Credit Shocks and Populism

Online Appendix

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Contents

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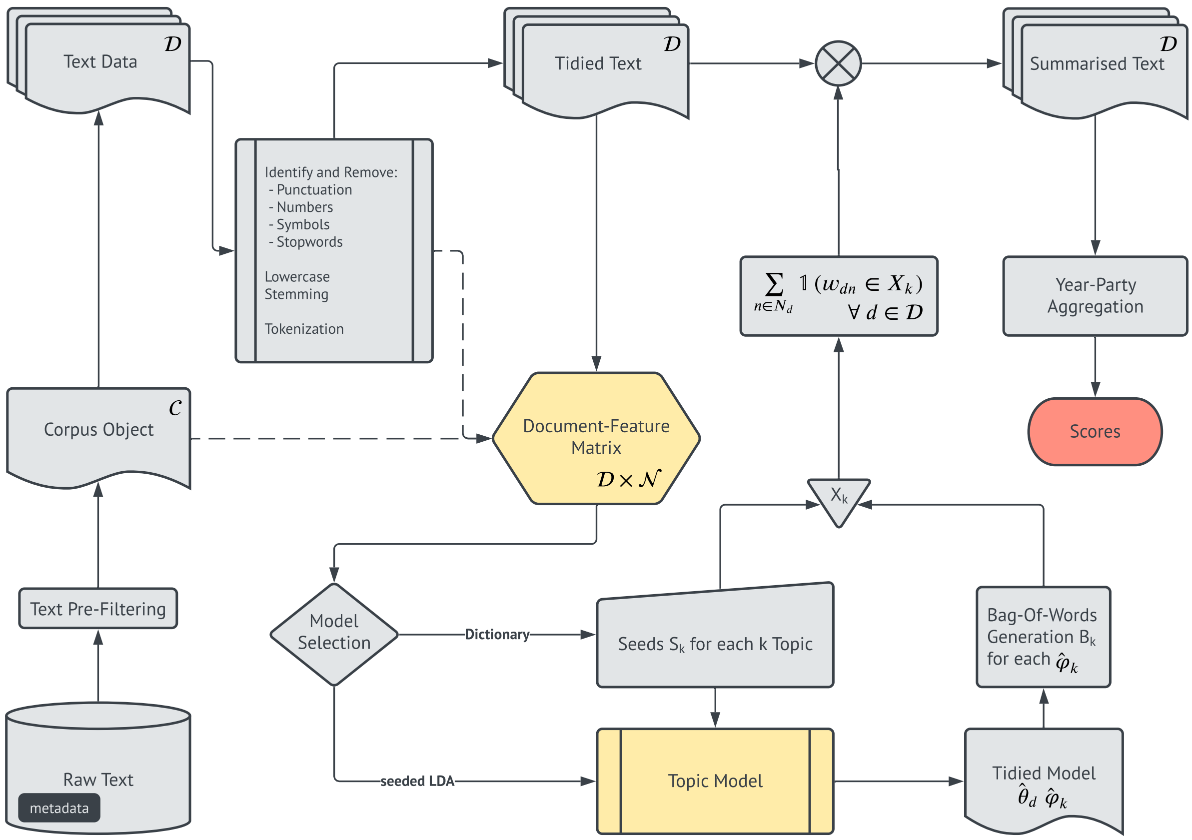
A Text Analysis Workflow with Topic Modelling

Figure A1: Flowchart of the Text Analysis Workflow including topic modelling

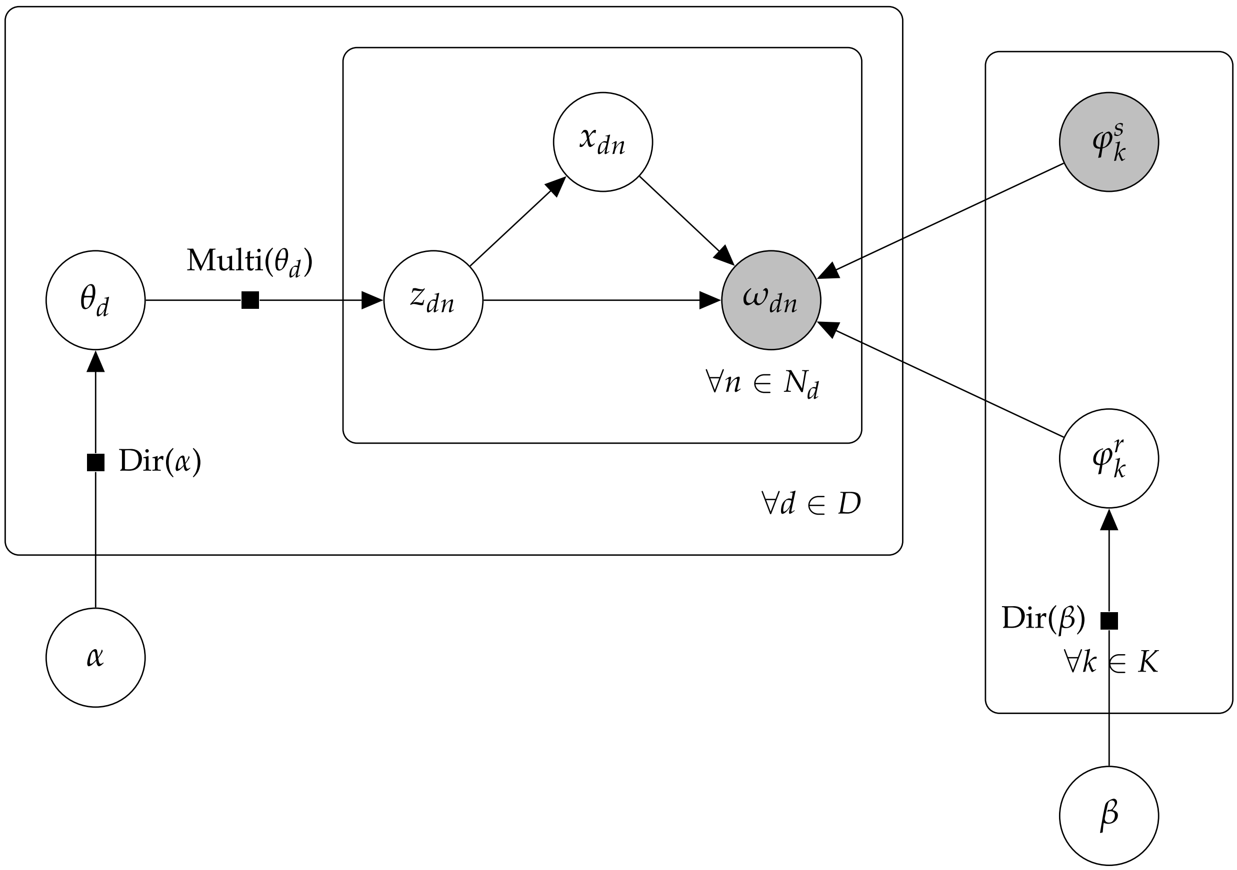


In Figure A1, we describe in detail the process of our text analysis workflow. The entry point is always the raw textual data, either from ParlSpeech (Rauh and Schwalbach, 2020, v2) or the *Comparative Manifesto Database* (Burst et al., 2020) with some related metadata describing in particular the party, the year and the contributor. The raw text is pre-filtered using simple adjustments on metadata and common mistakes, and shaped as a Corpus object. Once the text is shaped as a data-frame, we pre-process it. In particular, we identify and remove punctuation, numbers, symbols and stopwords[1]. For simplicity, we transform the text data as lowercase to perform the tokenisation in uni-grams. From the token data, we create the document-feature matrix at which we either apply the topic model or not based on the model selection decision, and we calculate the sum of matched terms for each topic using either the bag-of-words obtained as in (A.1) or the seeds lexicon. After that, we apply the aggregation decision at year-party level as described by Equation (5) or (6) in Section 6. Theoretical guidance for the right level of aggregation is often

[1]For the identification of stopwords, we both use the standard dictionary of German stopwords in the `quanteda` R package and an extended dictionary from the Github repository of `solariz`.

limited, which makes it an important dimension along which to check the sensitivity of results. This is an additional reason to why we also include textual data from political manifestos, where aggregation is irrelevant as we have one single manifesto for each election year and each party.

Figure A2: Plate Notation Diagram of the seeded Latent Dirichlet Allocation (seededLDA)



We illustrate the Bayesian network of topic model applied to the workflow using the plate notation in Figure A2. We define $\mathcal{D}$ and $\mathcal{N}$ as respectively the row and column dimensions of the document-feature matrix $\mathcal{D} \times \mathcal{N}$ obtained from the corpus $\mathcal{C}$. $\theta_d \sim \text{Dir}(\alpha)$ and $\varphi_k^r \sim \text{Dir}(\beta)$ are respectively independent draws for each document $d \in \mathcal{D}$ and for each topic $k \in K$ to generate the document-specific topic distribution and the per-topic general words distribution. In our exercise, the hyper-parameters α and β are sparsely selected ($\alpha = 0.5, \beta = 0.1$). Each (observed) word ω_{dn} in document d is generated from a *two-step* process:

(i) draw the topic assignment $z_{dn} \sim \text{Multinomial}(\theta_d)$ which gives a Markov blanket with α as parent and $z_{dn} \; \forall \; n \in N_d \subset \mathcal{N}$ as children;

(ii) draw $\omega_{dn} \sim \text{Multinomial}\left(\varphi_k^f \mid x_{dn}\right)$ with $f = \{r, s\}$, where x_{dn} is a switch variable drawn from a Beta distribution for each topic and on the basis of the value of x_{dn} either the draw from the general per-topic words distribution φ_k^r or the draw from the prioritised named entity words distribution from the (observed) seeds φ_k^s is selected.

In our application, we perform Bayesian inference using Gibbs sampling as Markov Chain Monte Carlo algorithm. In this case, as in the simpler formats of LDA, the Dirichlet distribution is particularly useful because when blended with a Multinomial distribution returns again a Dirichlet posterior. From the Bayesian network we obtain two main important predictions for our purpose:

(a) $\hat{\theta}_d$ the document-specific posterior probability distribution of topics, which we use to identify the most salient documents for each topic k as in the examples of Section C;

(b) $\hat{\varphi}_k$ the per-topic posterior probability distribution of (unique) words, which we use to create the bag-of-words for the creation of the time-party index for each topic.

We can think of $\hat{\varphi}$ simply as a $\mathcal{B} \times \mathcal{K}$ matrix of posterior probability scores, with $\mathcal{B} = \{b_1, b_2, \ldots, b_B\} \subset \mathcal{N}$ the set of unique words in the corpus $\mathcal{C}$ and $\hat{\varphi}_k = (\hat{\varphi}_{kb_1}, \hat{\varphi}_{kb_2}, \ldots, \hat{\varphi}_{kb_B})$ the set of posterior probabilities for each unique word in the topic k. On the basis of each $\hat{\varphi}_k$, we can retrieve the subset of $\nu < B$ features with the highest posterior probability within a topic $k \in K = \{BF, POP\}$ as the following set:

$$B_k := \left\{ b_j : \hat{\varphi}_{kb_j} \geq \hat{\varphi}_{kb_r} \; \forall \, \mathcal{B} \setminus \{b_1, b_2, \ldots, b_\nu\} \right\} \tag{A.1}$$

where $j = \{1, 2, \ldots, \nu\}$ is an index to identify any j word in the ν set of words fulfilling the requirements in the set rule. The obtained set from (A.1) defines the bag-of-word for each topic k used in the year-party aggregation at (5) in Section 6, where $\nu = 20$.

B Text Analysis Seeds and Lexicons

We input two main sets of keywords in order to perform both text analysis approaches, i.e. seeded LDA and dictionary technique. While the terms are the same we use them differently depending on the approach. For seeded LDA, we use them as initial 'seeds' to guide the topic model (see Section A for more details). For the dictionary approach, we use them as lexicons, meaning that we compute the frequency of these terms in each document (weighted by the number of terms in each document).

In order to capture the discussions on banking, finance and the crisis, we create four different subgroups based on a parsimonious selection of terms. The lists of stemmed terms for each subtopic are the following:

- Banking: 'bank*', 'kredit*';
- Finance: 'finanz*';
- Central banking: 'ezb', 'europaeische zentralbank', 'euro';

- Crisis: ‘krise’, ‘finanzkrise’, ‘bankenkrise’.

We use the list of terms provided by Rooduijn and Pauwels (2011) to capture populist rhetoric. This list is made of the following twenty stemmed terms: ‘elit*’, ‘konsens*’, ‘undemokratisch*’, ‘referend*’, ‘korrupt*’, ‘propagand*’, ‘politiker*’, ‘taüsch*’, ‘betrüg*’, ‘betrug*’, ‘*verrat*’, ‘scham*’, ‘schäm*’, ‘skandal*’, ‘wahrheit*’, ‘unfair*’, ‘unehrlich*’, ‘establishm*’, ‘*herrsch*’, ‘lüge*’.

C Examples of Speeches

In this section we provide some examples of speeches that feature a high score as captured by the seeded LDA relative to other speeches. For each example we report the original text and the translation using Google Translate and DeepL[2].

Populist Rhetoric. The following speeches score high in the seeded LDA trained on populist rhetoric:

Frau Präsidentin! Meine Damen und Herren! Wir lehnen diesen Antrag ab, und zwar allein deshalb, weil die peinliche Einbringungsrede des Bundesfinanzministers eine sofortige Antwort erfordert.
<u>Translation</u>: *Madam President! Ladies and Gentlemen! We reject this motion, for the sole reason that the embarrassing contribution speech of the Federal Minister of Finance requires an immediate response.*

Matthäus-Maier [SPD]: Dummes Zeug! Theo Waigel [CDU/CSU]: Das ist kein dummes Zeug, Frau Kollegin Matthäus-Maier.
<u>Translation</u>: *Matthäus-Maier [SPD]: Stupid stuff! Theo Waigel [CDU/CSU]: That's not stupid stuff, Ms Kollegin Matthäus-Maier.*

Hans-Dietrich Genscher (FDP, 1991): Herr Kollege, so ist es. Wenn Sie Unterlegenheitsgefühle haben, schlage ich Ihnen vor: Wirken Sie mit bei der Entwicklung des europäischen Pfeilers, dann werden Sie auch dieses letzte Gefühl der Unterlegenheit verlieren . Briefs [PDS/Linke Liste]: Sie glauben gar nicht, mit welch dumpfen Gefühlen Men - schen in Westeuropa die Politik dieser Bun - desregierung betrachten!
<u>Translation</u>: *Hans-Dietrich Genscher (FDP, 1991): Sir, that's how it is. If you feel inferior, I suggest that you help develop the European pillar, then you will lose that last feeling of inferiority. Briefs [PDS/Linke Liste] : You do not believe the dull feelings with which people in Western Europe view the policy of this federal government!*

Banking and Financial Crisis topic. The following speeches score high in the seeded LDA

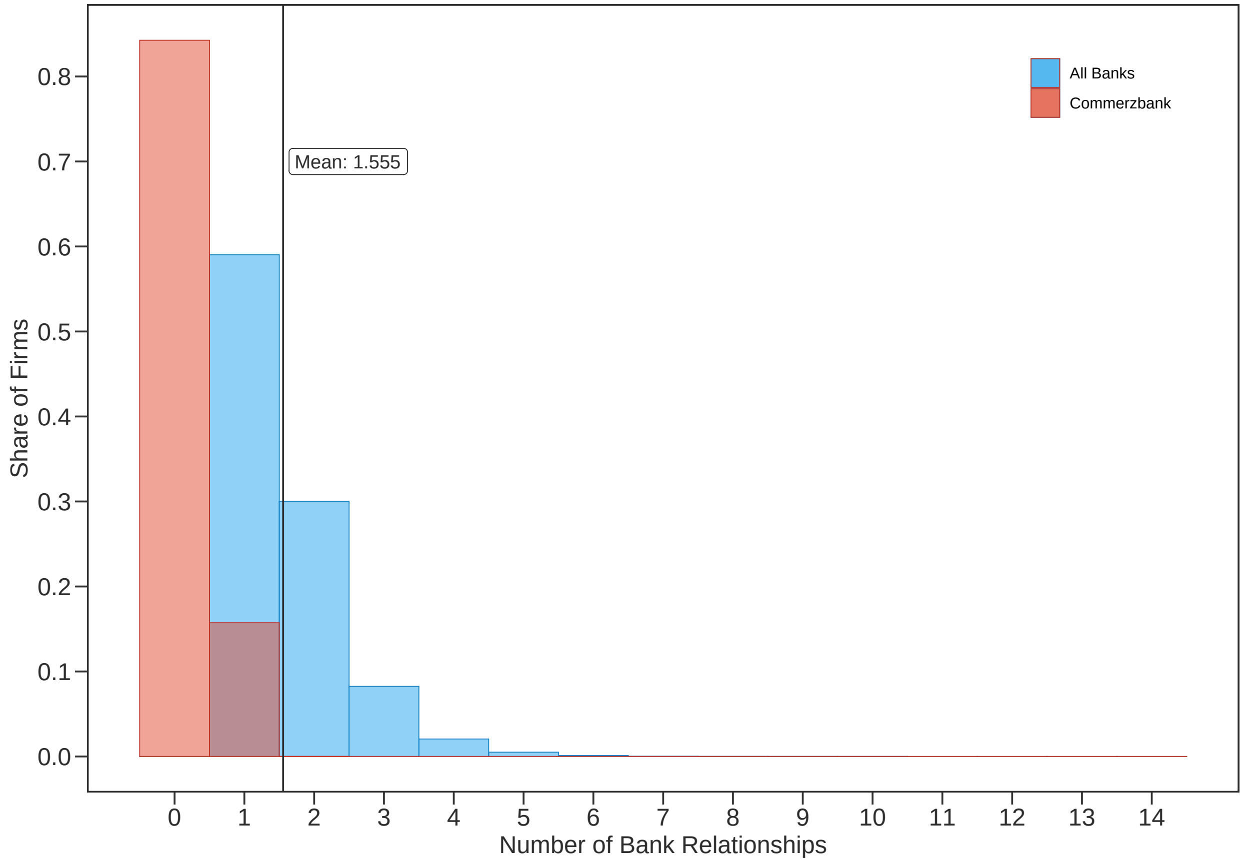
[2] A deep-learning powered translator freely available at https://www.deepl.com/translator.

trained to capture the topic of banking, finance and the crisis:

(TODO) ADD TOPIC EXAMPLES HERE.

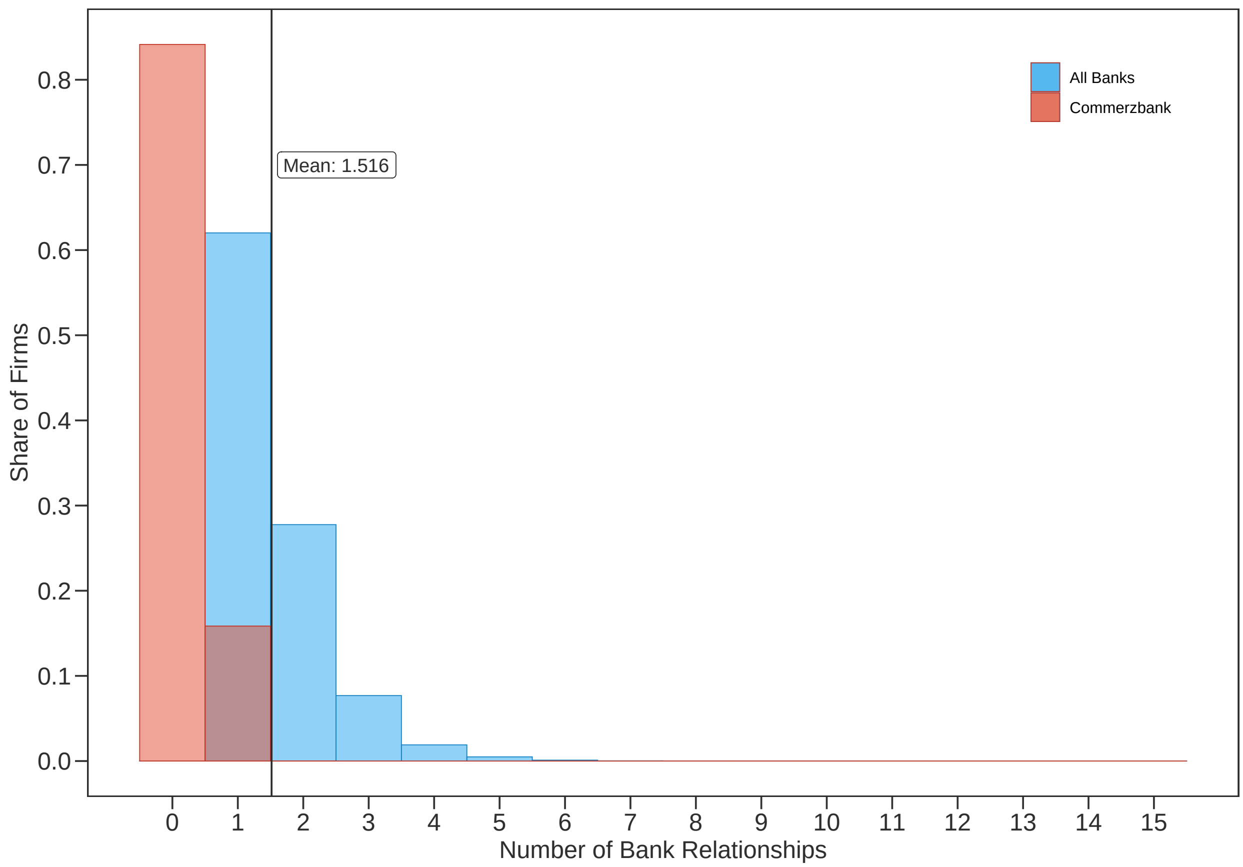
D Additional Figures

Figure A3: Distribution of the Number of Firm-Bank Relationships per firm



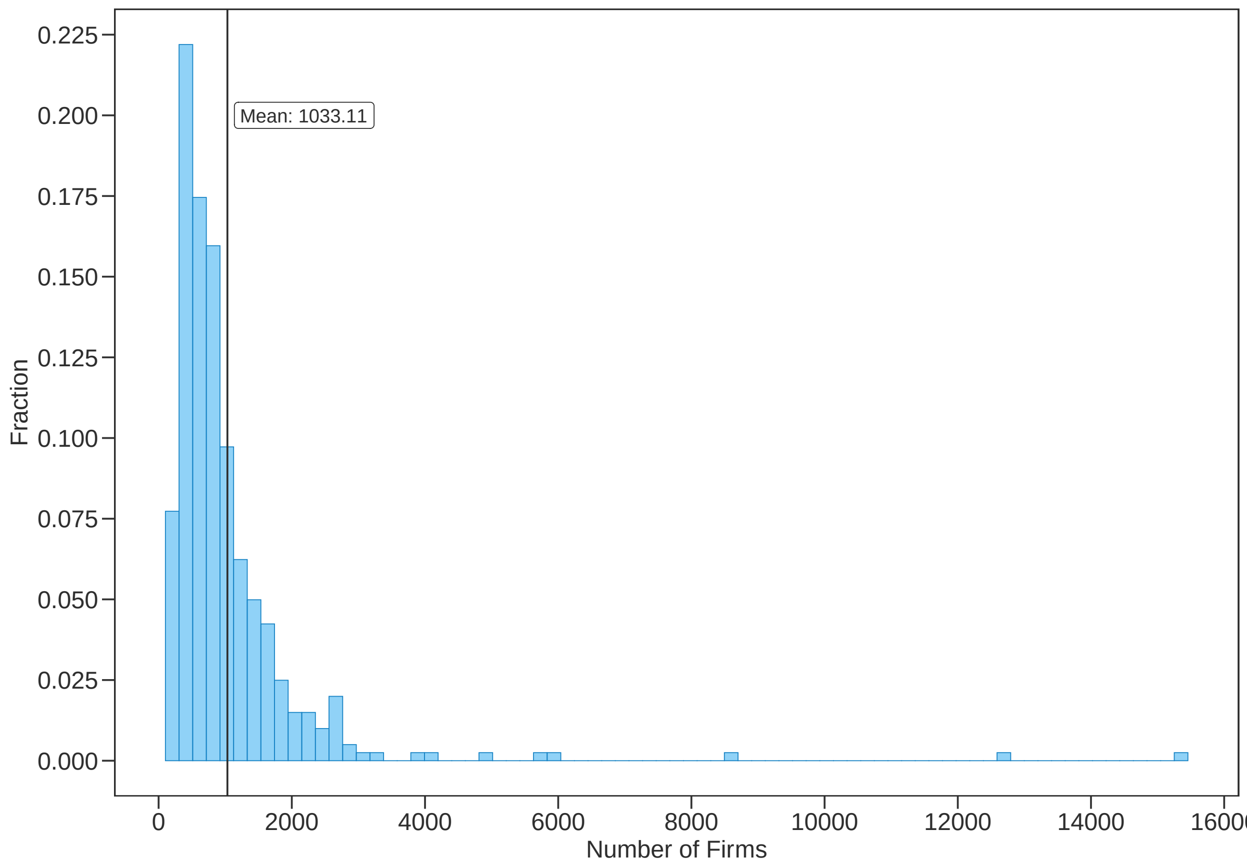
Notes: This figure displays the distribution of the number of total bank relationships for each firm in the sample, and the distribution of the number of those bank relationships that are with Commerzbank. On average, each firm has 1.5 bank relationships, as indicated by the labelled vertical line over the histogram. Frequencies of bank relationships and firms' sample are explained in Figure 4. Source(s): Amadeus, Amadeus Bankers and authors' calculation.

Figure A4: Distribution of the Number of Firm-Bank Relationships per firm



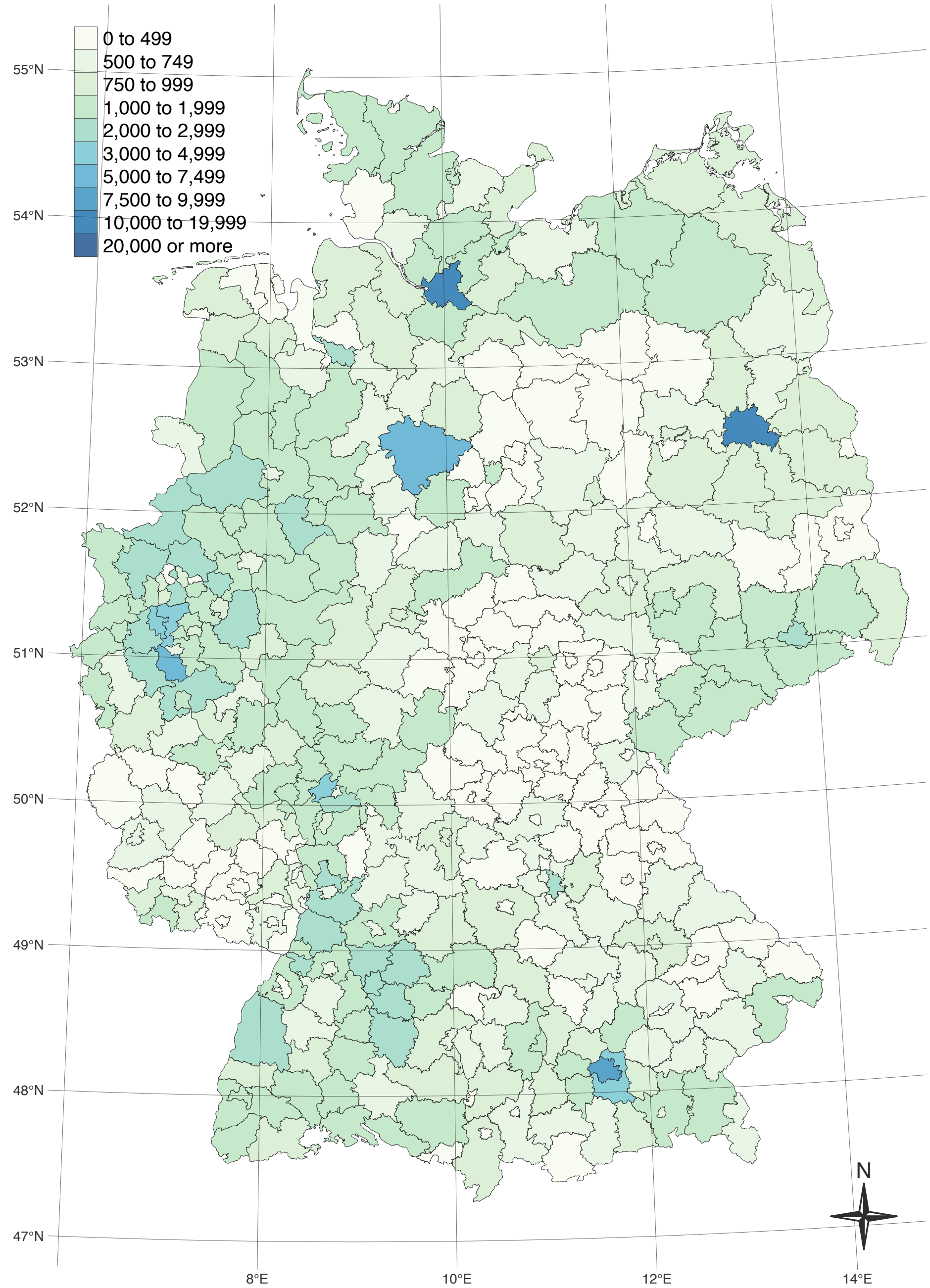
Notes: This figure displays the distribution of the number of total bank relationships for each firm in the sample, and the distribution of the number of those bank relationships that are with Commerzbank. On average, each firm has 1.5 bank relationships, as indicated by the labelled vertical line over the histogram. We include financial and public sector firms in the sample, having a similar distribution when excluding those firms. Frequencies of bank relationships and firms' sample are explained in Figure 4. Source(s): Amadeus, Amadeus Bankers and authors' calculation.

Figure A5: Distribution of the Number Firms in the sample per County



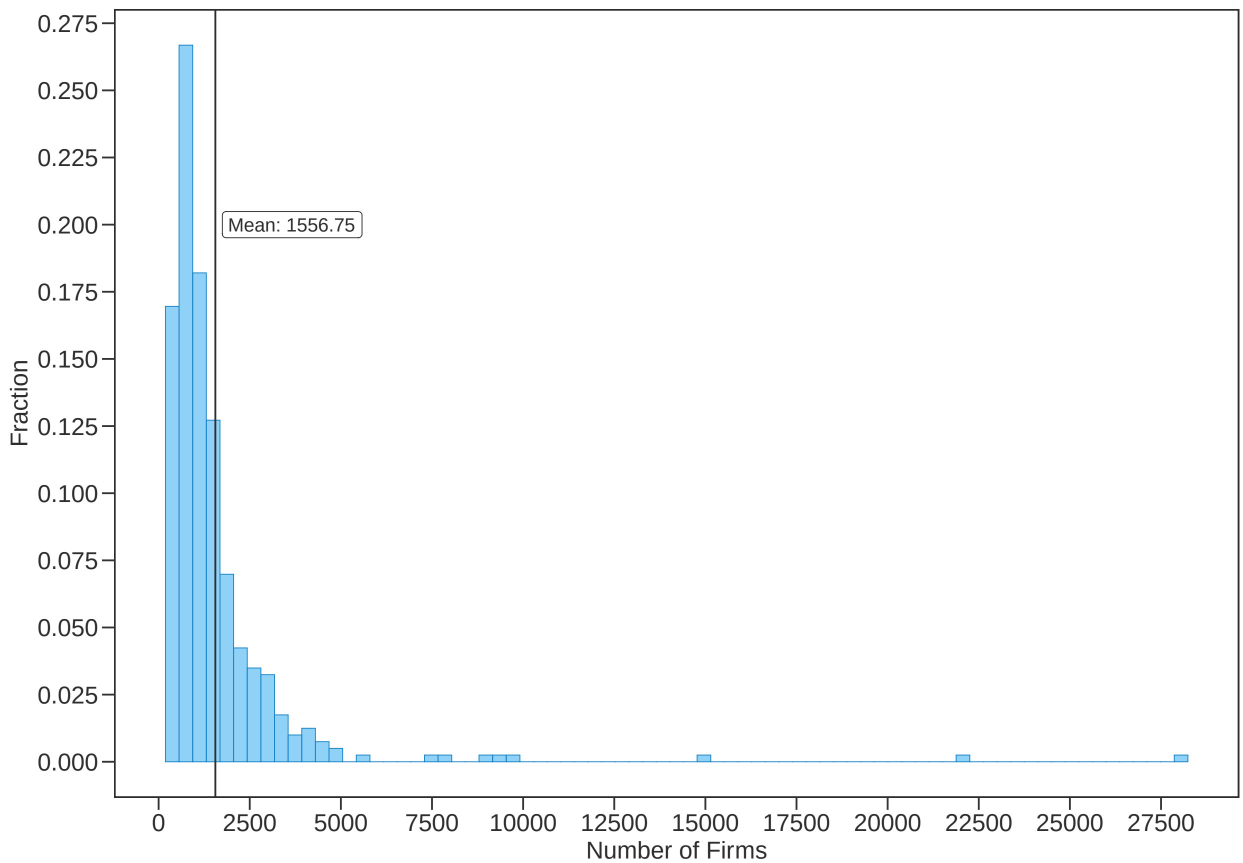
Notes: This figure plots the distribution of the number of firms per county in the sample, using 75 bins. On average, for each county there are 1003 firms, from a total of 414277 firms excluding those in the financial and public sector industry codes. Figure 4 provides a more detailed description of the firms' sample. Source: Amadeus and authors' calculation.

Figure A6: Spatial Distribution of the Firms Sample in Germany



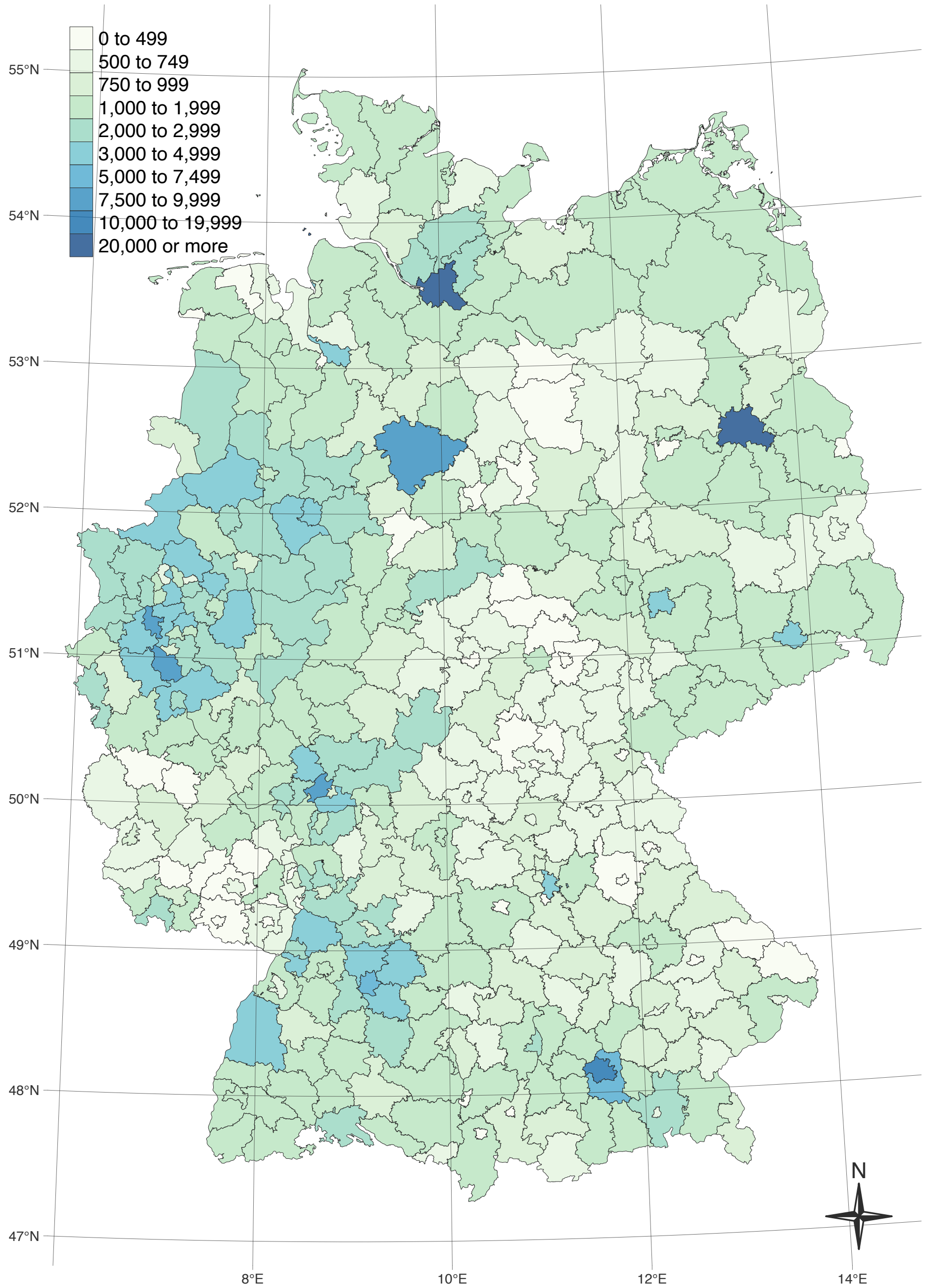
Notes: This figure maps the distribution in Figure A5 over the German counties, binning the frequencies by fixed breaks. Frequencies of bank relationships and firms' sample are explained in Figure 4. Source(s): Amadeus, BKG, and authors' calculation.

Figure A7: Distribution of the Number Firms in the sample per County



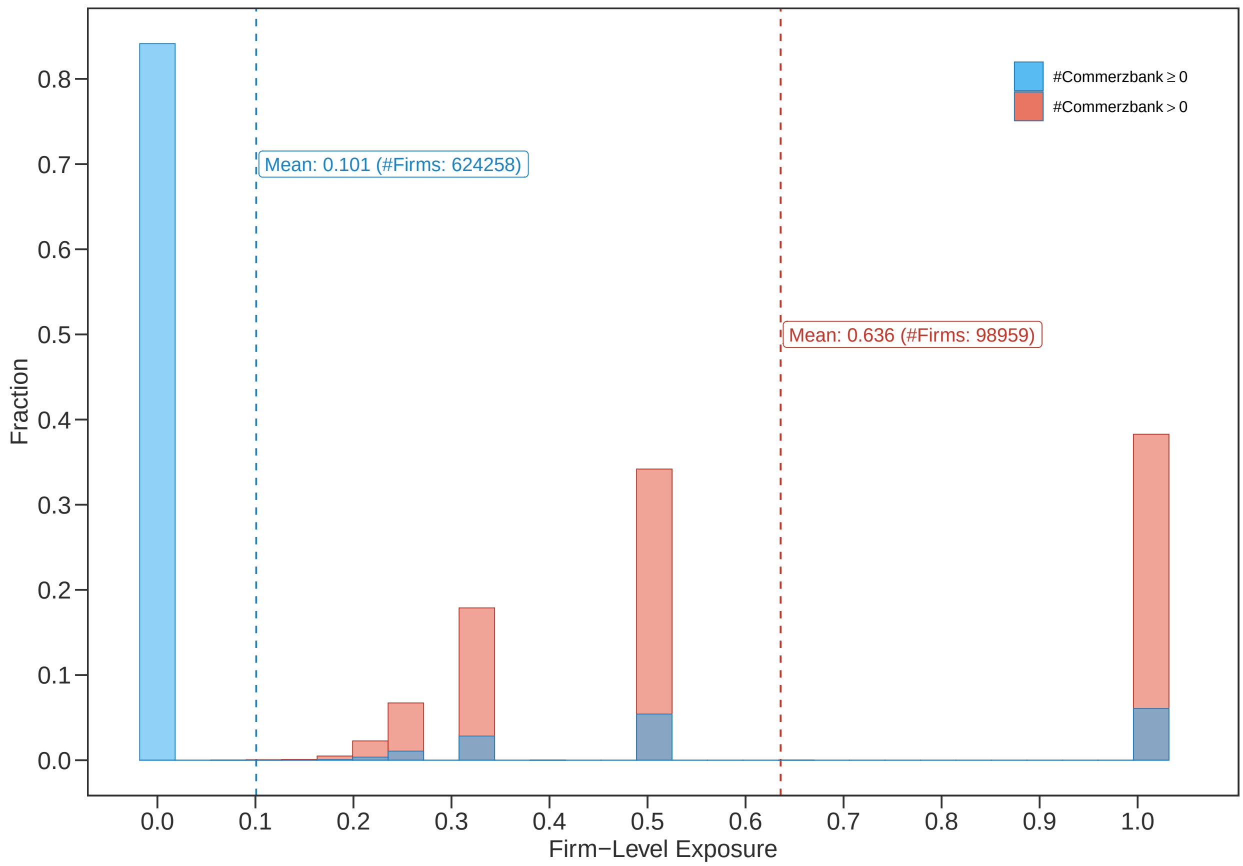
Notes: This figure plots the distribution of the number of firms per county in the sample, using 75 bins. On average, for each county there are 1557 firms, from a total of 624258 firms. Figure 4 provides a more detailed description of the firms' sample. Source: Amadeus and authors' calculation.

Figure A8: Spatial Distribution of the Firms Sample in Germany



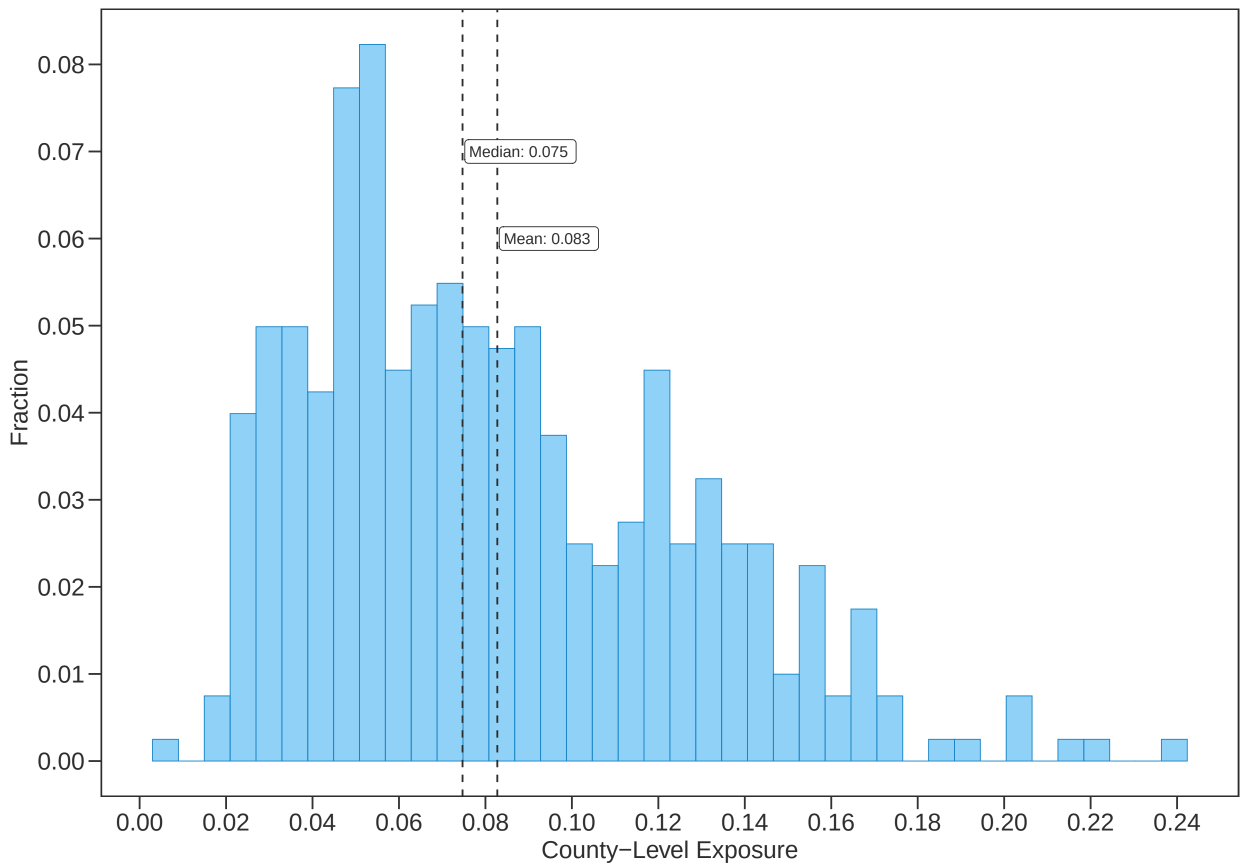
Notes: This figure maps the distribution in Figure A5 over the German counties, binning the frequencies by fixed breaks. Frequencies of bank relationships and firms' sample are explained in Figure A9. Source(s): Amadeus, BKG, and authors' calculation.

Figure A9: Distribution of Firm-Level Commerzbank Dependence



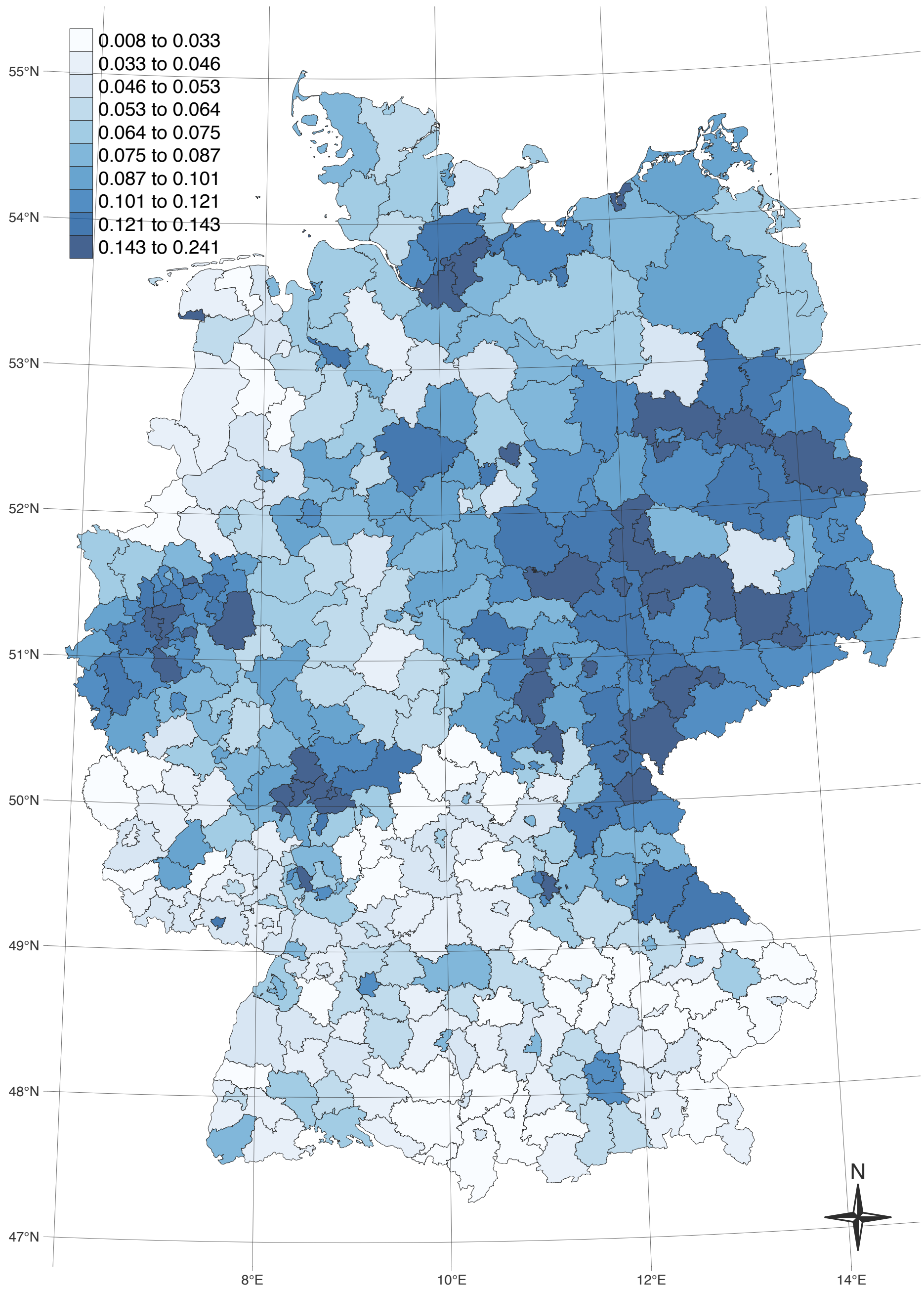
Notes: This picture displays the distribution of the firm-specific Commerzbank dependence at the firms' sample. We provide overlapping histograms of a) the unconditional distribution of the firm-level Commerzbank dependence for all firm, and b) the conditional distribution of the firm-level Commerzbank dependence for those firms having at least one bank relationship with Commerzbank. The dashed lines indicate the average firm exposure of respectively the unconditional and conditional distribution. The labels next to the lines indicate the exact mean value and the number of firms involved in the computation. We include firms in the financial and public sectors. See Figure 4 for the description of the sample and the firm-bank relationships. Source(s): Amadeus, Amadeus Bankers, and authors' calculation.

Figure A10: Distribution of County-Level Commerzbank Dependence



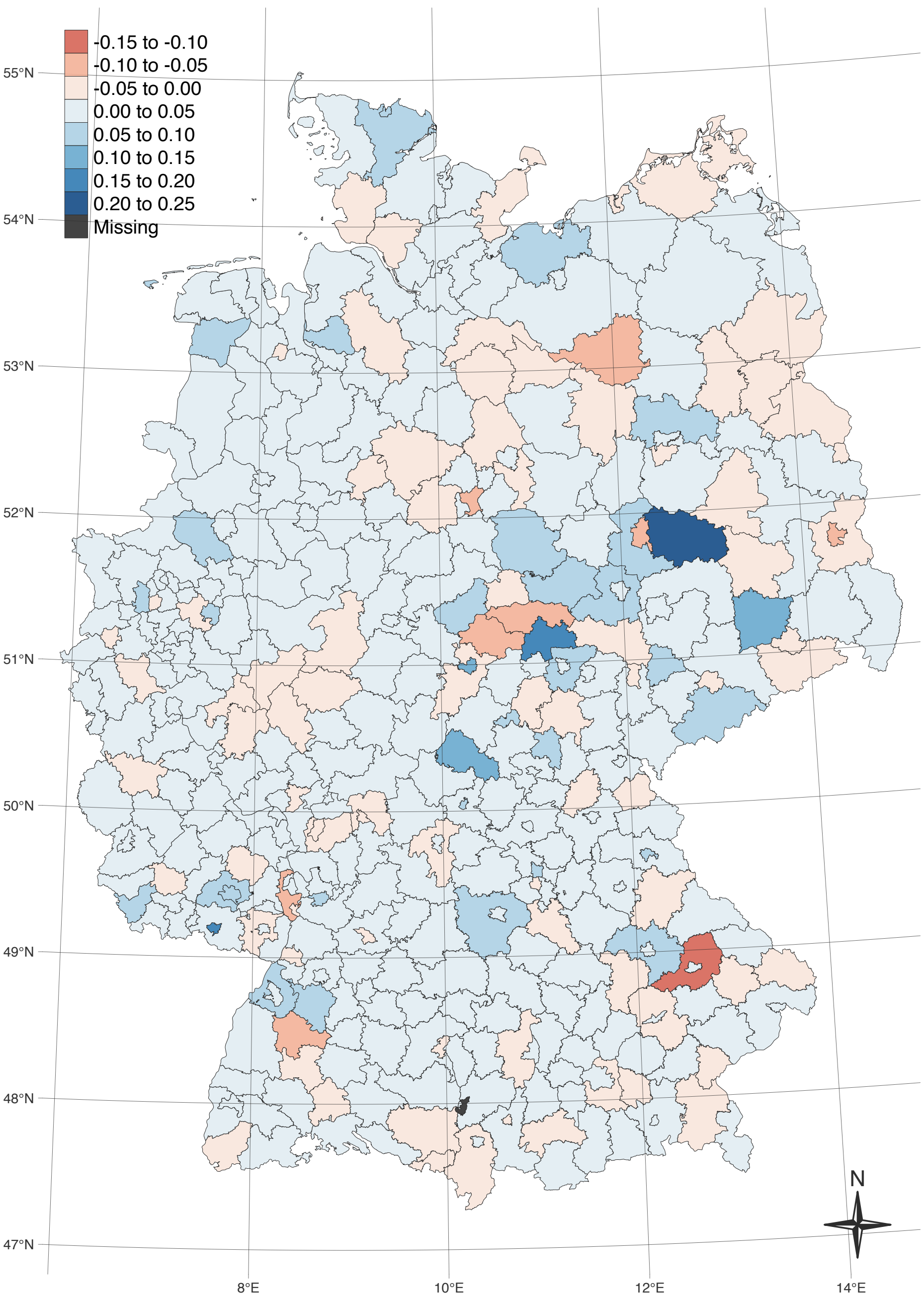
Notes: This figure plots the distribution of the measure of Commerzbank dependence calculated as in (4) at county level in 40 bins. We use equal weights to firms within each county. We highlight the mean and the median of the distribution with the dashed lines labelled by the exact number. We include financial and public sector firms in the calculation. The description of the underlying firms' sample is included in Figure A9. Source(s): Amadeus, Amadeus Bankers and authors' calculation.

Figure A11: Spatial Variation of the proxy for Exposure



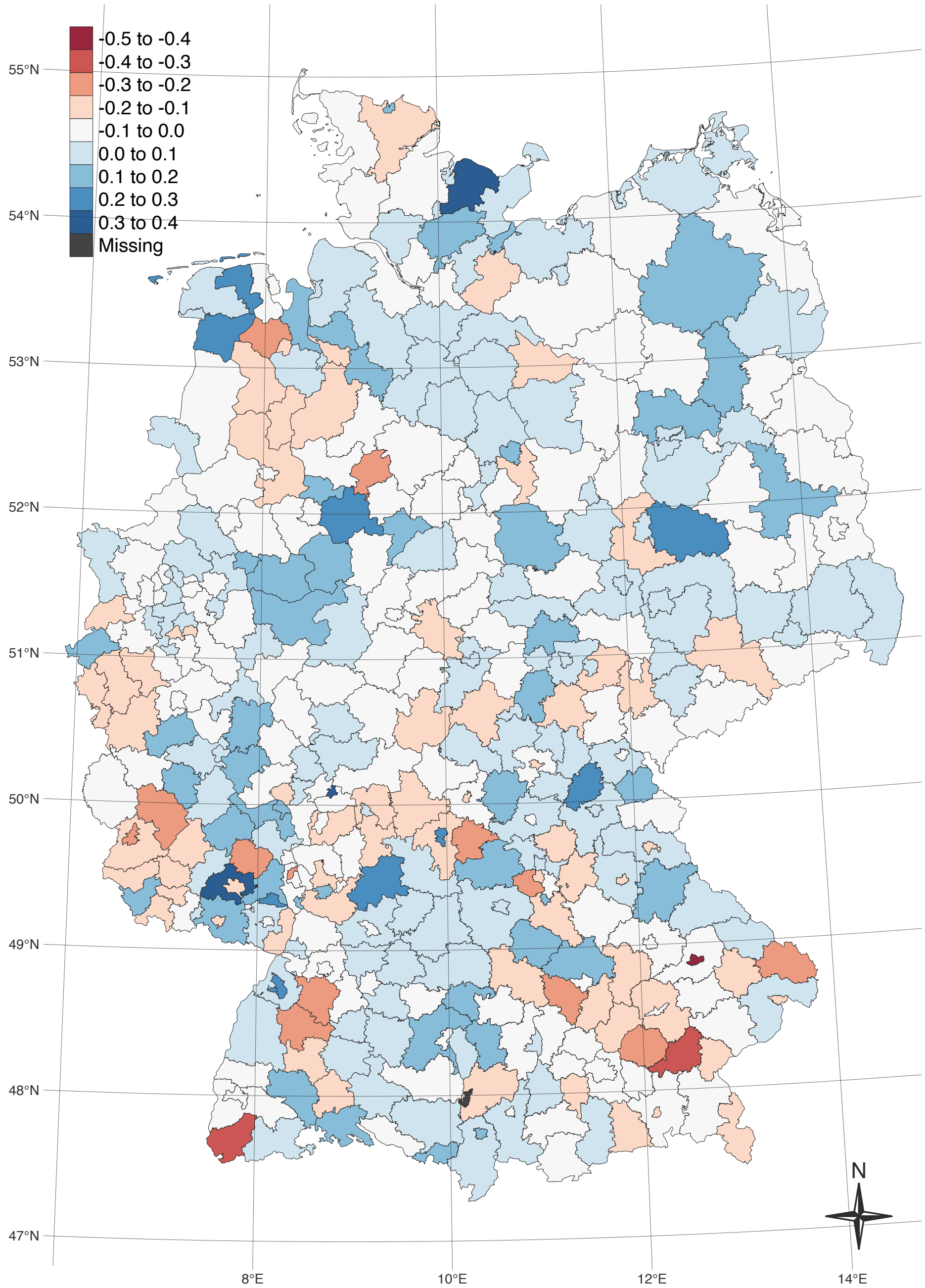
Notes: This picture maps the distribution of the measure of Commerzbank dependence in A10 calculated as in (4) over the German counties. We use equal weights to firms within each county. Different values of exposure are binned by deciles. We include financial and public sector firms in the calculation. The description of the underlying firms' sample is included in Figure A9. Source(s): Amadeus, Amadeus Bankers, BKG, and authors' calculation.

Figure A12: Difference in Average Populist Preferences after the Credit Shock



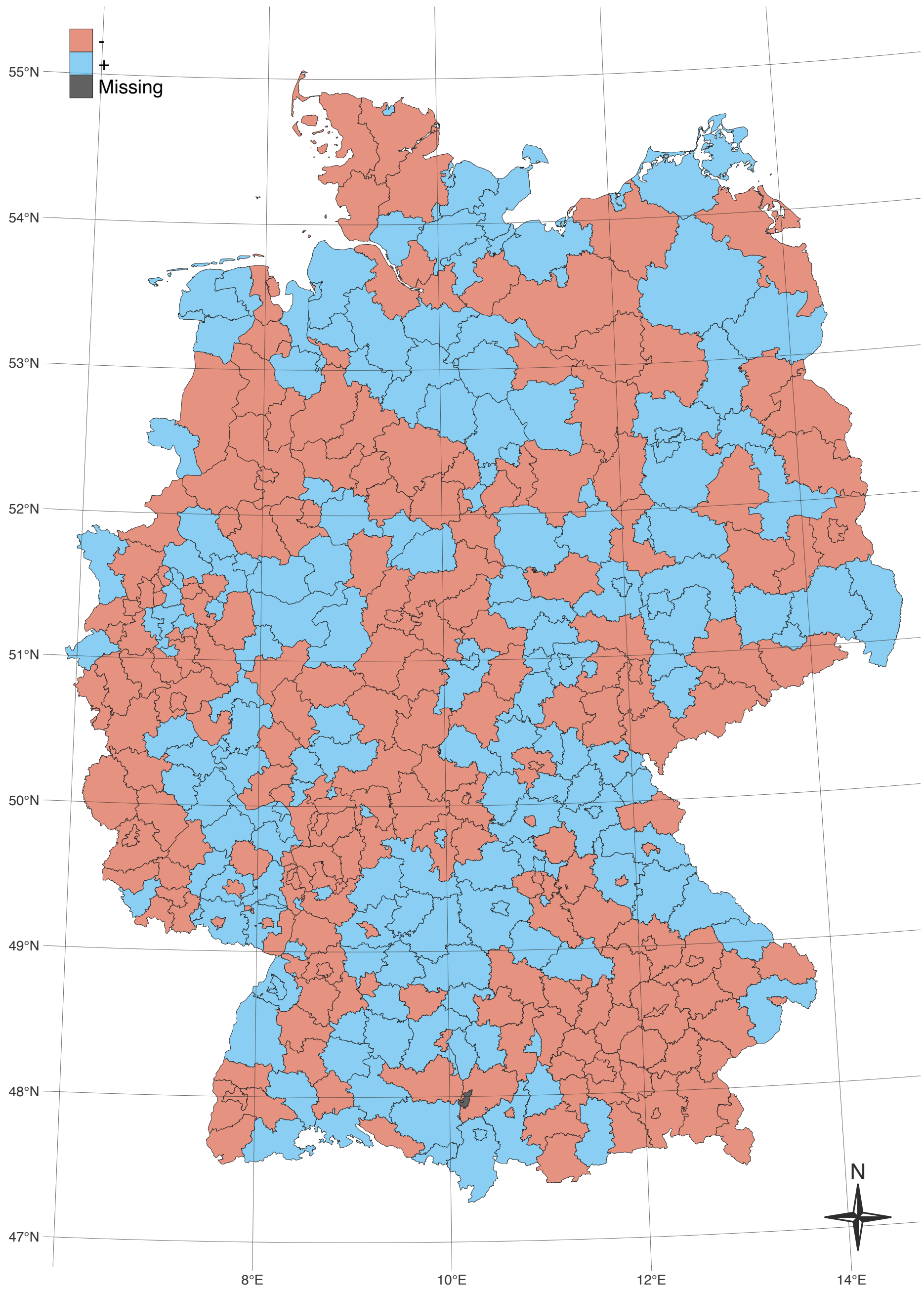
Notes: This figure depicts the difference in the share of populist preferences at county level from the relative question in the German Socio-Economic Panel (SOEP) described in Section 4.3 as percentage points before and after 2009, extending Figure 5 with a more granular representation of the variation. We calculate the sample-weighted mean at county level of the binary question on political support pooling all the respondents for all years before the credit shock and all years after, and we take the difference of the two shares of populist preferences. The sample includes individuals at least at the age of 16, considers self-stated politically inactive individuals as non-populist, and excludes non-respondents or invalid answers. Non-respondents or invalid answers on political party preferences are only around 2% in the entire sample among those individuals that affirmatively answer to the first question, whereas individuals that refuse to answer the question are around 0.5% in the sample. Source(s): German Socio-Economic Panel (SOEP, Goebel et al., 2019, v36), BKG and authors' calculation.

Figure A13: Difference in Average Political Support after the Credit Shock



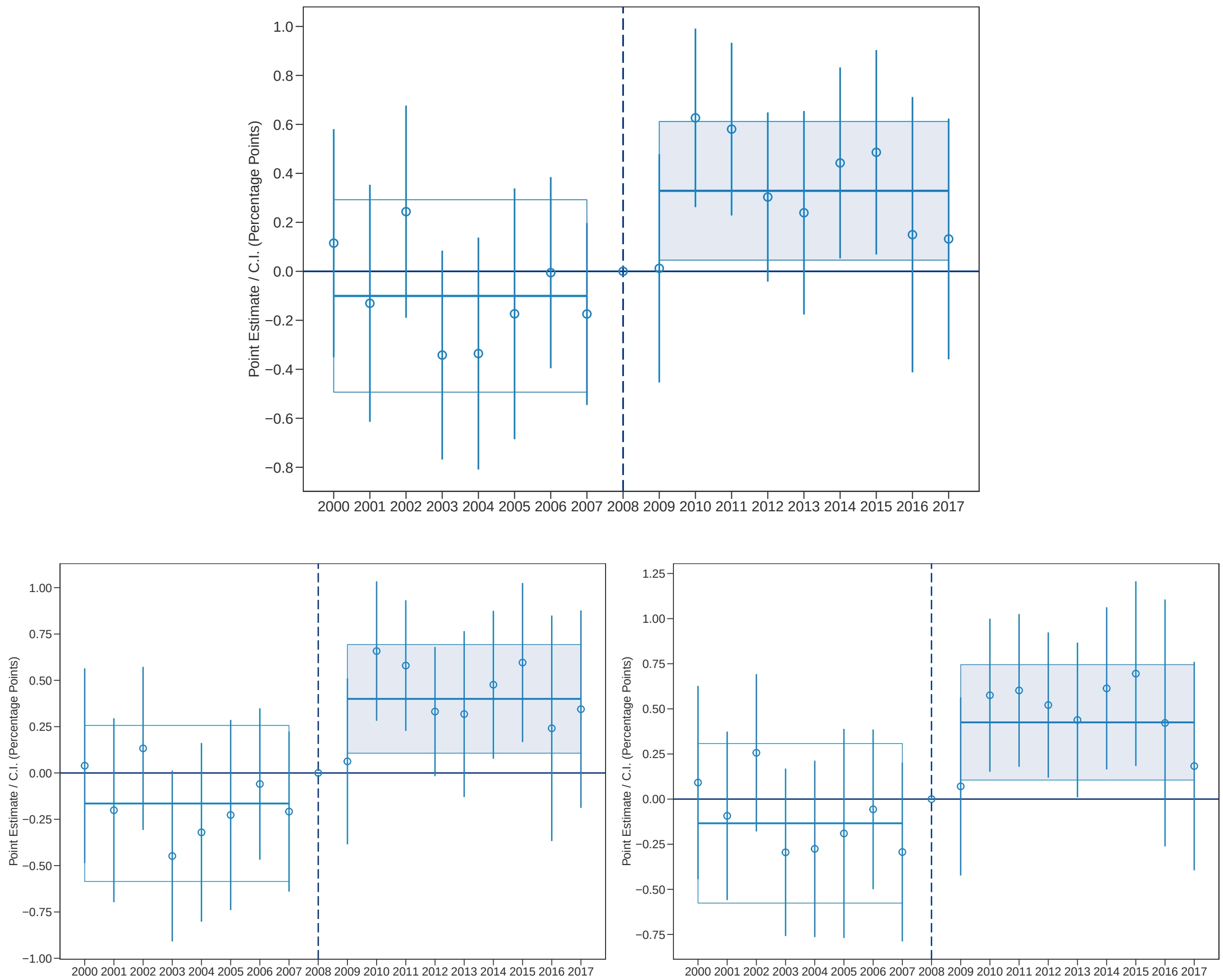
Notes: This figure describes the difference in the share of political support at county level from the relative question in the German Socio-Economic Panel (SOEP) depicted in **??** as percentage points before and after (including) 2009. We calculate the sample-weighted mean at county level of the binary question on political support pooling all the respondents for all years before the credit shock and all years after, and we take the difference of the two shares of political support. The sample includes individuals at least at the age of 16, and excludes non-respondents (<0.5% of the total sample) or invalid answers. Source(s): German Socio-Economic Panel (SOEP, Goebel et al., 2019, v36), BKG and authors' calculation.

Figure A14: Difference in Average Political Support after the Credit Shock



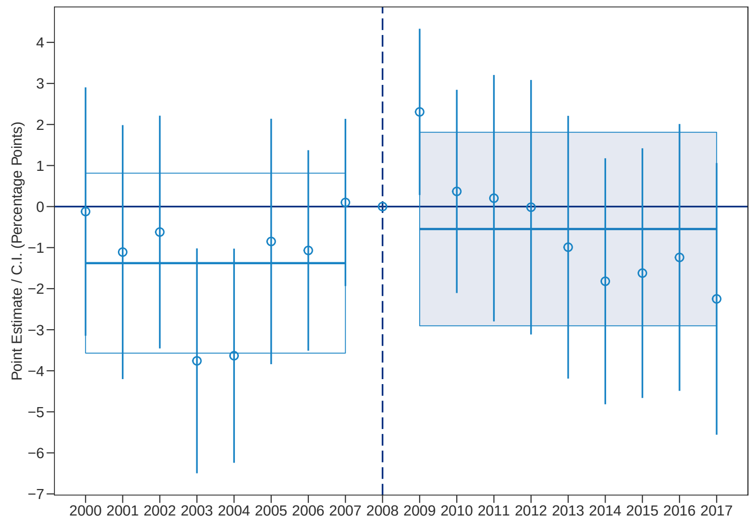
Notes: This figure depicts the German counties with a higher difference in the share of political support after the credit shock as calculated in Figure A13. We construct an indicator variable equal to one if the difference in the share is above the median of the distribution. We distinguish between counties that present a difference in the share above the median of the distribution and counties below or at the median of the distribution. Other details are provided in Figure A13. Source(s): German Socio-Economic Panel (SOEP, Goebel et al., 2019, v36), BKG and authors' calculation.

Figure A15: The Effect of the Credit Shock on Populist Preferences: Difference-in-Differences Estimates (with Continuous Treatment)

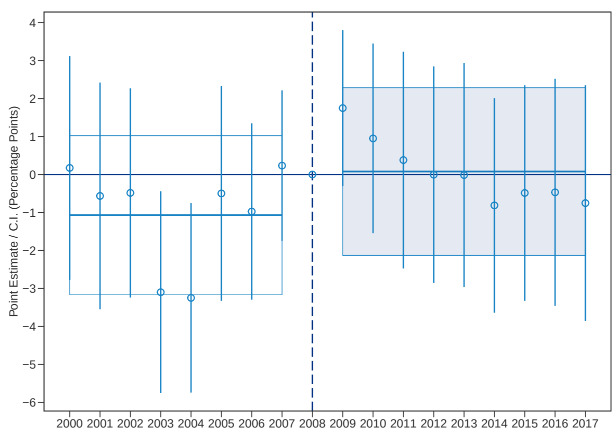


Notes: The plots are symmetric to Figure 9 and 10, estimating Equation (2) and Equation (3) on the same samples respectively. In these estimates, instead of qualifying a cut-off s, we interact the (standardized) continuous treatment respectively with the year fixed effects of Equation (2) and with a 2000–2007 dummy and a 2009–2017 dummy for the estimates of Equation (3). Therefore, the interpretation of the point estimates will be given by a one standard deviation increase in exposure on populist preferences for each interacted time window. In the more aggregated difference-in-differences design with three time periods, estimates of the interactions between the 2000–2007 dummy and the 2009–2017 dummy respectively for each panel are the following: (**??**) $\beta = -0.101$ ($p = 0.615$); $\beta = 0.329$ ($p = 0.023$); (**??**) $\beta = -0.165$ ($p = 0.463$); $\beta = 0.400$ ($p = 0.008$); (**??**) $\beta = -0.134$ ($p = 0.551$); $\beta = 0.425$ ($p = 0.009$); All regressions include sampling weights as well as county and year fixed effects. Coefficient estimates on the year interactions are plotted as dots with their 95% confidence intervals indicated with vertical lines. Coefficient estimates on the aggregate interactions are shown with horizontal lines, and their 95% confidence intervals are indicated as boxes, unshaded or shaded for the pre- and post-period, respectively. All the point estimates and 95% confidence bands are re-scaled by 100 to be interpreted as percentage points difference from the baseline, and standard errors are clustered at the county level.

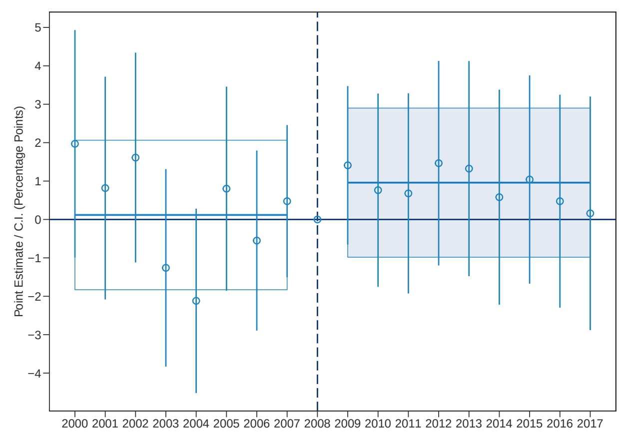
Figure A16: The Effect of the Credit Shock on Political Support: Difference-in-Differences Estimates



(a) without controls



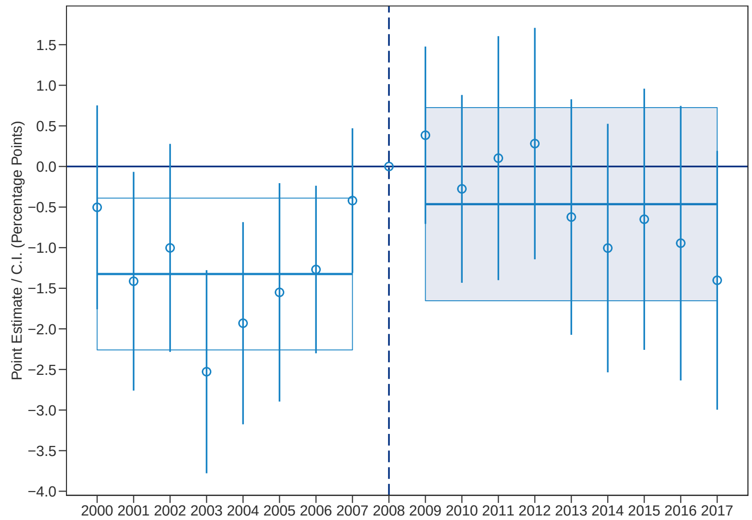
(b) with controls without individual fixed effects



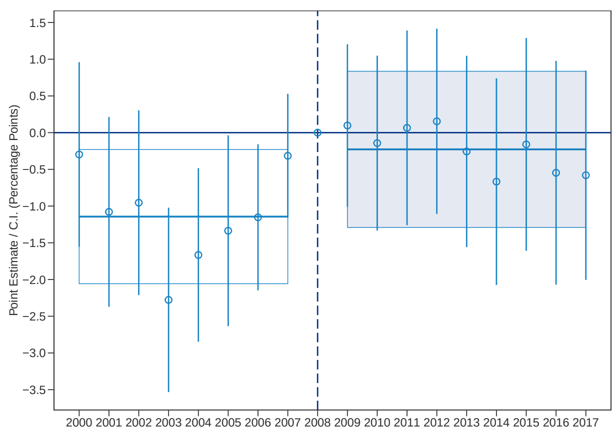
(c) with controls with individual fixed effects

Notes: In this graph we formally test for differences in the likelihood that individuals would be more actively supporting political parties in general after the occurrence of the credit shock, comparing individuals resident in a treated county at time t with and individuals resident in an untreated county at time t. A county k is considered as treated after the occurrence of the credit shock when its exposure to the credit shock – calculated as in Equation (4) with firms' equal weights within the county and excluding finance and public sector firms in the calculation – lies above a cut-off s of the treatment distribution. Here, we qualify the cut-off as $s = med\,(Exposure_k)$, the median of the treatment distribution. Year regression coefficients of interest from the flexible difference-in-differences design in Equation (2) are interactions between an indicator variable equal to one for treated counties and year fixed effects and are estimated relative to the omitted interaction with the first lag before the occurrence of the credit shock. In the more aggregated differences-in-differences design with three time periods in Equation (3), coefficients of interest are interactions between an indicator variable equal to one for treated counties and respectively between a 2000–2007 dummy and a 2009–2017 dummy, estimated relative to the omitted interaction with the first lag before the occurrence of the credit shock. In Panel A16a, regressions are estimated at individual level on the full sample of 385, 248 individual-year observations within 401 counties with no controls. In Panel A16b, regressions are estimated at the individual level the sample of 362, 122 individuals-year observations within 401 counties with individual-, household- and county-specific controls. In Panel A16c regressions are estimated at the individual level the sample of 351, 304 individuals-year observations within 401 counties adding individual fixed effects to the controls and omitting time-invariant individual-level covariates. For the three panels, the coefficient of interest on the interactions between the indicator variable for the treated counties and the pooled dummies are respectively: A16a: $\beta = -1.378$ ($p = 0.217$) and $\beta = -0.547$ ($p = 0.648$); A16b: $\beta = -1.072$ ($p = 0.315$) and $\beta = 0.078$ ($p = 0.944$); A16c: $\beta = 0.117$ ($p = 0.906$) and $\beta = 0.959$ ($p = 0.332$). All regressions include sampling weights as well as county and year fixed effects. Coefficient estimates on the year interactions are plotted as dots with their 95% confidence intervals indicated with vertical lines. Coefficient estimates on the aggregate interactions are shown with horizontal lines, and their 95% confidence intervals are indicated as boxes, unshaded or shaded for the pre- and post-period, respectively. All the point estimates and 95% confidence bands are re-scaled by 100 to be interpreted as percentage points difference from the baseline, and standard errors are clustered at the county level.

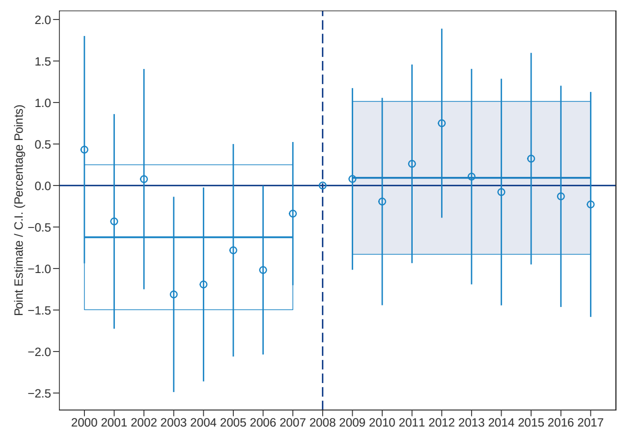
Figure A17: The Effect of the Credit Shock on Political Support: Difference-in-Differences Estimates (with Continuous Treatment)



(a) without controls



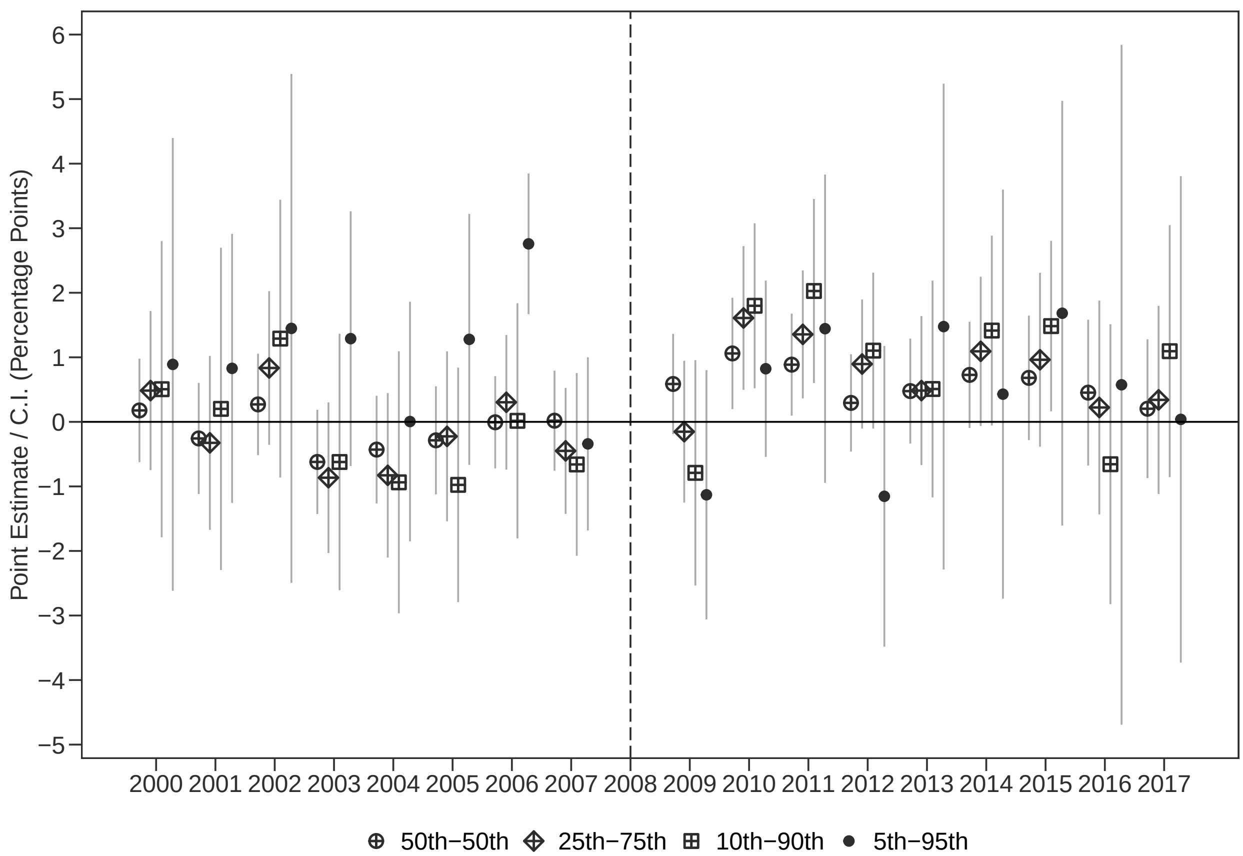
(b) with controls without individual FE



(c) with controls with individual FE

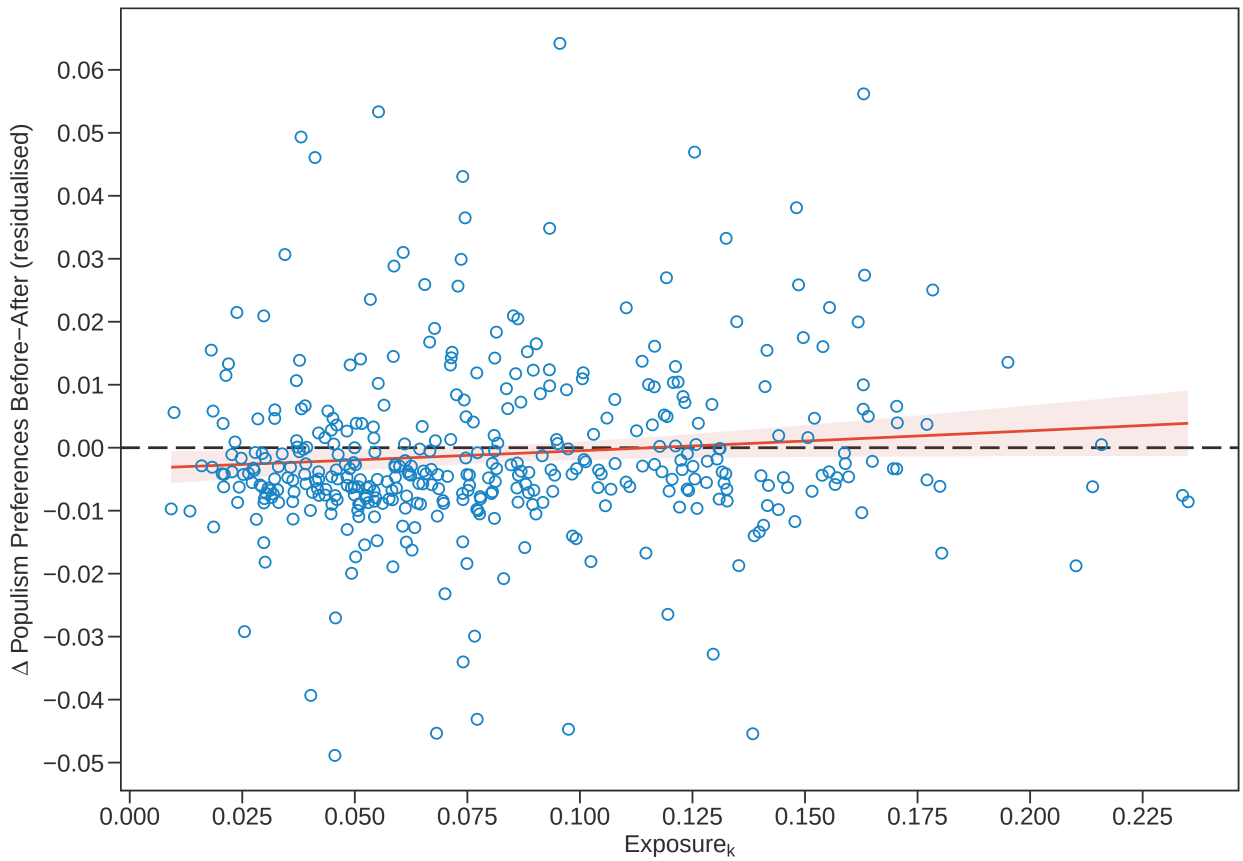
Notes: The plots are symmetric to Figure A16, estimating Equation (2) and Equation (3) on the same samples respectively. In these estimates, instead of qualifying a cut-off s, we interact the (standardized) continuous treatment respectively with the year fixed effects of Equation (2) and with a 2000–2007 dummy and a 2009–2017 dummy for the estimates of Equation (3). Therefore, the interpretation of the point estimates will be given by a one standard deviation increase in exposure on populist preferences for each interacted time window. In the more aggregated difference-in-differences design with three time periods, estimates of the interactions between the 2000–2007 dummy and the 2009–2017 dummy respectively for each panel are the following: (A17a) $\beta = -1.324$ ($p = 0.006$); $\beta = 0.464$ ($p = 0.443$); (A17b) $\beta = -1.143$ ($p = 0.014$); $\beta = 0.228$ ($p = 0.674$); (A17c) $\beta = -0.623$ ($p = 0.161$); $\beta = 0.093$ ($p = 0.843$); All regressions include sampling weights as well as county and year fixed effects. Coefficient estimates on the year interactions are plotted as dots with their 95% confidence intervals indicated with vertical lines. Coefficient estimates on the aggregate interactions are shown with horizontal lines, and their 95% confidence intervals are indicated as boxes, unshaded or shaded for the pre- and post-period, respectively. All the point estimates and 95% confidence bands are re-scaled by 100 to be interpreted as percentage points difference from the baseline, and standard errors are clustered at the county level.

Figure A18: The Effect of the Credit Shock on Populist Preferences: Difference-in-Differences Estimates on different Treatment Indicators



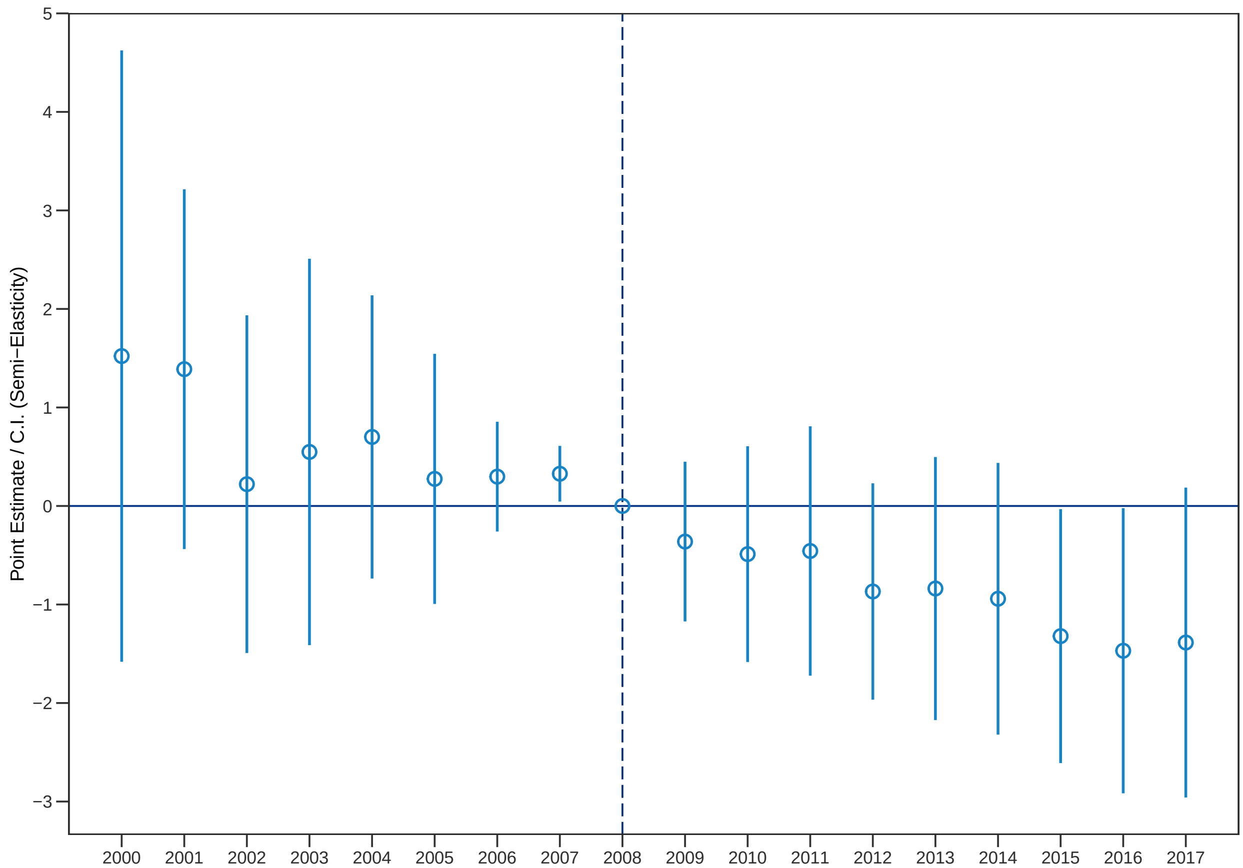
Notes: In these graphs, test for the linearity of the treatment effect of the credit shock on populist preferences. We compare treated individuals with untreated individuals at time t, where the treatment is assigned by the intensity of the exposure to the credit shock of their county of residence, calculated as in Equation (4). Year regression coefficients of interest from the flexible difference-in-differences design in Equation (2) are interactions between an indicator variable equal to one for treated counties and zero for the counties considered as untreated, and year fixed effects and are estimated relative to the omitted interaction with the first lag before the occurrence of the credit shock. We estimate Equation (2) in separate regressions where treatment indicators are differently defined based on the position of a county's exposure in the treatment distribution. In particular, the indicator variable assumes value one when the individual lives in a county with treatment above a certain threshold of the treatment distribution, and zero when the individual lives in a county below a certain threshold of the same distribution, defined as it follows: a) above the median and below the median; b) above the 75^{th} percentile and below the 25^{th} percentile; c) above the 90^{th} percentile and below the 10^{th} percentile; d) above the 95^{th} percentile and below the 5^{th} percentile. Regressions are run without additional controls. Coefficient estimates on the year interactions are plotted as different dots for each treatment-control selection with their 95% confidence intervals indicated with vertical lines. All the point estimates and 95% confidence bands are re-scaled by 100 to be interpreted as percentage points difference from the baseline, and standard errors are clustered at the county level.

Figure A19: Functional Form of the Populist Preferences on the Exposure to the Credit Shock: Accounting for Treatment Heterogeneity (including individual fixed effects)



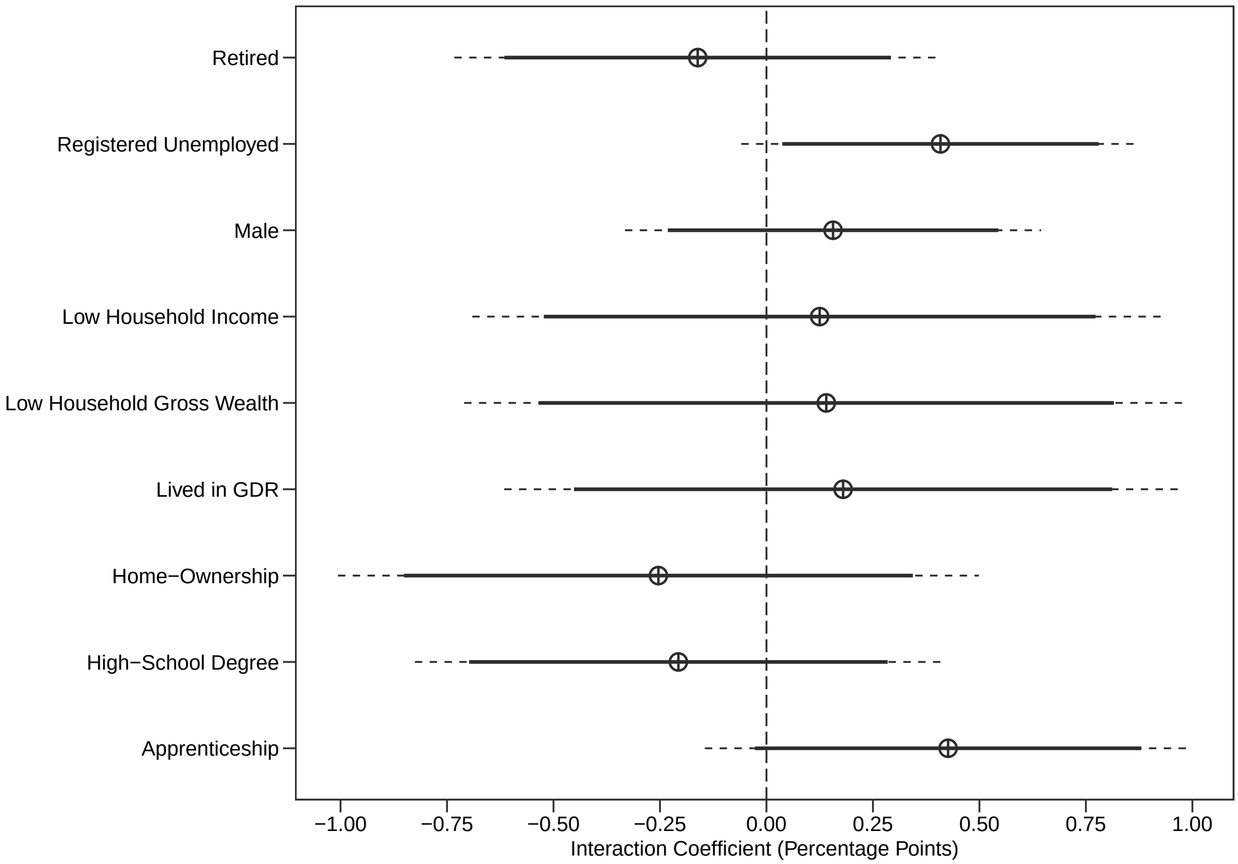
Notes: This picture repeats the exercise in Figure 11 while including individual-level fixed effects when residualising. We use a sample of 314,765 individuals-year observations within 400 counties with individual-, household- and county-specific controls, introducing individual fixed effects, and omitting time-invariant individual-level covariates. Further details on the specification are provided in Figure 11.

Figure A20: The Effect of the Credit Shock on Local Economic Performance: Difference-in-Differences Estimates



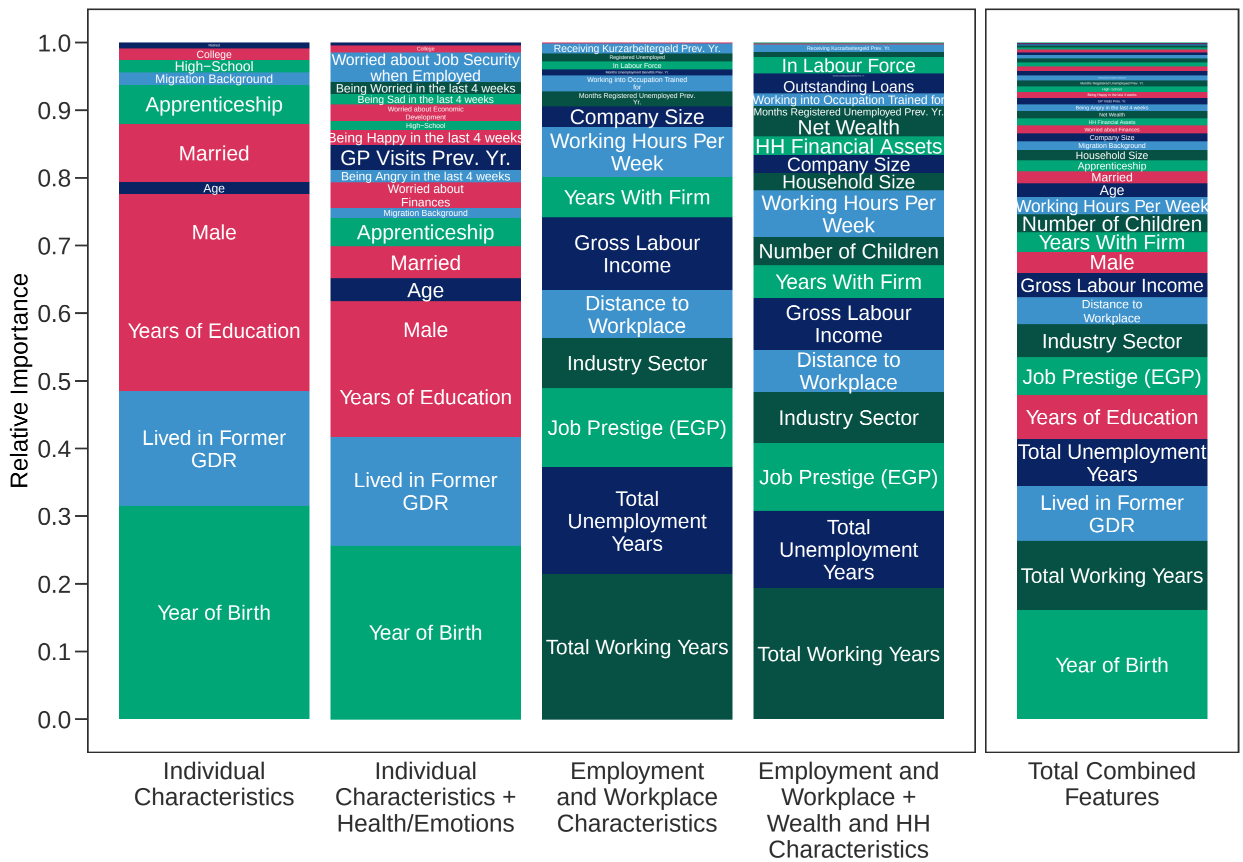
Notes: In this graph, we describe the evolution of the semi-elasticity of the local employment in 1,000 units between treated and untreated counties after the occurrence of the credit shock. Estimates are obtained with the same settings of Figure 12. The weighted average of all time average treatment effects on the treated is -0.9% (*std.err.* 0.0039). Estimating the coefficient of interest β on the continuous treatment, we obtain a 0.75% decrease in GDP for each standard deviation increase in the treatment dose (*std.err.* $= 0.00368$, $t = -2.046$).

Figure A21: The Effect of the Credit Shock on Local Economic Performance: Difference-in-Differences Estimates



Notes: This figure explores the heterogeneity at individual level behind the effect of the credit shock on populist preferences. It presents estimates from separate regressions as in table A5 of the interaction of each of the indicated characteristics with the treatment variable and the indicator variable for the periods after the shock on a balanced panel of individuals from 2006 to 2012 with county, time and individual fixed effects. The estimate expresses the cumulative effect in percentage points of belonging to the pointed subpopulation. The outcome variable is our binary indicator for individual populist preferences. Specifically, we consider the following subpopulations of individuals: a) retired, b) officially registered as unemployed, c) male, d) low household income, e) low household wealth, f) lived in East Germany before Reunification, g) home-ownership, h) high-school degree, and j) having received an apprenticeship. All the subpopulations are specified as a dummy in case the individual belongs to that specific category and are fixed pre-shock at 2007. Low household income and wealth means income or wealth below the 25^{th} percentile. Solid bars indicate the 90% confidence bands, whereas thinner dashed lines indicate the 95% confidence intervals. All estimates are rescaled by 100 to be expressed as percentage points. Longitudinal sampling weights are applied on each regression and standard errors are clustered at county level.

Figure A22: Feature Importance in Explaining Populist Preferences' Response



Notes: add notes...

Figure A23: Feature Importance in Explaining Populist Preferences' Response: Shapley Summary Plot

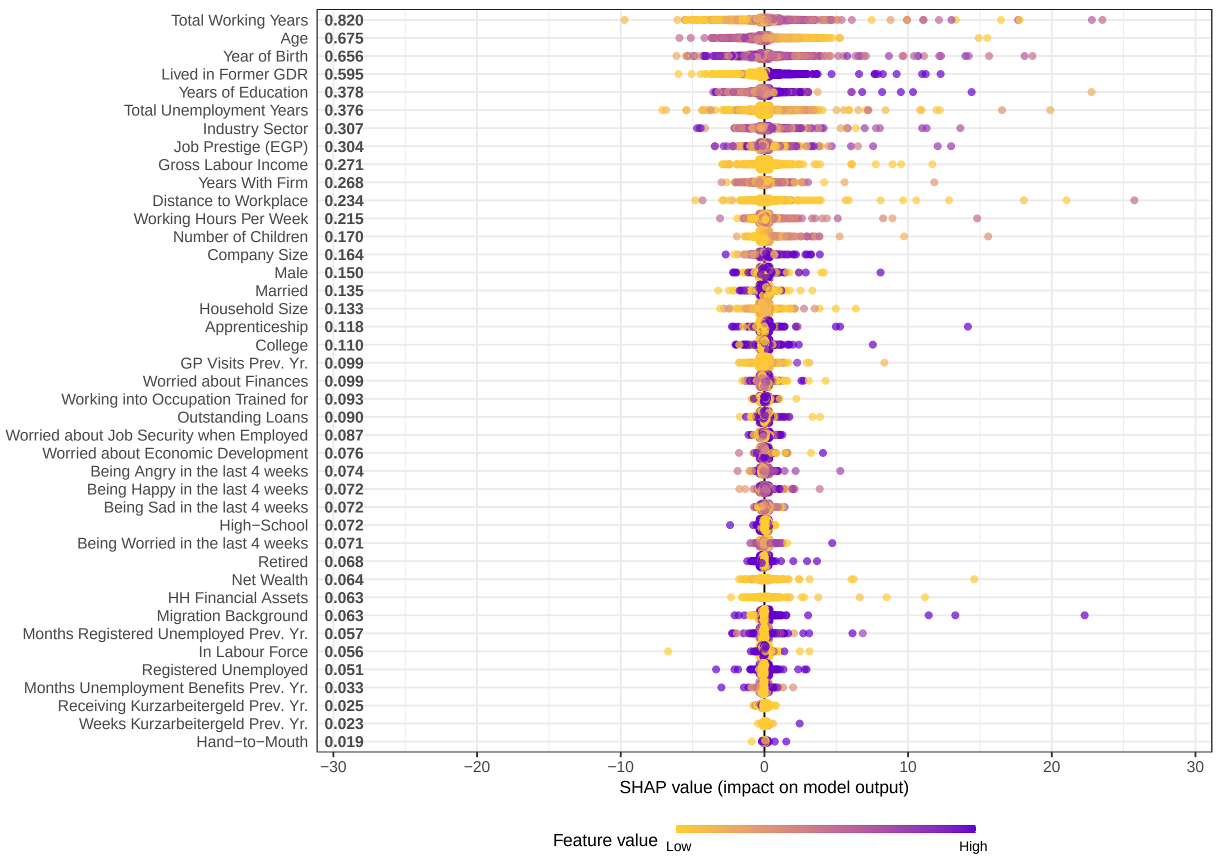


Figure A24: Top Twenty Terms by Posterior Probability using Seeded LDA for the electoral manifestos, Populism using the Rooduijn and Pauwels (2011) lexicon.

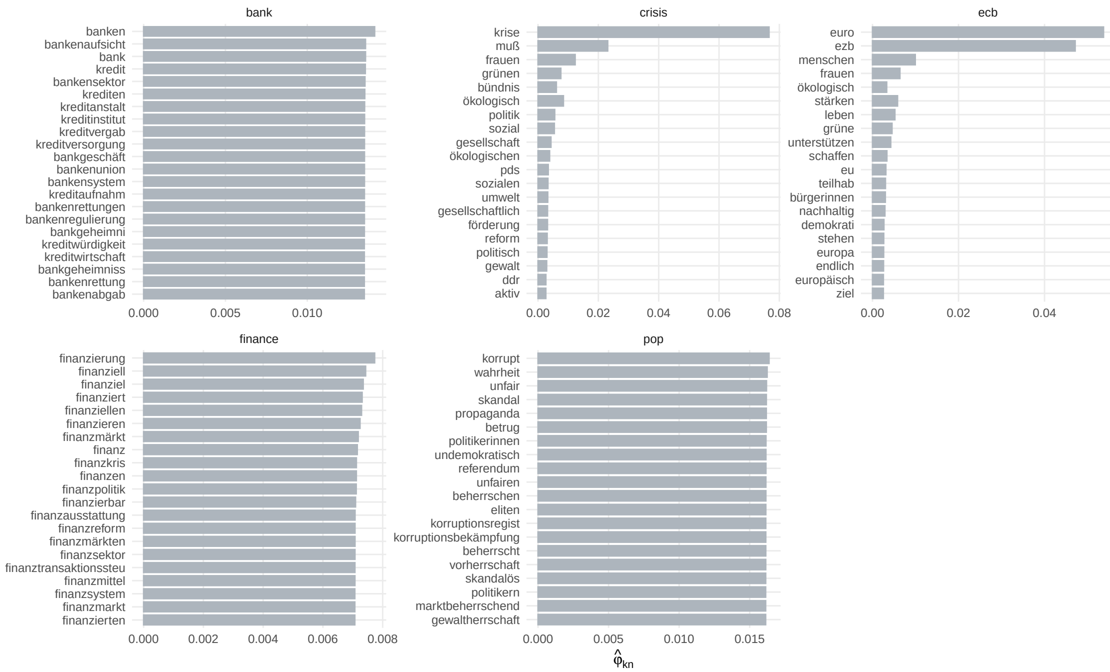


Figure A25: Focus on Banking & Finance in parliamentary speeches using dictionary approach, by political party (1991-2018)

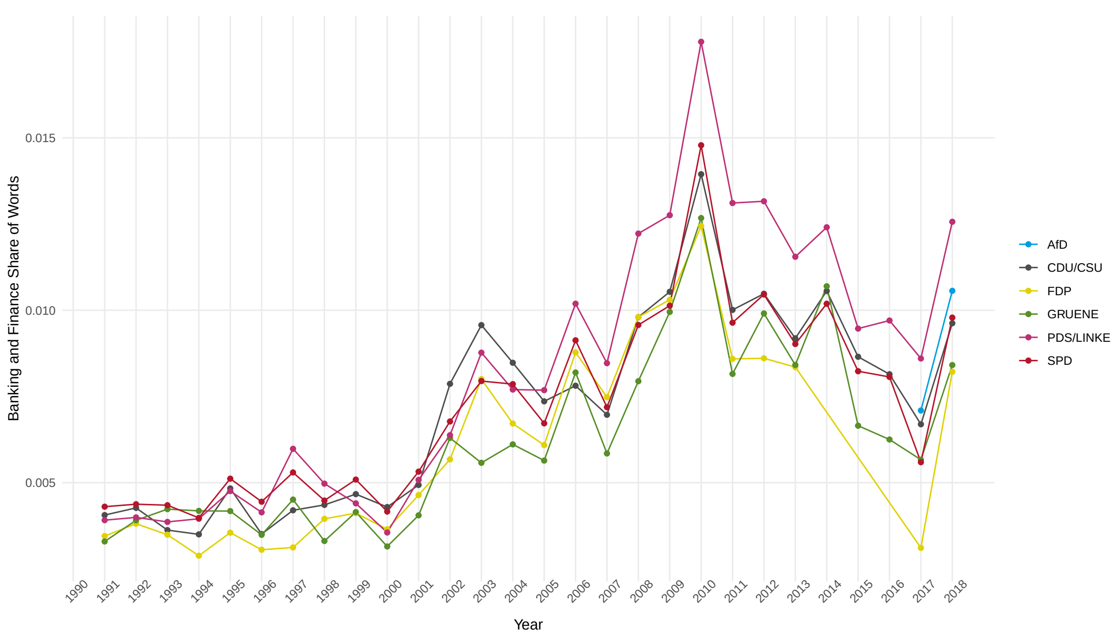


Figure A26: Populist Rhetoric using Rooduijn and Pauwels (2011) in parliamentary speeches using dictionary approach, by political party (1991-2018)

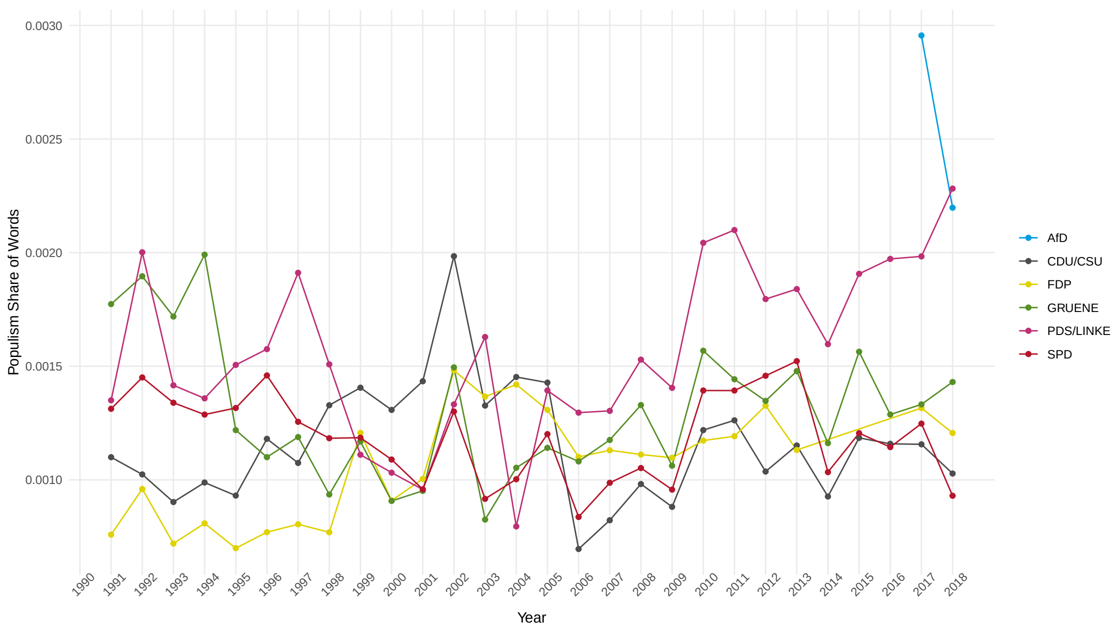


Figure A27: Focus on Banking & Finance in electoral manifestos, by political party (1991-2018)

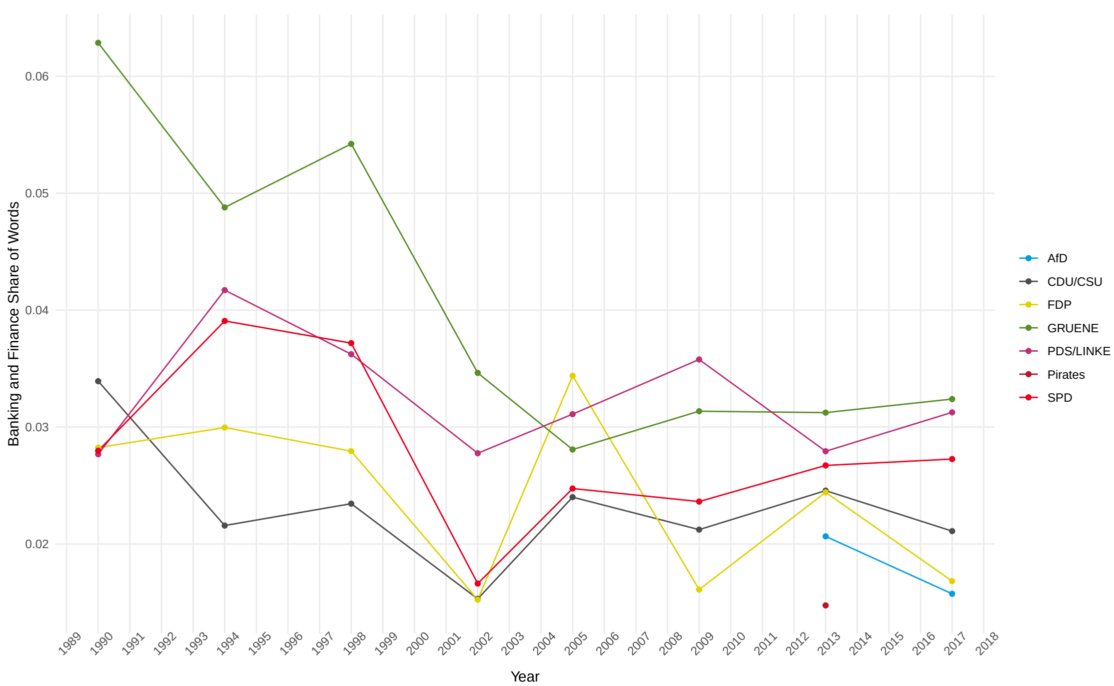
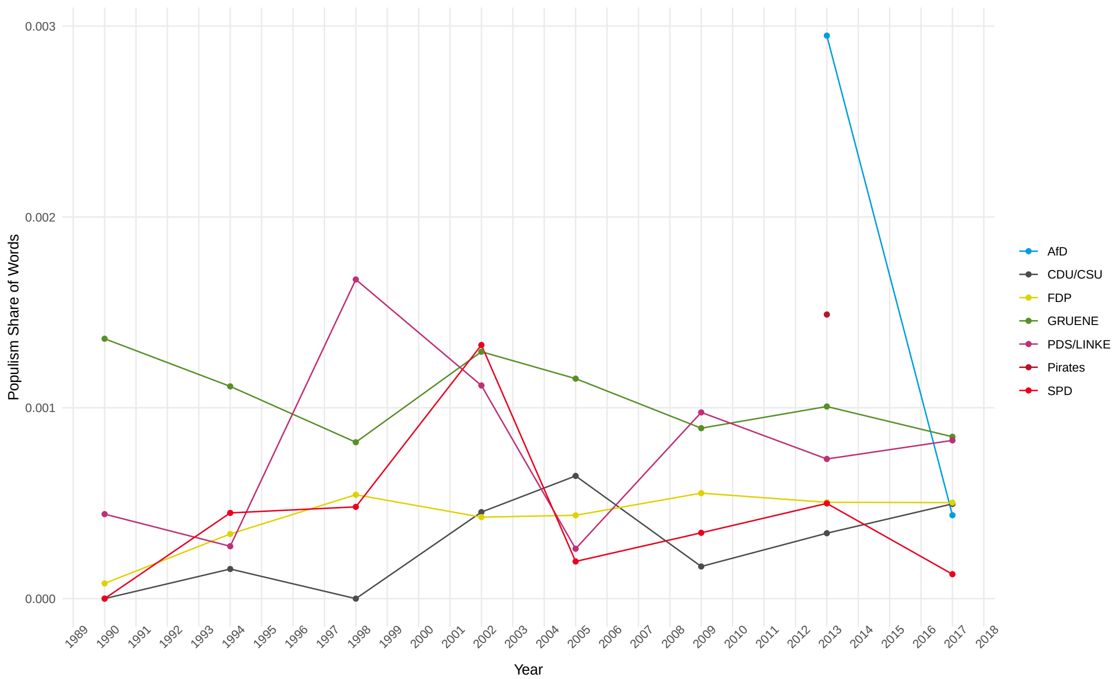


Figure A28: Populist Rhetoric using Rooduijn and Pauwels (2011) in electoral manifestos, by political party (1991-2018)



E Additional Tables

Table A1: The Effect of the Credit Shock on Populist Preferences: Difference-in-Differences Results

	(1)	(2)	(3)	(4)	(5)
$Exposure_k \times Post$	0.511***	0.522***	0.533***	0.536***	0.600***
	(0.186)	(0.191)	(0.193)	(0.191)	(0.157)
Number of Observations	366,403	351,470	351,304	351,304	351,304
Number of Counties	401	401	401	401	401
Outcome Mean (%)	3.34	3.362	3.363	3.363	3.363
$\sigma\,(Exposure_k)$ (%)	4.86	4.862	4.862	4.862	4.862
Adjusted R^2	0.521	0.526	0.526	0.526	0.528
County-Level FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes
Individual Controls	No	Yes	Yes	Yes	Yes
Household Controls	No	No	Yes	Yes	Yes
Regional Controls	No	No	No	Yes	No
County Time Trends	No	No	No	No	Yes

Notes: This table is symmetric to Table 2, reporting the results of the estimation of Equation (1) where the dependent variable is the populist preferences indicator of an individual i resident in county k at time t, constructed as depicted in Section 6.1, and the variable of interest is the (standardized) exposure to the credit shock of county k, as calculated in Equation (4) using equal weights for all firms within each county, interacted with an indicator variable equal to one for all years after the occurrence of the credit shock. The difference with Table 2 stems from the introduction of individual fixed effects throughout all specifications. For all specifications that include individual-level controls, we remove time-invariant individual covariates. For additional details on the columns, we refer to Table 2. The coefficients of interest are scaled by 100 to be interpreted as the percentage points increase of the outcome mean of one-σ units increase of treatment after the occurrence of the shock. Standard errors are clustered by county for all specifications, and *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Table A2: The Effect of the Credit Shock on Political Support: Difference-in-Differences Results

	(1)	(2)	(3)	(4)	(5)
$Exposure_k \times Post$	0.712	0.854^{**}	0.819^{**}	0.785^{*}	0.881^{*}
	(0.485)	(0.413)	(0.411)	(0.413)	(0.466)
Number of Observations	385,248	362,295	362,122	362,122	362,122
Number of Counties	401	401	401	401	401
Outcome Mean (%)	45.349	45.942	45.941	45.941	45.941
$\sigma\,(Exposure_k)$ (%)	4.863	4.861	4.861	4.861	4.861
Adjusted R^2	0.046	0.130	0.131	0.131	0.137
County-Level FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Individual FE	No	No	No	No	No
Individual Controls	No	Yes	Yes	Yes	Yes
Household Controls	No	No	Yes	Yes	Yes
Regional Controls	No	No	No	Yes	No
County Time Trends	No	No	No	No	Yes

Notes: This table is symmetric to Table 2, reporting the results of the estimation of Equation (1), but here the dependent variable is the political support indicator of an individual i resident in county k at time t, stemming from the affirmative answer to the question described in Section 4.3, and the variable of interest is the (standardized) exposure to the credit shock of county k, as calculated in Equation (4) using equal weights for all firms within each county, interacted with an indicator variable equal to one for all years after the occurrence of the credit shock. For additional details on the columns, we refer to Table 2. The coefficients of interest are scaled by 100 to be interpreted as the percentage points increase of the outcome mean of one-σ units increase of treatment after the occurrence of the shock. Standard errors are clustered by county for all specifications, and *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Table A3: The Effect of the Credit Shock on Political Support: Difference-in-Differences Results

	(1)	(2)	(3)	(4)	(5)
$Exposure_k \times Post$	0.584*	0.623*	0.624*	0.609*	0.905**
	(0.340)	(0.338)	(0.337)	(0.338)	(0.451)
Number of Observations	366,403	351,470	351,304	351,304	351,304
Number of Counties	401	401	401	401	401
Outcome Mean (%)	45.552	46.116	46.116	46.116	46.116
$\sigma\,(Exposure_k)$ (%)	4.86	4.862	4.862	4.862	4.862
Adjusted R^2	0.548	0.550	0.551	0.551	0.553
County-Level FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes
Individual Controls	No	Yes	Yes	Yes	Yes
Household Controls	No	No	Yes	Yes	Yes
Regional Controls	No	No	No	Yes	No
County Time Trends	No	No	No	No	Yes

Notes: This table is symmetric to Table A2, reporting the results of the estimation of Equation (1) where the dependent variable is the political support indicator of an individual i resident in county k at time t, stemming from the affirmative answer to the question described in Section 4.3, and the variable of interest is the (standardized) exposure to the credit shock of county k, as calculated in Equation (4) using equal weights for all firms within each county, interacted with an indicator variable equal to one for all years after the occurrence of the credit shock. The difference with Table A2 stems from the introduction of individual fixed effects throughout all specifications. For all specifications that include individual-level controls, we remove time-invariant individual covariates. For additional details on the columns, we refer to Table 2. The coefficients of interest are scaled by 100 to be interpreted as the percentage points increase of the outcome mean of one-σ units increase of treatment after the occurrence of the shock. Standard errors are clustered by county for all specifications, and *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Table A4: The Effect of the Credit Shock on Political Support: Difference-in-Differences Estimates with Binary Treatment

	Median		75th		90th		25th – 75th		10th – 90th	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\mathbf{1}\left(Exposure_k > s\right) \times Post$	1.029	0.861	1.499	0.954	3.127**	2.535***	2.271*	1.459	4.350**	3.493**
	(0.888)	(0.762)	(1.113)	(0.817)	(1.313)	(0.947)	(1.317)	(1.092)	(1.667)	(1.566)
Number of Observations	362,122	351,304	362,122	351,304	362,122	351,304	179,100	173,196	71,851	69,441
Number of Counties	401	401	401	401	401	401	208	208	82	82
Outcome Mean (%)	45.941	46.116	45.941	46.116	45.941	46.116	45.634	45.869	46.535	46.762
s (%)	8.949	8.949	13.093	13.093	16.495	16.495	5.834	5.834	3.886	3.886
Adjusted R^2	0.131	0.551	0.131	0.551	0.131	0.551	0.134	0.547	0.140	0.544
County-Level FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Time Trends	No	No	No	No	No	No	No	No	No	No

Notes: This table is similar to Table 3, with the only difference that here the dependent variable is the indicator variable for political support, which is equal to one in case of affirmative answer to the question described in Section 4.3, and zero otherwise. The coefficients of interest are scaled by 100 to be interpreted as the percentage points increase of the outcome mean for individuals located in counties with exposure to the credit shock above the indicated threshold against individuals located in counties that have a lower exposure beforehand. Standard errors are clustered by county for all specifications, and *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Table A5: The Effect of the Credit Shock on Populist Preferences: Difference-in-Differences with Balanced Panels

	Full Sample	Balanced Panels		
		2006–2012	2004–2013	2000–2015
	(1)	(2)	(3)	(4)
$Exposure_k \times Post$	0.418**	0.611***	0.705**	0.195
	(0.173)	(0.209)	(0.281)	(0.428)
Number of Observations	385,248	71,049	78,647	82,663
Number of Counties	401	391	392	383
Outcome Mean (%)	3.347	3.938	3.732	3.666
$\sigma\,(Exposure_k)$ (%)	4.863	4.862	4.868	4.916
Adjusted R^2	0.049	0.623	0.570	0.506
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Individual FE	No	Yes	Yes	Yes

Notes: This table reports the results of the estimation of our difference-in-differences specification in Equation (1) applied to the balanced panels of individuals indicated in each column. More specifically, we estimate a difference-in-differences design where all the variables are the same of Equation (1), but we add α_i individual fixed effects, and no additional controls. In this way, we are able to compare the same individuals before and after the occurrence of the shock. The dependent variable is our indicator variable of populist preferences of a same individual i resident in county k at time t, and the variable of interest is the (standardized) exposure to the credit shock of county k, as calculated in Equation (4) using equal weights for all firms within each county, interacted with an indicator variable equal to one for all years after the occurrence of the credit shock. Longitudinal weights are applied in every sample, and they are constructed as the sampling weights for the first wave of the considered period in the relative panel multiplay for each inverse staying probability weight of all the subsequent waves that are considered. Column 2 specifies the results for a balanced panel considering waves from 2006 to 2012, with three lags and three leads relative to the timing of the shock. Column 3 shows results for a panel from 2004 to 2013. Finally, Column 4 considers a longer sample following individuals from 2000 until 2015. The coefficients of interest are scaled by 100 to be interpreted as the percentage points increase of the outcome mean of one-σ units increase of treatment after the occurrence of the shock. Standard errors are clustered by county for all panels, and *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Table A6: The Differential Effect of the Credit Shock on Political Preferences: Split Samples on Pre-Shock Growth Rates

	$\overline{\Delta GDP}_k^{2001-2006}$		$\overline{\Delta Employment}_k^{2001-2006}$		ΔGDP_k^{2006}				$\Delta Employment_k^{2006}$			
					25th Percentile		50th Percentile		25th Percentile		50th Percentile	
	$\geq 50^{th}$	$< 50^{th}$	$\geq 50^{th}$	$< 50^{th}$	$\geq$	$<$	$\geq$	$<$	$\geq$	$<$	$\geq$	$<$
$Exposure_k \times Post$	0.390*	0.675***	0.149	0.756***	0.581**	0.421**	0.533**	0.672**	0.466**	0.848**	0.429	0.736***
	(0.231)	(0.255)	(0.193)	(0.240)	(0.235)	(0.180)	(0.255)	(0.270)	(0.227)	(0.335)	(0.311)	(0.189)
Number of Observations	183,842	178,280	181,563	180,559	271,131	90,991	179,550	182,572	274,933	87,189	187,165	174,957
Number of Counties	202	199	202	199	302	99	204	197	303	98	204	197
Outcome Mean (%)	3.065	3.682	1.948	4.907	3.487	3.042	3.091	3.65	3.299	3.61	3.419	3.324
$\sigma\ (Exposure_k)$ (%)	4.851	4.804	4.712	4.698	5.048	4.255	4.173	5.256	5.156	3.752	5.557	3.922
Adjusted R^2	0.053	0.066	0.037	0.062	0.060	0.057	0.056	0.063	0.060	0.059	0.058	0.062
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	No	No	No	No	No	No	No	No	No	No	No	No
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: add notes...

References

Burst, Tobias, Werner Krause, Pola Lehmann, Jirka Lewandoski, Theres Matthieß, Nicolas Merz, Sven Regel, and Lisa Zehnter. 2020. "Manifesto Corpus."

Goebel, Jan, Markus M. Grabka, Stefan Liebig, Martin Kroh, David Richter, Carsten Schröder, and Jürgen Schupp. 2019. "The German Socio-Economic Panel (SOEP)." *Jahrbücher für Nationalökonomie und Statistik*, 239(2): 345–360.

Rauh, Christian, and Jan Schwalbach. 2020. "The Parlspeech V2 Data Set: Full-Text Corpora of 6.3 Million Parliamentary Speeches in the Key Legislative Chambers of Nine Representative Democracies."

Rooduijn, Matthijs, and Teun Pauwels. 2011. "Measuring Populism: Comparing Two Methods of Content Analysis." *West European Politics*, 34(6): 1272–1283.