first digit, such as 400,000 or one million. Second, the number of unemployed has not crossed this round number in at least two years. This second criterion guarantees to include only cases that have a historical news value because their occurrence is rare. For example, due to seasonality, the number of unemployed sometimes repeatedly falls below and exceeds a round number within a few months, but these movements likely do not have additional news value.

Figure 2: Milestones in the national number of unemployed

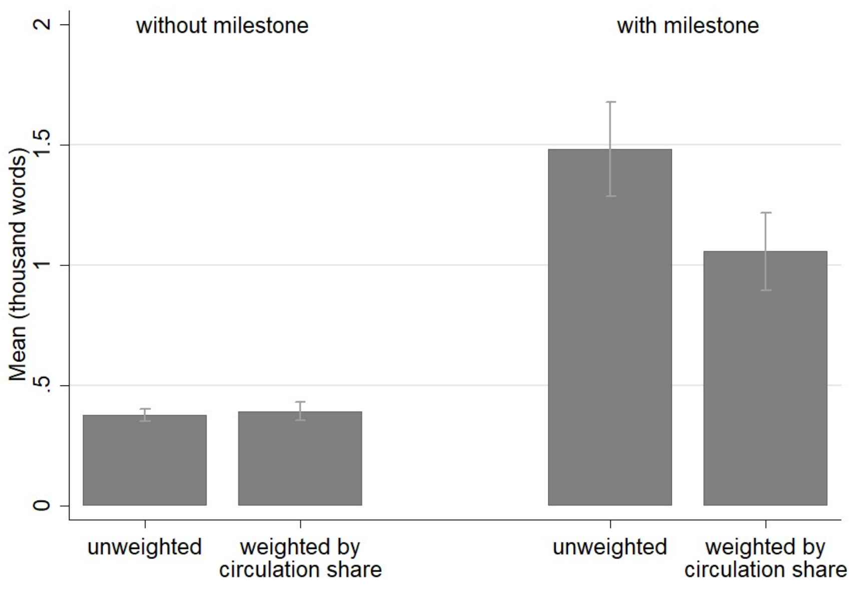


Notes: Milestones are denoted as circles. The figure shows seasonally unadjusted data.

Figure 2 illustrates these considerations, using the national number of unemployed as an example. January 2005 can be considered as a milestone because the number exceeded the five-million threshold for the first time since World War II. Shortly after, in May 2005, the number fell below this threshold, only to exceed it again in January 2006. However, I do not consider these two cases as milestones because they are unlikely to have the same additional historical news value as in the case of January 2005. There is another milestone in November 2006, when the number first fell below four million; but not in April 2007 when it crossed this threshold again. The pattern is even clearer regarding the three-million threshold. There is a milestone in October 2008 because the number fell below this threshold for the first time since 1992. Afterwards, crossing the threshold becomes quite common, with the number of unemployed oscillating around three million people in the following years.

The combination of both attributes – the salience of round numbers and the historical news value of a milestone – causes the press to expand its unemployment coverage over the usual level. Figure 3 provides graphical evidence of this increase. On average, the front-page coverage on the day after the press conference of the FEA amounts to approximately 380 words when there are no milestones. However, this average increases to a value between 1,055 and 1,482 words in the case of milestones.[9]

Figure 3: Amount of news coverage, by news value of unemployment statistics



Notes: The figure shows the sum of words of front-page unemployment coverage, averaged over newspapers and time.

I construct an instrumental variable that indicates if the national or a state's number of unemployed reached a milestone. The instrument is coded as a binary variable because it is not clear "how much" additional news value the individual milestones have. Accordingly, there are three milestones in the number of unemployed at the national level, and 15 milestones at the state level; see Table A2 for details. In the case of the national milestones, the instrument takes the value 1 in the relevant month in all federal states; in case of the state-level milestones, the

[9] This effect could be a result of demand or supply forces in the news market. That is, news consumers and news producers might both want to pay more attention to the number of unemployed when it reaches a milestone.

dummy takes this value only in the relevant state; and it takes the value 0 in the absence of milestones.

The intuition of the instrument is that reaching a milestone in the number of unemployed leads to additional news coverage, above and beyond factors that otherwise explain the volume of unemployment reporting. The additional news coverage – which is not grounded on changes in economic fundamentals but merely reflects a mathematical coincidence – increases the chances that people reevaluate their views about the economy. The exogeneity of this mechanism derives from the milestone having no actual economic meaning, or at least no more meaning than some arbitrary value slightly below or above the milestone. This rationale is similar to that used by previous studies that emphasize the salience of round numbers in their identification strategies (Kleven and Waseem, 2013; Begley, 2015; Foellmi, Legge, and Schmid, 2016; Best and Kleven, 2017).

I assume that the additional news value of the milestones does not depend on the overall salience of unemployment in the public. A violation of this assumption could cast doubt on the validity of the instrument. For example, profit-maximizing media outlets might have a stronger incentive to report about reaching a milestone when households perceive the economy to be in a bad state, and a weaker incentive when households think the economy is in good shape. The existence of such a pattern can be tested empirically by regressing the amount of unemployment news on interactions between the milestone variable and people's evaluations of the economy. Column (1) in Table 1 summarizes the results of this test. In Columns (2) and (3), I additionally interact the milestone dummy with the national and the state unemployment rates, respectively. However, none of the interactions have a statistically significant effect, which indicates that the additional news value is not conditioned by the (perceived) state of the economy.

Another concern could be that the newspapers anticipate the milestones and report about them before the official release of the statistics. Figure A1 in the Appendix suggests that this is not the case though. The publication pattern is very similar to that when no milestones are involved (cp. Figure 1).

Table 1: Unemployment news and interacted milestone effects

	(1)	(2)	(3)
Milestone × perceptions	0.669		
	(0.428)		
Milestone × national unemployment rate		-0.0280	
		(0.0523)	
Milestone × state unemployment rate			-0.00466
			(0.0256)
Year fixed effects	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes
R-square	0.535	0.540	0.540
States	11	11	11
Press conferences	119	120	120
Observations	1,309	1,320	1,320

Notes: OLS estimates. Dependent variable: sum of words of front-page unemployment articles. All models contain the national unemployment rate, the state unemployment rate, the national inflation rate, the national index of industrial production, the absolute monthly change in these variables, the constituent terms of the interacted variables, the national election cycle, the state election cycle, and an intercept (output omitted). Newey-West standard errors (in parentheses) are robust to arbitrary autocorrelation up to order 12 and arbitrary heteroscedasticity.
* p<0.10, ** p<0.05, *** p<0.01

2.4.2 Competing newsworthy events

I use (a) the EM-DAT International Disaster Database of the Center for Research on Epidemiology at the Catholic University of Louvain and (b) the Global Terrorism Database of the National Consortium for the Study of Terrorism and Responses to Terrorism (START) at the University of Maryland to check whether the most important natural disasters and terrorist attacks in Germany and worldwide were covered by the newspapers in the sample. This kind of identification has been previously used in the context of disaster news (Eisensee and Strömberg, 2007), coverage of political scandal (Nyhan, 2014), coverage of election campaigns (Garcia-Jimeno and Yildirim, 2017), reports about prominent tax evaders (Garz and Pagels, 2017), news about politicians under criminal investigation (Garz and Sörensen, 2017), and coverage of terrorist attacks (Jetter, 2017). I construct a variable that counts – by month and state – how many of the newspapers covered the corresponding event on the front page. When considering unemployment news weighted by circulation shares in the regressions, a modified version of this count variable is used; i.e., the event variable is weighted and normalized analogous to the unemployment news variable (cp. Equation 3). There are large differences in the importance of some events between states, as the spatial proximity of an event is a major news factor. For instance, the tempest of May 2008, which caused the majority of its damage in the south west of Germany, was mostly covered by newspapers in Hesse, North Rhine-Westphalia, and Rhineland-Palatinate. See Table A3 for details.

A threat to the validity of this instrument is that disasters or terrorist attacks may influence households through channels other than the crowding out of unemployment news. For example, households could get worried that a disaster inflicts a monetary burden large enough to affect the economy. Such effects are very unlikely though, because the monetary damage of natural disasters in Germany has been tiny, at least in relation to GDP. For instance, the most severe disaster listed in the EM-DAT database in the period under consideration, the 2013 floods, was estimated to have caused a total damage of 12.9 million USD, which amounts to 0.0004% of Germany's GDP in that year.

Table 2: Effect of non-competing newsworthy events on perceptions

	(1) Perceptions
Non-competing newsworthy events	-0.00844
	(0.00820)
Year fixed effects	Yes
State fixed effects	Yes
R-square	0.262
States	11
Press conferences	120
Observations	1,320

Notes: OLS estimates. All models contain the national unemployment rate, the state unemployment rate, the national inflation rate, the national index of industrial production, the absolute monthly change in these variables, the national election cycle, the state election cycle, and an intercept (output omitted). Newey-West standard errors (in parentheses) are robust to arbitrary autocorrelation up to order 12 and arbitrary heteroscedasticity.
* p<0.10, ** p<0.05, *** p<0.01

There might still be a difference between the actual damage and perceptions of the severity of these events, and it cannot be explicitly tested whether competing newsworthy events have effects on households other than through the crowding out of unemployment reports. However, it is possible to check if natural disasters and terrorist attacks that do not coincide with the press conference of the FEA affect household perceptions. For that purpose, I construct a dummy variable that indicates the occurrence of the ten most severe, non-competing natural disasters and terrorist attacks in Germany in the period under consideration; as well as the ten most severe, non-competing natural disasters and terrorist attacks in North America and Western Europe, using the number of deaths as the criterion for severity. This indicator can then be used for placebo estimations, as shown in Table 2. The estimates do not suggest any effects of the non-competing events on people's perceptions. From the perspective of households, there is no reason why natural disasters and terrorist attacks should differ, depending on whether these events coincide with the press conference of the FEA or not. The only difference relates to the crowding out of unemployment reports, so that the results of the placebo regression substantiates the credibility of the exclusion restriction.[10]

Another concern could be that the FEA sets the dates of its monthly press conference according to predictable newsworthy events (Durante and Zhuravskaya, 2016). For example, when the numbers it has to publish are unfavorable, the FEA might schedule the release in a way that it receives as little media attention as possible; conversely, the release of positive unemployment numbers might be set for a date on which no competing news stories are expected. Looking at the procedural regulations though, it is highly unlikely that the FEA would be able to successfully implement this kind of behavior. The press conference takes place exactly on the first day of a month, unless this day coincides with a weekend, a holiday, a Monday, or a Friday. In this case, the release is set for the Tuesday, Wednesday, or Thursday closest to the first day of the month. The possibility of strategic behavior is further complicated by the dates of the conferences being scheduled several months in advance.

[10] Two additional placebo exercises provide further support for the validity of the instruments. First, I check whether the exogenous variation in unemployment news affects past perceptions of the state of the economy. There should be no effects because it is very unlikely for households to anticipate this kind of news coverage. Second, exogenous variation in unemployment news should not influence contemporary unemployment. Even if changes in sentiment caused by the news coverage affected economic fundamentals, labor market rigidities should prevent effects on unemployment in the same month. Tables A5 and A6 in the Appendix confirm these considerations. When using the competing events and milestone instruments, unemployment news neither affects past perceptions nor current changes in the state unemployment rate.

3. Results

3.1 Baseline specifications

In the baseline specifications, I check whether the amount of unemployment news affects absolute changes in the mean of the survey evaluations. I refrain from modeling the dynamics of the time series; e.g., by testing for and determining some lag order of the dependent and independent variables. Such an approach would not be very informative when the time series are contaminated with expectations, which is very likely with the data at hand. Instead, I use an IV approach and compute autocorrelation- and heteroscedasticity-robust standard errors.[11] Specifically, I use two-stage least squares to estimate versions of the following set of equations:

$$w_{s,t} = \alpha_1 + \alpha_2 event_{s,t} + \alpha_3 milestone_{s,t} + \alpha_4 X_{s,t} + \epsilon_{s,t} \tag{6}$$

$$\left|\Delta\bar{p}_{s,t}\right| = \beta_1 + \beta_2 \widehat{w}_{s,t} + \beta_3 X_{s,t} + \varepsilon_{s,t} \tag{7}$$

In the first stage (Equation 6), the amount of unemployment news coverage w in state s and month t is regressed on the two instruments $event$ (i.e., the number of newspapers covering a competing newsworthy event at the day after the monthly press conference of the FEA) and $milestone$ (i.e., a dummy indicating milestones in the national and state number of unemployed). The instruments are excluded from the second stage (Equation 7) in which the absolute monthly change in perceptions $|\Delta\bar{p}|$ is regressed on the predicted amount of news coverage $\widehat{w}$. Accordingly, β_2 captures the local average treatment effect of unemployment news on perceptions of the state of the economy. The variable vector X contains the set of control variables, including the national unemployment rate, the state unemployment rate, the national inflation rate, the national index of industrial production, the absolute monthly change in these variables, the national election cycle, the state election cycle, as well as year and state fixed effects.

[11] I refrain from clustering standard errors by states, because of the likely bias due to the small number of clusters. However, a robustness check described in Section 3.2 shows that within-cluster correlation is not an issue with the data at hand.

Table 3: Effect of unemployment news on perceptions

	(1) Perceptions (OLS)	(2) Coverage (OLS)	(3) Perceptions (IV)
Number of words (thousand)	0.0227***		0.0475***
	(0.00712)		(0.0155)
Competing newsworthy events		-0.0189***	
		(0.00523)	
Milestones		0.759***	
		(0.101)	
Year fixed effects	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes
F-statistic, 1st stage			45.46
Hansen J, p-value			0.406
R-square	0.266	0.542	0.260

Notes: N = 1,320 (11 states, 120 press conferences). All models contain the national unemployment rate, the state unemployment rate, the national inflation rate, the national index of industrial production, the absolute monthly change in these variables, the national election cycle, the state election cycle, and an intercept (output omitted). Newey-West standard errors (in parentheses) are robust to arbitrary autocorrelation up to order 12 and arbitrary heteroscedasticity.
* p<0.10, ** p<0.05, *** p<0.01

Table 3 summarizes the estimation results. Column (1), which provides the OLS estimate, indicates a highly significant, positive relationship between the amount of unemployment news and the absolute change in perceptions. The first stage of the IV estimates in Column (2) shows that the instruments have the expected impact on the news amount. With one additional newspaper covering a natural disaster or a terrorist attack, front-page coverage of unemployment decreases by 18.9 words. The effect is significant at the 1% level but the magnitude is rather small, considering that the state-month average of front-page unemployment coverage is about 415 words. When the number of unemployed reaches a milestone, front-page coverage increases by 759 words. The effect is large in magnitude and statistically highly significant. In Column (3), the second-stage estimate indicates that the effect of unemployment news on household perceptions is also significant at the 1% level. The coefficient is about twice as large as the OLS estimate. An increase in front-page coverage by 1,000 words affects the index of perceptions by 0.0475 points. The average monthly change in this index amounts to 0.121 points, of which a one standard deviation increase in unemployment news (= 496 words) is 19.5%. The F-statistic for exclusion of the instruments is well above 10; and according to Hansen's test on overidentifying restrictions, the joint null hypothesis that the instruments are valid cannot be rejected.

Table 4: Effect of unemployment news on perceptions, news amounts weighted by circulation shares

	(1) Perceptions (OLS)	(2) Coverage (OLS)	(3) Perceptions (IV)
Number of words (thousand)	0.00577*		0.0514***
	(0.00340)		(0.0185)
Competing newsworthy events		-0.0501***	
		(0.00532)	
Milestones		0.516***	
		(0.113)	
Year fixed effects	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes
F-statistic, 1st stage			77.26
Hansen J, p-value			0.559
R-square	0.262	0.242	0.199

Notes: N = 1,320 (11 states, 120 press conferences). All models contain the national unemployment rate, the state unemployment rate, the national inflation rate, the national index of industrial production, the absolute monthly change in these variables, the national election cycle, the state election cycle, and an intercept (output omitted). Newey-West standard errors (in parentheses) are robust to arbitrary autocorrelation up to order 12 and arbitrary heteroscedasticity.
* p<0.10, ** p<0.05, *** p<0.01

Table 4 summarizes the results when estimating the same specification with unemployment news weighted by the newspapers' circulation shares ($w_{s,t}^{n}$, cp. Equations 2 and 3). Here, the significance and the magnitude of the correlation between news and perceptions decrease (Column 1). The IV estimate remains highly significant though, and the effect increases to a value of 0.0514 (Column 3). Accordingly, a one standard deviation increase in unemployment news (= 714 words) accounts for 30.3% of the average monthly change in the index of perceptions. In the first stage (Column 2), the effect of competing news events on unemployment news is almost three times as large, compared to the unweighted data. One additional newspaper covering a competing event leads to a decrease in unemployment news by 50.1 words. The milestone effect amounts to an increase of 516 words.

3.2 Alternative specifications

I test the robustness of the results in several ways. First, it is useful to evaluate the estimates when using the two instruments individually. Table B1 in the Appendix provides the results of this exercise for the raw news coverage and Table B2 for the news amounts weighted by circulation shares. In the case of only using the occurrence of competing newsworthy events as an instrument, the effect of unemployment news is estimated less precisely, whereas the magnitude remains similar. For the weighted news amounts, the significance of the media effect is slightly above the 10% level ($p = 0.145$), and slightly below for the raw news amounts. Using the milestones variable as the only instrument results in estimates of the media effect that are very similar to the baseline specification, both in terms of statistical significance and size.

Second, I re-estimate the baseline specifications but compute cluster-robust instead of Newey-West standard errors. Since the number of clusters is very small (11 states), I use the wild cluster bootstrap approach proposed by Davidson and MacKinnon (2010) and Cameron and Miller (2015) to apply a finite-cluster correction. However, as Tables B3 and B4 show, within-cluster correlation hardly affects the confidence intervals of the coefficients of interest. The effect of unemployment news on perceptions remains significant at the 1% and 5% level, respectively.

Next, instead of the sum of words, I use three alternative measures of unemployment news: the average number of words, the number of articles, and the share of newspapers with front-page coverage per month and state. The average number of words accounts for variation in the number of newspapers per state. The number of articles eliminates certain nuances of the news coverage, but this measure is less sensitive to potential distortions resulting from variation in the density of newspapers' front pages (e.g., a quality newspaper might have more text on the front page than a tabloid) and changes in visibility due to different font sizes. The share of newspaper reporting about unemployment is the crudest measure of news coverage. It has the advantage of not being affected by variation in front-page design or the volume of newspapers. Tables B5 and B6 summarize the corresponding estimates, all of which confirm the results of the baseline specifications.

Further robustness checks evaluate modifications in the set of control variables. First, I address the lack of monthly GDP data in a different way. That is, I substitute the GDP proxy used in the baseline models – the index of industrial production – with a linear interpolation of quarterly data on real GDP per capita. Second, in the baseline specification, controlling for actual changes in the state of the economy is based on assumptions about the timing: The values of the macroeconomic controls in the previous month are linked to the news coverage and people's perceptions in the current month. As a robustness check, I also include current-month values of the unemployment, inflation, and industrial production variables. However, as Tables B7 and B8 indicate, both modifications do not change the estimates in a substantial way.

The baseline specifications only use a modest set of fixed effects, due to concerns about multicollinearity. It is nonetheless useful to check the robustness when expanding this set. Tables B9 and B10 show estimation results when additionally including state × year (Columns 1 to 3), calendar month (Columns 4 to 6), and state × calendar month fixed effects (Columns 7 to 9). While the coefficients remain very similar to those of the baseline specifications, the media effect is found to be only significant at the 5% level in some cases. However, variance inflation factors – which are not tabulated explicitly – are larger than 350 for some variables here, so that the specifications with the additional sets of fixed effects have to be interpreted with care.

Finally, to ease the assumption that the effects of good and bad unemployment news are symmetric, I estimate specifications using both kinds of coverage separately. As detailed in Appendix C, a simple dictionary of contextual negative and positive words serves to classify the articles in the sample. Instead of using the absolute monthly change in people's perceptions of the state of the economy ($|\Delta\bar{p}_{s,t}|$), the models in Tables C3 and C4 contain the (directional) monthly change in the variable ($\Delta\bar{p}_{s,t}$); the same modification applies to the macroeconomic controls. The estimated coefficients suggest that bad unemployment news leads to an increase in the index of perceptions (Columns 1 and 3), which implies that people perceive the economy in a more negative way. There is no statistically significant effect in the case of good news (Columns 2 and 4). In addition, the instruments are less able to predict good compared to bad news, as the lower first-stage F-statistics indicate; i.e., the models are under-identified when using the good news variable. In Table C4, the rejection of Hansen's test for over-identifying restrictions calls for caution when interpreting the coefficients that pertain to weighted data.

Since this test does not cast doubts on the validity of the instruments in any of the previously discussed regressions, the rejection most likely indicates problems with the model specification. Presumably, the good and bad news variables that are weighted by the newspapers' circulation shares are imperfect measures. Keeping this caveat in mind, the magnitude of the effect of negative news ranges from 0.07 to 0.12, which implies that a one standard deviation increase in bad news worsens the perceptions of the state of the economy by 19.9% to 31.8% of the index's average monthly change. The dominance of the effect of negative news is a well-known prediction of prospect theory (Kahneman and Tversky, 1979) and confirms previous insights about unemployment-related news (Larcinese, Puglisi, and Snyder, 2011; Garz, 2013, 2014; Heinz and Swinnen, 2015).

4. Conclusion

This study presents evidence of effects of news coverage on economic perceptions. On the one hand, I use the extraordinary newsworthiness of milestones in the number of unemployed to identify the effects. These milestones are characterized by increases in the volume of reporting, compared to the regular unemployment coverage, which in turn affects the likelihood that households revise their evaluations of the state of the economy. On the other hand, I exploit the occurrence of natural disasters and terrorist attacks to identify effects that are based on competition in the news agenda. The presence of competing newsworthy events at the time of the monthly release of the unemployment statistics causes newspapers to reduce the amount of front-page unemployment coverage, compared to times with a relaxed news agenda. IV estimates indicate that a one standard deviation increase in unemployment news exerts an effect on households that accounts for approximately one quarter of the average monthly change of people's economic perceptions, after controlling for economic fundamentals.

The empirical approach used in this study helps to shed light on the causal relationship between unemployment news and the perceptions of households. However, the results rely on several strong assumptions. In particular, I assume that the respondents of the Politbarometer surveys actually read the newspapers in my sample, that the control variables sufficiently account for the underlying economic developments, and that the instruments do not affect people's perceptions other than through the unemployment reports in my data set. This last condition is likely the strongest assumption of the identification strategy because it requires that the news variables adequately capture the actual unemployment coverage. Although I carefully checked the reports in my sample, it is conceivable that the keyword-based search procedure does not retrieve all truly relevant articles while extracting some false positives, which involves subtle concerns about measurement error. More substantial concerns relate to the selection of news outlets. The assumption that the instruments only affect economic perceptions through the newspapers in my sample implies that other, omitted news sources – e.g., newscasts, online news, or interpersonal communication – provide similar information about the monthly unemployment statistics. Therefore, as in many empirical applications, my findings cannot be interpreted in a strictly causal but close to causal way.

However, the results have important implications. First, the mechanisms of news production investigated in this study lead to regional differences in reporting, which in turn may result in regional disparities in economic perceptions and behavior. Second, economic news coverage does not perfectly echo changes in economic variables, but the reporting is subject to random accentuation and neglect. While reaching a milestone provides an opportunity to attract readers, the exaggerations have effects that can be measured in aggregate variables. From a purely economic point of view, profit-maximizing media companies simply respond to incentives that result from the preferences of news consumers. However, many news outlets are self-committed to media ethics and certain journalistic standards, which require to balance economic self-interests against those of society. Maintaining this balance might be particularly relevant in times of economic recession or crisis to avoid the amplification of downward trends. Third, the insight that the public pays more attention when an economic variable reaches a milestone creates incentives to manipulate the underlying statistics for political purposes. For example, politicians could be interested in reducing unemployment below a certain threshold when elections are close. In Germany, various mechanisms would likely prevent this kind of manipulation. However, in countries with weaker institutions, political actors might be able to change statistical procedures in order to reach or to avoid reaching a milestone.

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Appendix A (description of the data)

Table A1: Summary of the newspaper sample

	State(s)	Source	Within-sample circulation share, in % (2005–2014 average)
Aachener Zeitung	NRW	Genios	1.6
Allgemeine Zeitung Mainz	RP	Genios	0.7
B.Z.	BE	Genios	2.9
Badische Zeitung	BW	Genios	1.8
Berliner Kurier	BE	Genios	1.4
Berliner Morgenpost	BE	Genios	1.6
Berliner Zeitung	BE	Genios	1.8
Bild	National	DIGAS	33.3
Bonner General-Anzeiger	NRW	Genios	1.0
Der Tagesspiegel	BE	Genios	1.7
Express	NRW	Genios	2.3
Frankfurter Allgemeine Zeitung	National	DIGAS	4.5
Frankfurter Neue Presse	HE, RP	Genios	1.0
Frankfurter Rundschau	National	Nexis	1.5
Hamburger Abendblatt	HH, SH, LS	Genios	2.8
Hamburger Morgenpost	HH	Genios	1.3
Handelsblatt	National	DIGAS	1.8
Kölner Stadt-Anzeiger	NRW	Genios	2.7
Kölnische Rundschau	NRW	Genios	1.3
Main-Post	BY, BW	Genios	2.0
Main-Spitze	HE	Genios	0.1
Neue Westfälische	NRW	Genios	3.1
Nürnberger Nachrichten	BY	Genios	3.5
Passauer Neue Presse	BY	Genios	2.1
Rhein-Zeitung	RP	Genios	2.6
Rheinische Post	NRW	Genios	4.6
Saarbrücker Zeitung	SL	Genios	1.8
Süddeutsche Zeitung	National	DIGAS	5.4
Südkurier	BW	Genios	1.6
TAZ	National	Nexis	0.7
Trierischer Volksfreund	RP	Genios	1.1
Welt	National	DIGAS	3.1
Wiesbadener Kurier	HE	Genios	0.7
Wiesbadener Tagblatt	HE	Genios	0.1
Wormser Zeitung	RP	Genios	0.2
			100.0

Notes: BW: Baden-Wuerttemberg, BY: Bavaria, BE: Berlin, BR: Bremen, HE: Hesse, HH: Hamburg, LS: Lower Saxony, NRW: North Rhine-Westphalia, RP: Rhineland-Palatinate, SL: Saarland, SH: Schleswig-Holstein. Data to calculate the relative circulation come from IVW (Informationsgemeinschaft zur Feststellung der Verbreitung von Werbeträgern – German audit bureau of circulation; see www.ivw.eu). DIGAS is a press archive by Axel Springer Syndication (www.axelspringer-syndication.de/beitrag/ipe_beitrag_1720551.html); the Genios database is maintained by Frankfurter Allgemeine Zeitung and Verlagsgruppe Handelsblatt (www.genios.de); access to Nexis is provided by the LexisNexis Group (www.nexis.com).

Table A2: Milestones in the numbers of unemployed, 2005–2014

Unemployment statistic	Date	Explanation	For the first time since
BW	2005m2	exceeding 400,000	ever
BW	2006m12	falling below 300,000	2002m10
BW	2009m8	exceeding 300,000	2007m2
BY	2006m10	falling below 400,000	2002m11
BY	2007m10	falling below 300,000	2001m6
BE	2013m11	falling below 200,000	1993m9
BR	2005m1	exceeding 50,000	ever
BR	2007m9	falling below 40,000	2002m10
HH	2005m5	exceeding 100,000	ever
HE	2005m2	exceeding 300,000	ever
HE	2008m6	falling below 200,000	2001m11
LS	2008m6	falling below 300,000	1993m5
National	2005m1	exceeding 5 million	ever
National	2006m11	falling below 4 million	2002m10
National	2008m10	falling below 3 million	1992m11
NRW	2005m2	exceeding 1 million	ever
SL	2007m10	falling below 40,000	1992m11
SH	2008m10	falling below 100,000	1995m10

Notes: BW: Baden-Wuerttemberg, BY: Bavaria, BE: Berlin, BR: Bremen, HE: Hesse, HH: Hamburg, LS: Lower Saxony, NRW: North Rhine-Westphalia, RP: Rhineland-Palatinate, SL: Saarland, SH: Schleswig-Holstein. The list contains all dates on which the national or state number of unemployed exceeded or fell below a round number for the first time in at least two years. Here, a round number is any value that contains only zeros after the first digit. The milestones relate to the official FEA statistics and are coded in a binary way when constructing the instrument (1 if a round number was passed in given month/state, 0 otherwise; national milestones take the value 1 in all federal states).

Table A3: Natural disasters and terrorist attacks with front-page coverage, 2005–2014

Event	FEA press conference	Number of newspapers											
		Nat.	BW	BY	BE	BR	HE	HH	LS	NRW	RP	SL	SH
Indian Ocean tsunami	04.01.2005	4	0	0	1	0	0	0	0	0	0	0	0
Hurricane Katrina	31.08.2005	5	0	0	1	0	0	0	0	1	1	1	0
Floods Elbe river	30.03.2006	2	0	0	1	0	1	1	1	1	0	1	1
Tempest Saxony	29.06.2006	1	0	0	0	0	1	0	0	0	1	1	0
Train bombing plot Hamm/Koblenz	01.08.2006	3	0	0	4	0	1	0	0	2	2	1	0
Tempest south-west Germany	29.05.2008	1	0	0	0	0	1	0	0	2	1	0	0
Mumbai attacks	27.11.2008	6	0	1	4	0	4	1	1	3	3	1	1
Cold wave Germany	07.01.2009	0	1	0	1	0	1	0	0	1	3	1	0
Attacks German armed forces Afghanistan	30.04.2009	3	1	0	0	0	0	0	0	2	0	1	0
Attacks Mallorca airport	30.07.2009	5	1	1	4	0	1	1	1	5	3	1	1
Sumatra earthquakes	30.09.2009	5	0	1	2	0	3	0	0	0	4	1	0
Cold wave Germany	05.01.2010	0	0	0	0	0	1	0	0	0	2	0	0
Moscow Metro bombings	31.03.2010	2	0	0	0	0	0	0	0	0	0	1	0
Cold wave Germany	30.11.2010	1	0	0	0	0	0	1	0	1	0	0	0
Hurricane Sandy	30.10.2012	5	1	1	1	0	2	2	1	5	3	1	1
Floods Elbe river	29.05.2013	0	1	0	0	0	0	0	0	0	0	0	0
Arson attack city train Berlin	28.08.2014	0	0	0	1	0	0	0	0	0	0	0	0

Notes: BW: Baden-Wuerttemberg, BY: Bavaria, BE: Berlin, BR: Bremen, HE: Hesse, HH: Hamburg, LS: Lower Saxony, NRW: North Rhine-Westphalia, RP: Rhineland-Palatinate, SL: Saarland, SH: Schleswig-Holstein. The table shows how many newspapers per federal state covered the listed disasters/terrorist attacks on their front page; these numbers are used to construct the competing events instrument.

Table A4: Summary statistics

	Mean	SD	Min.	Max.	Source(s)
Perceptions (index)	1.945	0.299	1.185	2.765	Politbarometer
-absolute change	0.121	0.114	0.000	0.770	
-change	-0.007	0.166	-0.697	0.770	
Unemployment news (thousand words)	0.415	0.496	0.000	3.123	DIGAS, Genios, Nexis
-bad news	0.110	0.321	0.000	3.073	
-good news	0.230	0.366	0.000	2.115	
Unemployment news weighted (thousand words)	0.415	0.714	0.000	6.505	DIGAS, Genios, Nexis, IVW
-bad news	0.110	0.338	0.000	3.007	
-good news	0.230	0.472	0.000	4.186	
Unemployment news (number of articles)	2.206	1.829	0.000	9.000	DIGAS, Genios, Nexis
Unemployment news weighted (number of articles)	2.206	2.407	0.000	8.621	DIGAS, Genios, Nexis, IVW
Competing events (number of newspapers covering)	0.448	1.479	0.000	10.000	DIGAS, Genios, Nexis, EM-DAT, START
Competing events weighted (number of newspapers covering)	0.448	1.620	0.000	8.584	DIGAS, Genios, Nexis, IVW, EM-DAT, START
Placebo: non-competing events (dummy)	0.139	0.346	0.000	1.000	EM-DAT, START
Milestones (dummy)	0.035	0.183	0.000	1.000	Federal Statistical Office
State unemployment rate (%)	9.365	3.616	3.700	22.300	Federal Statistical Office
-absolute change	0.255	0.288	0.000	5.200	
-change	-0.031	0.382	-1.000	5.200	
National unemployment rate (%)	9.267	1.937	7.000	14.100	Federal Statistical Office
-absolute change	0.263	0.260	0.000	1.700	
-change	-0.041	0.367	-0.700	1.700	
National industrial production (volume index)	103.654	9.354	82.900	119.520	OECD Main Economic Indicators
-absolute change	6.123	4.953	0.000	16.900	
-change	0.268	7.837	-16.900	15.800	
Yearly national inflation rate (%)	1.572	0.754	-0.700	3.100	Federal Statistical Office
-absolute change	0.235	0.208	0.000	1.000	
-change	-0.011	0.315	-1.000	0.700	
National election cycle (months until next election)	24.100	14.789	0.000	47.000	Federal Statistical Office
State election cycle (months until next election)	26.895	16.490	0.000	59.000	Federal Statistical Office

Notes: N = 1,320 (11 states, 120 press conferences).

Table A5: Unemployment news, actual unemployment, and past perceptions

	(1) Coverage (OLS)	(2) Abs. monthly change in state unemployment (IV)	(3) Coverage (OLS)	(4) Previous month's abs. change in perceptions (IV)
Number of words (thousand)		0.0228		0.0134
		(0.0430)		(0.0203)
Competing newsworthy events	-0.0183^{***}		-0.0189^{***}	
	(0.00608)		(0.00523)	
Milestones	0.856^{***}		0.759^{***}	
	(0.0973)		(0.101)	
Year fixed effects	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes
F-statistic, 1st stage		51.93		61.12
Hansen J, p-value		0.318		0.0301
R-square	0.521	0.654	0.542	0.254

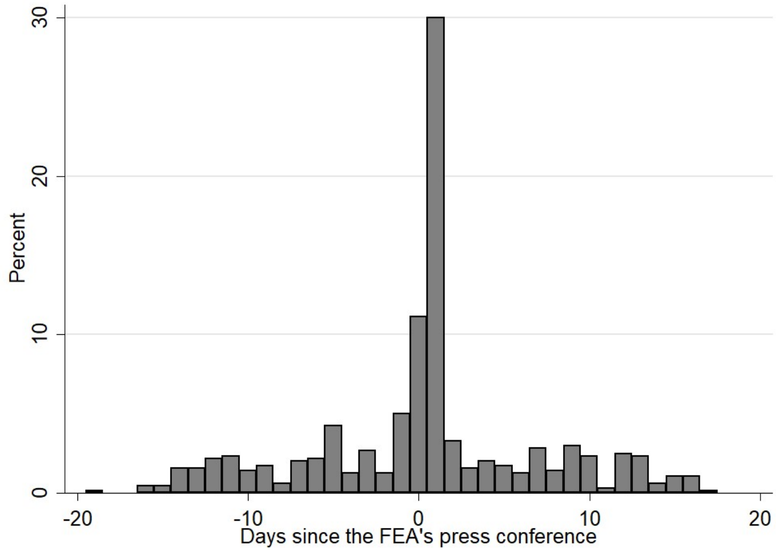
Notes: N = 1,309 (11 states, 119 press conferences). All models contain the national unemployment rate, the state unemployment rate (except for Columns 1 to 3), the national inflation rate, the national index of industrial production, the absolute monthly change in these variables, the national election cycle, the state election cycle, and an intercept (output omitted). Newey-West standard errors (in parentheses) are robust to arbitrary autocorrelation up to order 12 and arbitrary heteroscedasticity.
* p<0.10, ** p<0.05, *** p<0.01

Table A6: Unemployment news, actual unemployment, and past perceptions (news amounts weighted by circulation shares)

	(1) Coverage (OLS)	(2) Abs. monthly change in state unemployment (IV)	(3) Coverage (OLS)	(4) Previous month's abs. change in perceptions (IV)
Number of words (thousand)		-0.0134 (0.0753)		0.00382 (0.0212)
Competing newsworthy events	-0.0342*** (0.00613)		-0.0501*** (0.00532)	
Milestones	0.469*** (0.0820)		0.516*** (0.113)	
Year fixed effects	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes
F-statistic, 1st stage		45.74		88.16
Hansen J, p-value		0.108		0.0557
R-square	0.196	0.651	0.242	0.255

Notes: N = 1,309 (11 states, 119 press conferences). All models contain the national unemployment rate, the state unemployment rate (except for Columns 1 to 3), the national inflation rate, the national index of industrial production, the absolute monthly change in these variables, the national election cycle, the state election cycle, and an intercept (output omitted). Newey-West standard errors (in parentheses) are robust to arbitrary autocorrelation up to order 12 and arbitrary heteroscedasticity.
* p<0.10, ** p<0.05, *** p<0.01

Figure A1: Timing of publication of unemployment news related to milestones in the national and state number of unemployed



Notes: N = 637 articles.

Appendix B (alternative specifications)

Table B1: Effect of unemployment news on perceptions (individual instruments)

	(1) Coverage (OLS)	(2) Perceptions (IV)	(3) Coverage (OLS)	(4) Perceptions (IV)
Number of words (thousand)		0.0872*		0.0448***
		(0.0509)		(0.0162)
Competing newsworthy events	-0.0339***			
	(0.00571)			
Milestones			0.783***	
			(0.100)	
Year fixed effects	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes
F-statistic, 1st stage		34.36		59.69
R-square	0.482	0.225	0.540	0.262

Notes: N = 1,320 (11 states, 120 press conferences). All models contain the national unemployment rate, the state unemployment rate, the national inflation rate, the national index of industrial production, the absolute monthly change in these variables, the national election cycle, the state election cycle, and an intercept (output omitted). Newey-West standard errors (in parentheses) are robust to arbitrary autocorrelation up to order 12 and arbitrary heteroscedasticity.
* p<0.10, ** p<0.05, *** p<0.01

Table B2: Effect of unemployment news on perceptions, news amounts weighted by circulation shares (individual instruments)

	(1) Coverage (OLS)	(2) Perceptions (IV)	(3) Coverage (OLS)	(4) Perceptions (IV)
Number of words (thousand)		0.0396		0.0604**
		(0.0272)		(0.0242)
Competing newsworthy events	-0.0588***			
	(0.00529)			
Milestones			0.580***	
			(0.115)	
Year fixed effects	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes
F-statistic, 1st stage		120.3		24.97
R-square	0.228	0.227	0.232	0.171

Notes: N = 1,320 (11 states, 120 press conferences). All models contain the national unemployment rate, the state unemployment rate, the national inflation rate, the national index of industrial production, the absolute monthly change in these variables, the national election cycle, the state election cycle, and an intercept (output omitted). Newey-West standard errors (in parentheses) are robust to arbitrary autocorrelation up to order 12 and arbitrary heteroscedasticity.
* p<0.10, ** p<0.05, *** p<0.01

Table B3: Effect of unemployment news on perceptions (clustered standard errors)

	(1) Perceptions (OLS)	(2) Coverage (OLS)	(3) Perceptions (IV)
Number of words (thousand)	0.0227***		0.0475***
	(0.00760)		(0.0140)
Competing newsworthy events		-0.0189***	
		(0.0039)	
Milestones		0.759***	
		(0.121)	
Year fixed effects	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes
R-square	0.266	0.542	0.260

Notes: N = 1,320 (11 states, 120 press conferences). All models contain the national unemployment rate, the state unemployment rate, the national inflation rate, the national index of industrial production, the absolute monthly change in these variables, the national election cycle, the state election cycle, and an intercept (output omitted). Standard errors are clustered by state, using wild cluster bootstrap resampling to account for the small number of clusters (1,000 bootstrap replications; see Davidson and MacKinnon, 2010; Cameron and Miller, 2015).
* p<0.10, ** p<0.05, *** p<0.01

Table B4: Effect of unemployment news on perceptions, news amounts weighted by circulation shares (clustered standard errors)

	(1) Perceptions (OLS)	(2) Coverage (OLS)	(3) Perceptions (IV)
Number of words (thousand)	0.00577		0.0514**
	(0.00446)		(0.02243)
Competing newsworthy events		-0.0501***	
		(0.0020)	
Milestones		0.516***	
		(0.095)	
Year fixed effects	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes
R-square	0.262	0.242	0.199

Notes: N = 1,320 (11 states, 120 press conferences). All models contain the national unemployment rate, the state unemployment rate, the national inflation rate, the national index of industrial production, the absolute monthly change in these variables, the national election cycle, the state election cycle, and an intercept (output omitted). Standard errors are clustered by state, using wild cluster bootstrap resampling to account for the small number of clusters (1,000 bootstrap replications; see Davidson and MacKinnon, 2010; Cameron and Miller, 2015).
* p<0.10, ** p<0.05, *** p<0.01

Table B5: Effect of unemployment news on perceptions (alternative news measures)

	(1) Perceptions (OLS)	(2) Coverage (OLS)	(3) Perceptions (IV)	(4) Perceptions (OLS)	(5) Coverage (OLS)	(6) Perceptions (IV)	(7) Perceptions (OLS)	(8) Coverage (OLS)	(9) Perceptions (IV)
Average number of words (thousand)	0.156***		0.553***						
	(0.0580)		(0.165)						
Number of articles				0.00377*		0.0184***			
				(0.00193)		(0.00635)			
Share of newspapers with front-page coverage							0.0309		0.185***
							(0.0211)		(0.0636)
Competing newsworthy events		-0.00425***			-0.0447*			-0.00583***	
		(0.000563)			(0.0237)			(0.00202)	
Milestones		0.0577***			1.963***			0.194***	
		(0.00870)			(0.301)			(0.0293)	
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-statistic, 1st stage			97.62			20.73			21.85
Hansen J, p-value			0.985			0.400			0.479
R-square	0.265	0.443	0.242	0.263	0.512	0.235	0.263	0.493	0.231

Notes: N = 1,320 (11 states, 120 press conferences). All models contain the national unemployment rate, the state unemployment rate, the national inflation rate, the national index of industrial production, the absolute monthly change in these variables, the national election cycle, the state election cycle, and an intercept (output omitted). Newey-West standard errors (in parentheses) are robust to arbitrary autocorrelation up to order 12 and arbitrary heteroscedasticity.
* p<0.10, ** p<0.05, *** p<0.01

Table B6: Effect of unemployment news on perceptions, news amount weighted by circulation shares (alternative news measures)

	(1) Perceptions (OLS)	(2) Coverage (OLS)	(3) Perceptions (IV)	(4) Perceptions (OLS)	(5) Coverage (OLS)	(6) Perceptions (IV)	(7) Perceptions (OLS)	(8) Coverage (OLS)	(9) Perceptions (IV)
Average number of words (thousand)	0.0298		0.406^{**}						
	(0.0189)		(0.165)						
Number of articles				0.0000714		0.0140^{***}			
				(0.00120)		(0.00531)			
Share of newspapers with front-page coverage							-0.00164		0.137^{***}
							(0.0131)		(0.0516)
Competing newsworthy events		-0.00755^{***}			-0.180^{***}			-0.0190^{***}	
		(0.000740)			(0.0252)			(0.00260)	
Milestones		0.0413^{***}			1.934^{***}			0.193^{***}	
		(0.0149)			(0.389)			(0.0397)	
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-statistic, 1st stage			65.00			33.07			34.24
Hansen J, p-value			0.240			0.590			0.548
R-square	0.262	0.189	0.140	0.261	0.201	0.189	0.261	0.208	0.186

Notes: N = 1,320 (11 states, 120 press conferences). All models contain the national unemployment rate, the state unemployment rate, the national inflation rate, the national index of industrial production, the absolute monthly change in these variables, the national election cycle, the state election cycle, and an intercept (output omitted). Newey-West standard errors (in parentheses) are robust to arbitrary autocorrelation up to order 12 and arbitrary heteroscedasticity.
* p<0.10, ** p<0.05, *** p<0.01

Table B7: Effect of unemployment news on perceptions (modification of the controls)

	(1) Perceptions (OLS)	(2) Coverage (OLS)	(3) Perceptions (IV)	(4) Perceptions (OLS)	(5) Coverage (OLS)	(6) Perceptions (IV)
Number of words (thousand)	0.0214***		0.0442***	0.0202***		0.0488***
	(0.00696)		(0.0164)	(0.00759)		(0.0165)
Competing newsworthy events		-0.0203***			-0.0174***	
		(0.00628)			(0.00550)	
Milestones		0.692***			0.693***	
		(0.0964)			(0.105)	
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Macroeconomic variables: values of previous month	Yes	Yes	Yes	Yes	Yes	Yes
Macroeconomic variables: values of current month	No	No	No	Yes	Yes	Yes
Macroeconomic variables: real GDP per capita instead of production index	Yes	Yes	Yes	No	No	No
F-statistic, 1st stage			37.34			30.92
Hansen J, p-value			0.292			0.483
R-square	0.267	0.547	0.262	0.271	0.557	0.264
Observations	1,320	1,320	1,320	1,309	1,309	1,309

Notes: All models contain the national unemployment rate, the state unemployment rate, the national inflation rate, the national index of industrial production (unless stated otherwise), the absolute monthly change in these variables, the national election cycle, the state election cycle, and an intercept (output omitted). Newey-West standard errors (in parentheses) are robust to arbitrary autocorrelation up to order 12 and arbitrary heteroscedasticity.
* p<0.10, ** p<0.05, *** p<0.01

Table B8: Effect of unemployment news on perceptions, news amount weighted by circulation shares (modification of the controls)

	(1) Perceptions (OLS)	(2) Coverage (OLS)	(3) Perceptions (IV)	(4) Perceptions (OLS)	(5) Coverage (OLS)	(6) Perceptions (IV)
Number of words (thousand)	0.00532		0.0478**	0.00637*		0.0433**
	(0.00337)		(0.0196)	(0.00378)		(0.0196)
Competing newsworthy events		-0.0454***			-0.0618***	
		(0.00564)			(0.00755)	
Milestones		0.474***			0.351***	
		(0.109)			(0.103)	
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Macroeconomic variables: values of previous month	Yes	Yes	Yes	Yes	Yes	Yes
Macroeconomic variables: values of current month	No	No	No	Yes	Yes	Yes
Macroeconomic variables: real GDP per capita instead of production index	Yes	Yes	Yes	No	No	No
F-statistic, 1st stage			59.96			51.81
Hansen J, p-value			0.727			0.218
R-square	0.263	0.248	0.209	0.269	0.296	0.230
Observations	1,320	1,320	1,320	1,309	1,309	1,309

Notes: All models contain the national unemployment rate, the state unemployment rate, the national inflation rate, the national index of industrial production (unless stated otherwise), the absolute monthly change in these variables, the national election cycle, the state election cycle, and an intercept (output omitted). Newey-West standard errors (in parentheses) are robust to arbitrary autocorrelation up to order 12 and arbitrary heteroscedasticity.

* p<0.10, ** p<0.05, *** p<0.01

Table B9: Effect of unemployment news on perceptions (modification of fixed effects)

	(1) Perceptions (OLS)	(2) Coverage (OLS)	(3) Perceptions (IV)	(4) Perceptions (OLS)	(5) Coverage (OLS)	(6) Perceptions (IV)	(7) Perceptions (OLS)	(8) Coverage (OLS)	(9) Perceptions (IV)
Number of words (thousand)	0.0234***		0.0466***	0.0149*		0.0413**	0.0122		0.0458**
	(0.00706)		(0.0154)	(0.00787)		(0.0190)	(0.00757)		(0.0187)
Competing newsworthy events		-0.0199***			-0.0224***			-0.0223***	
		(0.00521)			(0.00639)			(0.00634)	
Milestones		0.766***			0.608***			0.623***	
		(0.0959)			(0.0995)			(0.0949)	
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × year fixed effects	Yes	Yes	Yes	No	No	No	No	No	No
Calendar month fixed effects	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
State × calendar month fixed effects	No	No	No	No	No	No	Yes	Yes	Yes
F-statistic, 1st stage			48.14			25.43			24.57
Hansen J, p-value			0.463			0.109			0.116
R-square	0.333	0.569	0.328	0.278	0.604	0.272	0.336	0.614	0.327

Notes: N = 1,320 (11 states, 120 press conferences). All models contain the national unemployment rate, the state unemployment rate, the national inflation rate, the national index of industrial production, the absolute monthly change in these variables, the national election cycle, the state election cycle, and an intercept (output omitted). Newey-West standard errors (in parentheses) are robust to arbitrary autocorrelation up to order 12 and arbitrary heteroscedasticity.
* p<0.10, ** p<0.05, *** p<0.01

Table B10: Effect of unemployment news on perceptions, news amount weighted by circulation shares (modification of fixed effects)

	(1) Perceptions (OLS)	(2) Coverage (OLS)	(3) Perceptions (IV)	(4) Perceptions (OLS)	(5) Coverage (OLS)	(6) Perceptions (IV)	(7) Perceptions (OLS)	(8) Coverage (OLS)	(9) Perceptions (IV)
Number of words (thousand)	0.00609*		0.0497***	0.00269		0.0430**	0.00241		0.0438**
	(0.00326)		(0.0184)	(0.00362)		(0.0187)	(0.00360)		(0.0181)
Competing newsworthy events		-0.0510***			-0.0860***			-0.0857***	
		(0.00550)			(0.00810)			(0.00810)	
Milestones		0.524***			0.216**			0.226**	
		(0.116)			(0.101)			(0.104)	
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × year fixed effects	Yes	Yes	Yes	No	No	No	No	No	No
Calendar month fixed effects	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
State × calendar month fixed effects	No	No	No	No	No	No	Yes	Yes	Yes
F-statistic, 1st stage			72.06			84.87			77.76
Hansen J, p-value			0.524			0.709			0.518
R-square	0.329	0.244	0.271	0.276	0.358	0.234	0.335	0.358	0.290

Notes: N = 1,320 (11 states, 120 press conferences). All models contain the national unemployment rate, the state unemployment rate, the national inflation rate, the national index of industrial production, the absolute monthly change in these variables, the national election cycle, the state election cycle, and an intercept (output omitted). Newey-West standard errors (in parentheses) are robust to arbitrary autocorrelation up to order 12 and arbitrary heteroscedasticity.
* p<0.10, ** p<0.05, *** p<0.01

Appendix C (good and bad news)

To distinguish between good and bad unemployment news, I analyze the sentiment of the articles using simple text-mining techniques. Specifically, I compare the language used in the unemployment reports with a list of positive and negative words. It is not possible to use a standard sentiment dictionary, because many words that have a positive connotation in the general use of the German language, have a negative one in the context of unemployment news (and vice versa). For instance, the SentiWS dictionary of polarity bearing German words (Remus, Quasthoff, and Heyer, 2010) lists the noun Rückgang (decrease) as a clearly negative term. When using the word in the context of unemployment it likely suggests good news though. Therefore, I compile a simple dictionary that accounts for the specific connotations of the language used in unemployment reports. For that purpose, I create a list of the 1,500 most frequently used words in my sample of unemployment articles, after removing stop words and punctuation. I manually search this list for terms with clear negative or positive economic implications. Table C1 shows the resulting ad-hoc dictionary.

Table C1: Frequent positive and negative words

Positive sentiment		Negative sentiment	
Herbstaufschwung	autumnal upswing	Rekordhöhe	all-time high
Herbstbelebung	autumnal upturn	Lehrstellenlücke	apprenticeship gap
zuversichtlich	confident	Abschwung	downturn
Rückgang	decrease	Konjunkturflaute	economic lull
Vollbeschäftigung	full employment	Eurokrise	euro crisis
Optimismus	optimism	Finanzkrise	financial crisis
Schwung	momentum	Finanzmarktkrise	financial market crisis
optimistisch	optimistic	bedrückend	gloomy
erfreulich	pleasant	Anstieg	increase
positiv	positive	Langzeitarbeitslose	long-term unemployed
Erholung	recovery	Schutzschirm	protective umbrella
Abbau	reduction	Rezession	recession
stabil	robust	Rekordarbeitslosigkeit	record unemployment
verstärkt	strengthened	Kurzarbeitergeld	short-time allowance
Wende	turnaround	Abschwächung	slowdown
Belebung	upturn	Konjunkturprogramm	stimulus program
kräftig	vigorous	schwach	weak

I use this dictionary to determine which unemployment reports are likely good news for households and which ones are bad. Articles that contain a larger number of sentences with negative than positive words are classified as bad news, whereas the opposite applies for good news. Based on this procedure, 22.7% of the reports are classified as negative and 45.2% as positive, which is in accordance with the overall decline in the unemployment rate between 2005 and 2014 in Germany. The plausibility of the classification is also confirmed by the correlations between the resulting good news and bad news variables and the unemployment rates. As Table C2 shows, there is a solid positive bivariate relationship between the number of words of bad unemployment news and the monthly change in the state (0.36) and national unemployment rates (0.38). In the case of good news, the correlation coefficients amount to -0.24 and -0.27, respectively. The correlations are similar when weighting the news variables by the newspapers' circulation shares.

Table C2: Bivariate correlations between unemployment news and actual unemployment

	State unemployment rate (monthly change)	National unemployment rate (monthly change)
Number of words:		
-bad news	0.355^{***}	0.384^{***}
-good news	-0.242^{***}	-0.266^{***}
-bad news, weighted by circulation	0.313^{***}	0.319^{***}
-good news, weighted by circulation	-0.188^{***}	-0.213^{***}

Notes: N = 1,309.
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table C3: Effects of good and bad coverage on perceptions

	(1)	(2)	(3)	(4)
Bad news, number of words (thousand)	0.0922**		0.117***	
	(0.0374)		(0.0453)	
Good news, number of words (thousand)		0.260		0.243
		(0.170)		(0.169)
Year fixed effects	Yes	Yes	Yes	Yes
Calendar month fixed effects	No	No	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes
F-statistic, 1st stage	48.24	7.938	27.37	9.693
Hansen J, p-value	0.432	0.711	0.332	0.282
R-square	0.0121	-0.118	0.0321	-0.0601

Notes: Dependent variable: monthly change in perceptions of the state of the economy. IV estimates, using competing newsworthy events and milestones as instruments. N = 1,309 (11 states, 119 press conferences). All models contain the national unemployment rate, the state unemployment rate, the national inflation rate, the national index of industrial production, the monthly change in these variables, the national election cycle, the state election cycle, and an intercept (output omitted). Newey-West standard errors (in parentheses) are robust to arbitrary autocorrelation up to order 12 and arbitrary heteroscedasticity.
* p<0.10, ** p<0.05, *** p<0.01

Table C4: Effects of good and bad coverage on perceptions, news amounts weighted by circulation shares

	(1)	(2)	(3)	(4)
Bad news, number of words (thousand)	0.0699**		0.0868***	
	(0.0274)		(0.0320)	
Good news, number of words (thousand)		0.0205		0.0166
		(0.0912)		(0.0971)
Year fixed effects	Yes	Yes	Yes	Yes
Calendar month fixed effects	No	No	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes
F-statistic, 1st stage	30.45	3.719	20.76	3.092
Hansen J, p-value	0.0735	0.0357	0.0704	0.0296
R-square	0.0162	0.0166	0.0403	0.0425

Notes: Dependent variable: monthly change in perceptions of the state of the economy. IV estimates, using competing newsworthy events and milestones as instruments. N = 1,309 (11 states, 119 press conferences). All models contain the national unemployment rate, the state unemployment rate, the national inflation rate, the national index of industrial production, the monthly change in these variables, the national election cycle, the state election cycle, and an intercept (output omitted). Newey-West standard errors (in parentheses) are robust to arbitrary autocorrelation up to order 12 and arbitrary heteroscedasticity.
* p<0.10, ** p<0.05, *** p<0.01

Appendix literature

Remus, R., Quasthoff, U., & Heyer, G. (2010). SentiWS – A Publicly Available German-Language Resource for Sentiment Analysis. *Proceedings of the 7th International Conference on Language Resources and Evaluation*, 1168–1171.