Supplementary Material A for "Whose News? Class-Biased Economic Reporting in the United States"

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February 19, 2021

*Jacobs, Matthews, and Hicks rotate author orderings across their joint papers to reflect equal contributions among themselves.

Contents

A1 Data Sources

Description	Variable(s)	Source(s)
Economic perceptions	E.g. $RetroBus_t$	Survey of Consumer Attitudes and Behavior, various years. `https://www.icpsr.umich.edu/icpsrweb/ICPSR/series/54`
Newspaper circulation	$Circulation_i$	Alliance for Audited Media, News Media Alliance, and Nielsen, "Audience Summary Database", Scarborough Release 1, 2017. `http://online.audiencefax.com/`
Income level/share, national-level, at various points in the income distribution	E.g. Inc_t^{P0-100}	World Inequality Database (Alvaredo et al. 2017). Specifically, for income growth and share, we use the "pretax national income" (ptinc) among equal-split (j) adults (992).
Income level/share, state-level, at various points in the income distribution	E.g. $Inc_{i,t}^{P0-100}$	Sommeiller et al. (2016)
Income level, state-level, mean	$Inc_{s,t}^{M}$	FRED: MEANAGICA6A052NCEN MEANAGICO8A052NCEN MEANAGIDC11A052NCEN MEANAGIFL12A052NCEN MEANAGIGA13A052NCEN MEANAGIIL17A052NCEN MEANAGIMA25A052NCEN MEANAGIMI26A052NCEN MEANAGIMN27A052NCEN MEANAGIMO29A052NCEN MEANAGINY36A052NCEN MEANAGIOH39A052NCEN MEANAGIOR41A052NCEN MEANAGIPA42A052NCEN MEANAGIRI44A052NCEN MEANAGITX48A052NCEN MEANAGIUT49A052NCEN
Unemployment, national-level	$Unemp_t$	FRED: LRHUTTTTUSQ156S
Unemployment, state-level	$Unemp_{s,t}$	FRED: CAUR COUR DCUR FLUR GAUR ILUR MAUR MIUR MNUR MOUR NYUR OHUR ORUR PAUR RIUR TXUR UTUR
Gross Domestic Product	GDP_t	FRED: GDP
Inflation	$Inflation_t$	FRED: CPIAUCSL
House price index, state-level	$HousePrice_{s,t}$	FRED: CASTHPI COSTHPI DCSTHPI FLSTHPI GASTHPI ILSTHPI MASTHPI MISTHPI MNSTHPI MOSTHPI NYSTHPI OHSTHPI ORSTHPI PASTHPI RISTHPI TXSTHPI USSTHPI UTSTHPI
Newspaper slant	$Slant_i$	Gentzkow and Shapiro (2010)
Newspaper ownership	E.g. $Private_{i,t}$	Dunaway and Lawrence (2015), with extensions by authors.
New York Stock Exchange Composite Index	$NYSE_t$	Moody's – FreeLunch.com
Standard & Poors S&P 500 Index	$S\&P500_t$	Yahoo! Finance

Table A1: Descriptions and sources for variables used in the analyses. "FRED" refers to the Federal Reserve Economic Data service from the Federal Reserve Bank of St. Louis, with variable identifiers from that database indicated.

A2 Validating the Economic News Tone Measure

We present here the details of the analyses that we use to validate our measure of economic news tone. The validation strategy is to assess whether our economic news tone measure is correlated with two kinds of "benchmark" variables with which it logically should be correlated.

1. **Proxy tone measure.** We assess the correlation between our news tone measure and an alternative, survey-based proxy for the tone of the economic news.
2. **Perceptions known to be influenced by news tone.** We assess the correlation between our news tone measure and other phenomena that news tone is widely believed to have an effect on. A range of prior studies have marshalled evidence that the economic news influences citizens' economic perceptions and evaluations (Blood and Phillips 1995; Nadeau et al. 1999; De Boef and Kellstedt 2004; Goidel et al. 2010; Hollanders and Vliegenthart 2011; Boydstun et al. 2018; Garz and Martin 2020). To the extent that the economic news affects mass perceptions, a good measure of the economic news tone should be well correlated with survey measures of mass economic perceptions and evaluations.

In addition to assessing these two kinds of correlations "naively," we make the validation tests more stringent by estimating relationships in a manner that partials out possible *alternative* reasons for a correlation between news tone and the benchmark variables – i.e., factors *other* than those on which the validity tests are premised. We explain these more stringent tests below. We emphasize that the aim of this exercise is not to establish a causal effect of our tone measure on economic perceptions. It is, rather, to test the validity of our measure by examining its correlation with other things that we have good reason to believe are strongly correlated with the phenomenon we seek to measure, while ruling out sources of such correlations that do not relate to the validity of the measure.

The analysis proceeds in several steps. We examine, in turn, (i) whether our tone measure predicts the survey-based proxy for news tone, reported receipt of economic information, (ii) whether our tone measure predicts mass economic perceptions and evaluations, (iii) whether these relationships hold as we make the test more specific by progressively excluding potential sources of a correlation other than those on which the test is premised, and (iv) whether these results hold specifically for lower- and middle-income respondents, groups of particular normative importance for the paper's analysis.

We undertake tasks (i)-(iv) by estimating models for each of three dependent variables based on survey questions that are asked monthly by the University of Michigan's Surveys of Consumers (SoC).

The survey-based *proxy* for economic news tone is derived from the following SoC item:

1. During the last few months, have you heard of any favorable or unfavorable changes in business conditions?

Respondents are asked to report specific things that they have heard about business conditions and classify them as favorable or unfavorable. We take the by-period summary measure of these responses provided by the SoC – calculated as $\%Favorable_t - \%Unfavorable_t + 100$ – and denote it as $NewsBus_t$.

We measure mass perceptions of the state of the economy and evaluations of the government's handling of the economy using the following two items, respectively:

2. Would you say that at the present time business conditions are better or worse than they were a year ago?

Respondents were given the choice of "Better now," "About the same," or "Worse now." We take the by-period summary measure of these responses provided by the SoC – calculated as $\%Better_t - \%Worse_t + 100$ – and denote it as $RetroBus_t$.

3. As the economic policy of the government – I mean steps taken to fight inflation or unemployment – would you say the government is doing a good job, only fair, or a poor job?

Respondents were given the choice of "Good job", "Only Fair", "Poor Job", and "Don't Know." Again, we take the by-period summary measure of these responses provided by the SoC – calculated as $\%Good_t - \%Poor_t + 100$ – and denote it as $GovtHandling_t$.[1] We discuss details of how we construct these three measures from the response categories in subsection B1.2.

We take the per-quarter mean of responses to each survey question to construct our time series for each dependent variable. As these dependent variables are measured at the national level, we create a national-level measure of our tone variable by taking a weighted average of $Tone_{i,t}$, where the weights are given by the relative magnitudes of the circulation numbers for the respective newspapers.[2] We standardize the resulting measure such that it has a mean

[1]Below we show that our findings are robust to plausible alternative approaches to summarizing the aggregated responses to the respective survey questions.

[2]As we have these data only for 2014, the weighting is based on circulation figures for that year, drawn from the Audience Summary Database at `online.audiencefax.com`.

of zero and a standard deviation of 1, yielding $\overline{Tone_t}$ as the main explanatory variable in the models.

We estimate OLS models in stages, gradually introducing covariates to generate increasingly conservative tests of measurement validity. By introducing controls, we do not seek to obtain an identified causal estimate. Rather, each set of covariates is introduced with the aim of making the validation test more difficult by ruling out a set of possible sources of an association between the two series *other than* those on which the validity tests themselves are premised — that is, that news tone and $RetroBus_t$ are capturing the same underlying phenomenon, and that news tone has an effect on $RetroBus_t$ and $GovtHandling_t$.

In our first, simplest set of models, we place on the righthand side only news tone and two types of covariates to take into account basic features of the data structure: a lagged dependent variable to soak up serial correlation in the error term (which might otherwise make our standard errors inappropriately small) and newspaper-inclusion fixed effects to take into account the fact that, due to data availability, some newspapers enter our sample earlier than others and some leave the sample for a period.

	(1)		(2)		(3)	
	b	se	b	se	b	se
$NewsBus_{t-1}$	0.61	0.06				
$RetroBus_{t-1}$			0.75	0.04		
$GovtHandling_{t-1}$					0.88	0.04
$\overline{Tone_t}$	0.43	0.08	0.30	0.06	0.12	0.05
Newspaper FE	Yes		Yes		Yes	
R^2	0.78		0.88		0.89	
N	135		135		135	
Portmanteau Q	46.5		41.8		45.7	
Portmanteau Q: p	0.22		0.39		0.25	

Table A2: Models of economic perceptions of: recently hearing of positive or negative changes in business conditions ($NewsBus$); current business conditions compared to one year ago ($RetroBus$); and views on government performance on economic policy ($GovtHandling$). Parameter estimates for an OLS regression. Time range is 1981–2014, inclusive, with newspapers entering the sample at different points. Newspapers and entry dates as indicated in Table B1.

This first set of estimates are shown in Table A2. As we can see from the quite large and precisely estimated coefficients on $\overline{Tone_t}$, our news tone measure is well correlated with the survey-based proxy for economic news tone, as well as with the economic and governmental evaluations that news tone influences (according to prior studies). For instance, a one standard deviation change in news tone is associated with a 0.43 standard deviation change in the proxy measure, a 0.30 standard-deviation change in retrospective economic evaluations, and a 0.12 standard deviation change in evaluations of government's handling of the economy.

We then proceed to make the test more stringent. In a second set of models, we introduce terms to rule out unmeasured factors that might drive the apparent association between news tone and our dependent variables. Specifically, we include a time trend to reduce the probability that we infer a correlation due to common or coincidentally aligned long-term drivers, and quarterly dummies to wash out (possibly common) seasonal fluctuations.

	(1)		(2)		(3)	
	b	se	b	se	b	se
$NewsBus_{t-1}$	0.60	0.06				
$RetroBus_{t-1}$			0.75	0.04		
$GovtHandling_{t-1}$					0.76	0.06
$\overline{Tone}_t$	0.43	0.08	0.30	0.06	0.15	0.05
$Time_t^{Std}$	0.00062	0.15	-0.032	0.11	-0.42	0.15
Newspaper FE	Yes		Yes		Yes	
Seasonal FE	Yes		Yes		Yes	
R^2	0.80		0.89		0.90	
N	135		135		135	
Portmanteau Q	48.7		43.5		41.4	
Portmanteau Q: p	0.16		0.32		0.41	

Table A3: Models of Surveys of Consumers measures of recently hearing of positive or negative changes in business conditions ($NewsBus$), perceptions of current business conditions compared to one year ago ($RetroBus$); and evaluations of government performance on economic policy ($GovtHandling$). Parameter estimates for an OLS regression. Time range is 1981–2014, inclusive, with newspapers entering the sample at different points. Newspapers and entry dates as indicated in Table B1.

The results of these tests are shown in Table A3. We see that news tone remains at least as well correlated with all three benchmark variables when time trends and seasonal fluctuations are accounted for as it was in the simpler models.

Next, we introduce sets of macroeconomic covariates to factor out any part of the correlation that might arise from a common effect of economic forces on both news tone and mass perceptions and evaluations. In the third set of models we include a basic set of macroeconomic covariates: GDP growth and change in the unemployment rate. In the fourth set of models, we introduce a broader set of macroeconomic covariates: quarterly mean pre-tax income growth (from the same income data series that we use throughout the main text); the Federal funds rate (as a measure of prevailing interest rates); the annual inflation rate measured as growth in the Consumer Price Index; and the quarterly growth rate of the S&P500 index.

We see in Tables A4 and A5 that the coefficient on $\overline{Tone}_t$ is highly stable and no less precisely estimated across these specifications. This indicates that that our news tone measure is well correlated with the benchmark variables, above and beyond any effect of objective economic developments on both tone and the benchmarks.

In a further step, we examine to what degree our tone measure is correlated with the three

	(1)		(2)		(3)	
	b	se	b	se	b	se
$NewsBus_{t-1}$	0.39	0.07				
$RetroBus_{t-1}$			0.61	0.05		
$GovtHandling_{t-1}$					0.77	0.06
$\overline{Tone}_t$	0.35	0.08	0.23	0.05	0.20	0.06
$Time_t^{Std}$	0.041	0.14	-0.077	0.10	-0.41	0.15
δGDP_t^{Std}	0.22	0.11	0.13	0.08	0.054	0.09
$\Delta Unemp_t^{Std}$	-0.48	0.16	-0.39	0.11	0.21	0.10
Newspaper FE	Yes		Yes		Yes	
Seasonal FE	Yes		Yes		Yes	
R^2	0.83		0.92		0.90	
N	135		135		135	
Portmanteau Q	32.0		40.4		43.4	
Portmanteau Q: p	0.81		0.45		0.33	

Table A4: Models of Surveys of Consumers measures of recently hearing of positive or negative changes in business conditions ($NewsBus$), perceptions of current business conditions compared to one year ago ($RetroBus$); and evaluations of government performance on economic policy ($GovtHandling$). Parameter estimates for an OLS regression. Time range is 1981–2014, inclusive, with newspapers entering the sample at different points. Newspapers and entry dates as indicated in Table B1.

	(1)		(2)		(3)	
	b	se	b	se	b	se
$NewsBus_{t-1}$	0.45	0.07				
$RetroBus_{t-1}$			0.64	0.06		
$GovtHandling_{t-1}$					0.74	0.06
$\overline{Tone}_t$	0.28	0.08	0.20	0.06	0.16	0.07
$Time_t^{Std}$	-0.42	0.17	-0.24	0.14	-0.45	0.17
δGDP_t^{Std}	0.14	0.11	0.11	0.08	0.13	0.09
$\Delta Unemp_t^{Std}$	-0.40	0.15	-0.32	0.11	0.34	0.11
$FedFundsRate_t^{Std}$	-0.40	0.15	-0.18	0.13	-0.012	0.13
$Inflation_t^{Std}$	-0.047	0.07	-0.049	0.06	-0.16	0.06
$\delta S\&P500_t^{Std}$	0.22	0.04	0.083	0.03	0.0019	0.04
$\delta Inc_t^{P0-100,Std}$	0.043	0.06	0.048	0.05	0.097	0.04
Newspaper FE	Yes		Yes		Yes	
Seasonal FE	Yes		Yes		Yes	
R^2	0.89		0.92		0.93	
N	130		130		130	
Portmanteau Q	45.2		46.6		49.0	
Portmanteau Q: p	0.26		0.22		0.15	

Table A5: Models of Surveys of Consumers measures of recently hearing of positive or negative changes in business conditions ($NewsBus$), perceptions of current business conditions compared to one year ago ($RetroBus$); and evaluations of government performance on economic policy ($GovtHandling$). Parameter estimates for an OLS regression. Time range is 1981–2014, inclusive, with newspapers entering the sample at different points. Newspapers and entry dates as indicated in Table B1.

benchmark variables among citizens at different points in the income distribution, since the consumption of economic news might vary across income groups. For the purposes of this paper's analysis, it would be problematic if, for instance, our tone measure tracked the perceptions only of the most affluent, and not those of lower- and middle-income citizens. The Surveys of Consumers data allow us to break down the sample by income tercile.[3] Tables A6, A7, and A8 display estimates for bottom-, middle- and top-tercile respondents for each economic perception dependent variable, respectively, using the same specification as in Table A4. Across the models we see that the proxy measure and economic perceptions and evaluations are associated with economic news tone roughly as strongly within as across income groups.

	(1)		(2)		(3)	
	b	se	b	se	b	se
$NewsBus^{Inc1}_{t-1}$	0.43	0.07				
$NewsBus^{Inc2}_{t-1}$			0.37	0.07		
$NewsBus^{Inc3}_{t-1}$					0.35	0.08
$\overline{Tone}_t$	0.32	0.08	0.35	0.08	0.35	0.08
$Time^{Std}_t$	0.033	0.14	0.0032	0.14	0.10	0.15
δGDP^{Std}_t	0.11	0.12	0.25	0.12	0.25	0.13
$\Delta Unemp^{Std}_t$	-0.56	0.16	-0.47	0.17	-0.48	0.18
Newspaper FE	Yes		Yes		Yes	
Seasonal FE	Yes		Yes		Yes	
R^2	0.83		0.82		0.80	
N	135		135		135	
Portmanteau Q	31.0		34.3		44.3	
Portmanteau Q: p	0.85		0.73		0.30	

Table A6: Models of Surveys of Consumers measures of recently hearing of positive or negative changes in business conditions ($NewsBus$). Models 1, 2, and 3 are estimated using responses only of those in the bottom, middle, and top income terciles, respectively. Parameter estimates for an OLS regression. Time range is 1981–2014, inclusive, with newspapers entering the sample at different points. Newspapers and entry dates as indicated in Table B1.

Finally, we speak to the possibility that the correlations we find are a result of the endogeneity of news tone to economic perceptions. As noted, a considerable range of studies adduce evidence that economic news affects mass perceptions. Other work has recently questioned that assumption, arguing that journalists may respond to consumer sentiment (Hopkins et al. 2017; Wlezien et al. 2017). If the latter is true, then the correlations we have observed so far could be a result of the effect of mass perceptions on news tone, meaning that our tone measure would only be picking up that component of the economic news that is, in a sense, purely epiphenomenal – i.e., a symptom of mass perceptions and of little political consequence in itself.

[3] In a study of non-response bias in the Survey of Consumers, Curtin et al. (2002) find some difference in response patterns by income group, with higher-income respondents being harder to contact and lower-income respondents being more likely to have initially refused to participate. However, the size of nonresponse bias appears small and constant over time, and thus should not affect measures of period-to-period change.

	(1)		(2)		(3)	
	b	se	b	se	b	se
$RetroBus^{Inc1}_{t-1}$	0.61	0.05				
$RetroBus^{Inc2}_{t-1}$			0.58	0.05		
$RetroBus^{Inc3}_{t-1}$					0.61	0.05
$\overline{Tone}_t$	0.24	0.06	0.23	0.06	0.23	0.06
$Time^{Std}_t$	-0.20	0.12	-0.099	0.11	0.019	0.11
δGDP^{Std}_t	0.012	0.09	0.17	0.08	0.16	0.09
$\Delta Unemp^{Std}_t$	-0.45	0.11	-0.40	0.11	-0.38	0.12
Newspaper FE	Yes		Yes		Yes	
Seasonal FE	Yes		Yes		Yes	
R^2	0.90		0.91		0.90	
N	135		135		135	
Portmanteau Q	47.4		47.3		37.1	
Portmanteau Q: p	0.20		0.20		0.60	

Table A7: Models of Surveys of Consumers measures of perceptions of current business conditions compared to one year ago ($RetroBus$). Models 1, 2, and 3 are estimated using responses only of those in the bottom, middle, and top income terciles, respectively. Parameter estimates for an OLS regression. Time range is 1981–2014, inclusive, with newspapers entering the sample at different points. Newspapers and entry dates as indicated in Table B1.

	(1)		(2)		(3)	
	b	se	b	se	b	se
$GovtHandling^{Inc1}_{t-1}$	0.74	0.07				
$GovtHandling^{Inc2}_{t-1}$			0.71	0.07		
$GovtHandling^{Inc3}_{t-1}$					0.70	0.06
$\overline{Tone}_t$	0.19	0.07	0.24	0.06	0.19	0.06
$Time^{Std}_t$	-0.37	0.17	-0.55	0.17	-0.53	0.16
δGDP^{Std}_t	0.069	0.11	0.050	0.10	0.075	0.09
$\Delta Unemp^{Std}_t$	0.28	0.13	0.24	0.12	0.15	0.11
Newspaper FE	Yes		Yes		Yes	
Seasonal FE	Yes		Yes		Yes	
R^2	0.85		0.88		0.90	
N	135		135		135	
Portmanteau Q	34.7		38.6		25.3	
Portmanteau Q: p	0.71		0.54		0.97	

Table A8: Models of Surveys of Consumers measures of evaluations of government performance on economic policy ($GovtHandling$). Models 1, 2, and 3 are estimated using responses only of those in the bottom, middle, and top income terciles, respectively. Parameter estimates for an OLS regression. Time range is 1981–2014, inclusive, with newspapers entering the sample at different points. Newspapers and entry dates as indicated in Table B1.

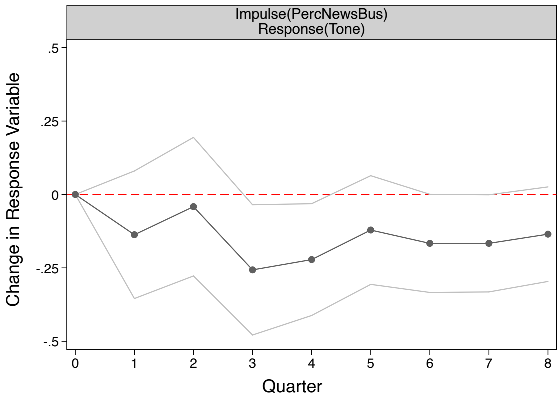
To examine whether we can rule out this possibility, we use reduced form vector autoregression (VAR) to tell us whether past values of endogenous variables predict the contemporaneous values of other variables in the system better than their past values alone (also known as Granger causality). In other words, this test will tell us whether lagged tone predicts current economic perceptions or vice versa. We estimate a pair of VARs for each of our economic perception measures with controls only for trending and yearly quarter.[4]

We emphasize that we do not seek to draw inferences from the VAR models about the causal effect of news tone on perceptions, only to rule out the reverse by showing that past values of mass perceptions have little ability to predict current values of tone. The full estimates are provided in Table A9 and Figure A1. Granger causality tests consistently indicate that tone Granger-causes economic perceptions rather than the reverse. It is thus unlikely that the association that we observe between tone and economic perceptions is due to the effect of the latter on the former.

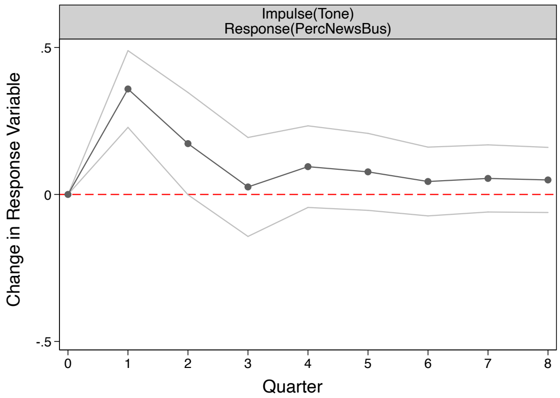
	(1) $NewsBus_t^{Std}$		$\overline{Tone_t}$		(2) $\overline{Tone_t}$		$RetroBus_t^{Std}$		(3) $\overline{Tone_t}$		$GovtHandling_t^{Std}$	
	b	se	b	se	b	se	b	se	b	se	b	se
L.$NewsBus_t^{Std}$	0.54	0.10	-0.14	0.13								
L2.$NewsBus_t^{Std}$	-0.042	0.11	0.11	0.15								
L3.$NewsBus_t^{Std}$	0.087	0.11	-0.27	0.14								
L4.$NewsBus_t^{Std}$	-0.020	0.08	0.11	0.10								
L.$\overline{Tone_t}$	0.36	0.08	0.58	0.10	0.59	0.10	0.27	0.05	0.56	0.09	0.16	0.05
L2.$\overline{Tone_t}$	-0.23	0.09	-0.017	0.11	-0.044	0.11	-0.20	0.06	0.020	0.10	-0.079	0.06
L3.$\overline{Tone_t}$	-0.017	0.09	0.29	0.11	0.22	0.11	0.0033	0.06	0.29	0.09	0.049	0.05
L4.$\overline{Tone_t}$	-0.033	0.09	0.063	0.11	0.12	0.11	-0.044	0.06				
δGDP_t^{Std}	0.28	0.11	-0.042	0.14	-0.020	0.14	0.15	0.08	0.00076	0.14	0.032	0.08
L.δGDP_t^{Std}	0.17	0.11	0.084	0.14	0.052	0.14	0.14	0.08	0.093	0.12	-0.059	0.07
L2.δGDP_t^{Std}	-0.22	0.10	-0.18	0.12	-0.24	0.12	-0.14	0.07	-0.24	0.12	-0.020	0.07
$Unemp_t^{Std}$	-0.93	0.42	-1.59	0.53	-1.35	0.53	-0.64	0.29	-0.91	0.43	0.052	0.25
L.$Unemp_t^{Std}$	1.04	0.41	1.63	0.52	1.36	0.50	0.68	0.28	0.91	0.42	-0.11	0.25
$Time_t^{Std}$	-0.082	0.07	0.037	0.09	0.058	0.09	-0.022	0.05	0.054	0.09	-0.13	0.06
L.$RetroBus_t^{Std}$					-0.18	0.17	0.77	0.09				
L2.$RetroBus_t^{Std}$					0.36	0.21	-0.033	0.12				
L3.$RetroBus_t^{Std}$					-0.40	0.21	0.14	0.11				
L4.$RetroBus_t^{Std}$					0.13	0.14	-0.082	0.07				
L.$GovtHandling_t^{Std}$									-0.023	0.15	0.94	0.09
L2.$GovtHandling_t^{Std}$									-0.045	0.20	-0.15	0.12
L3.$GovtHandling_t^{Std}$									-0.021	0.14	0.056	0.08
Seasonal FE	Yes		Yes		Yes		Yes		Yes		Yes	
R^2												
N	132				132				133			

Table A9: Vector Autoregression (VAR) estimates for the relationship between $\overline{Tone_t}$ and each of $NewsBus_t$, $RetroBus_t$, and $GovtHandling_t$.

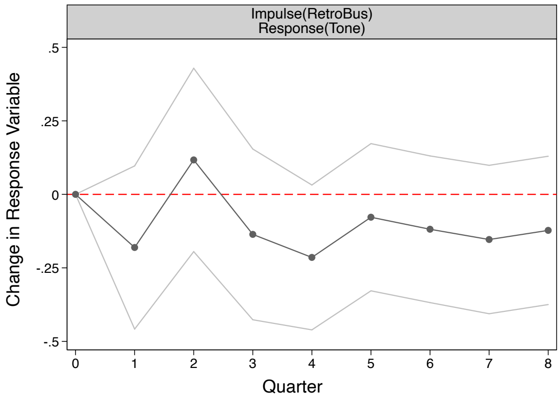
[4]Lag lengths of our endogenous variables were chosen based on a convergence of results of several tests – including likelihood ratio, information criteria, and the final prediction error – that together indicated including additional lags would fail to improve fit, and there was no evidence of serial correlation in the residuals based on the results of a Lagrange Multiplier test. Three lags were required for our models involving $NewsBus_t$, four lags for $RetroBus_t$, and three for $GovtHandling$.



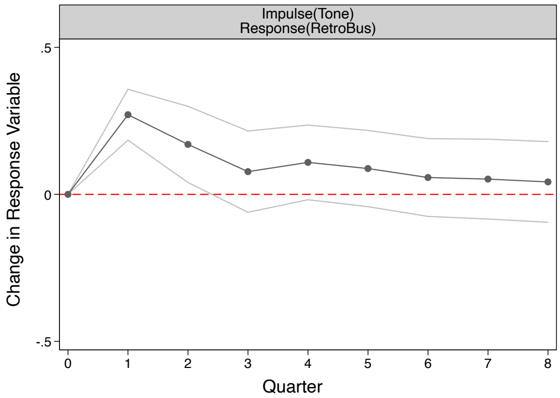
(a) $NewsBus_t \rightarrow \overline{Tone}_t$



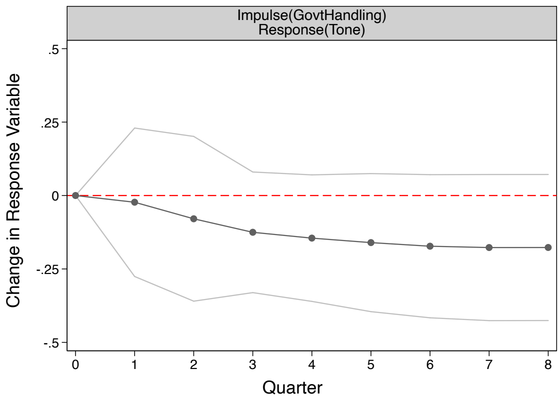
(b) $\overline{Tone}_t \rightarrow NewsBus_t$



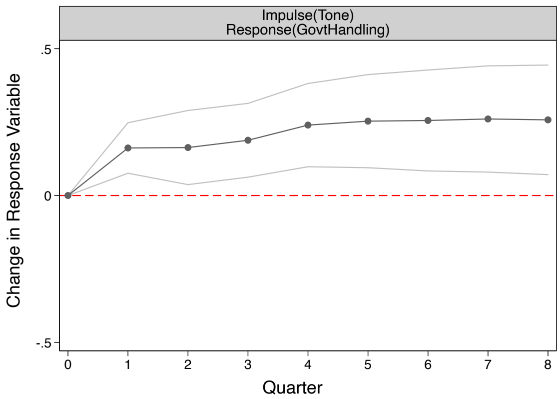
(c) $RetroBus_t \rightarrow \overline{Tone}_t$



(d) $\overline{Tone}_t \rightarrow RetroBus_t$



(e) $GovtHandling_t \rightarrow \overline{Tone}_t$



(f) $\overline{Tone}_t \rightarrow NewsBus_t$

Figure A1: Plots of impulse response functions for VAR models of the relationship between $\overline{Tone}_t$ and our various economic perceptions measures. The figures are based on the estimates presented in Table A9.

A3 Descriptive Statistics for Income Growth

	(1)				
	δInc_t^{P0-20}	δInc_t^{P20-40}	δInc_t^{P40-60}	δInc_t^{P60-80}	$\delta Inc_t^{P80-100}$
δInc_t^{P0-20}	1				
δInc_t^{P20-40}	0.803	1			
δInc_t^{P40-60}	0.684	0.900	1		
δInc_t^{P60-80}	0.600	0.816	0.962	1	
$\delta Inc_t^{P80-100}$	0.397	0.640	0.717	0.766	1

Table A10: Correlation matrix for the growth rates of all income quintiles.

	(1)						
	$\delta Inc_t^{P90-100}$	δInc_t^{P90-95}	$\delta Inc_t^{P95-100}$	δInc_t^{P90-99}	$\delta Inc_t^{P99-100}$	$\delta Inc_t^{P90-99.9}$	$\delta Inc_t^{P99.9-100}$
$\delta Inc_t^{P90-100}$	1						
δInc_t^{P90-95}	0.829	1					
$\delta Inc_t^{P95-100}$	0.996	0.778	1				
δInc_t^{P90-99}	0.914	0.964	0.879	1			
$\delta Inc_t^{P99-100}$	0.966	0.674	0.983	0.781	1		
$\delta Inc_t^{P90-99.9}$	0.968	0.919	0.946	0.982	0.875	1	
$\delta Inc_t^{P99.9-100}$	0.887	0.530	0.918	0.639	0.970	0.747	1

Table A11: Correlation matrix for the growth rates of top-income quantiles.

	(1)									
	δInc_t^{P0-10}	δInc_t^{P10-20}	δInc_t^{P20-30}	δInc_t^{P30-40}	δInc_t^{P40-50}	δInc_t^{P50-60}	δInc_t^{P60-70}	δInc_t^{P70-80}	δInc_t^{P80-90}	$\delta Inc_t^{P90-100}$
δInc_t^{P0-10}	1									
δInc_t^{P10-20}	0.804	1								
δInc_t^{P20-30}	0.613	0.898	1							
δInc_t^{P30-40}	0.559	0.803	0.959	1						
δInc_t^{P40-50}	0.556	0.734	0.874	0.958	1					
δInc_t^{P50-60}	0.478	0.657	0.794	0.888	0.966	1				
δInc_t^{P60-70}	0.446	0.624	0.753	0.849	0.935	0.981	1			
δInc_t^{P70-80}	0.450	0.603	0.745	0.844	0.923	0.958	0.983	1		
δInc_t^{P80-90}	0.455	0.551	0.698	0.797	0.878	0.918	0.951	0.974	1	
$\delta Inc_t^{P90-100}$	0.227	0.372	0.547	0.630	0.676	0.654	0.692	0.729	0.771	1

Table A12: Correlation matrix for the growth rates of all income deciles.

A4 Formalizing the Test for Class-biased Economic News

In the paper, we present statistical tests for the presence of a class (i.e., pro-rich) bias in the economic news that rely on a normative model of the relationship between the tone of economic news and income growth. In this section, we present the normative model and formally derive its implications for the construction of the test.

The normative model is grounded in the premise that every resident's welfare should receive equal weight in any assessment of a political unit's economic outcomes.[5] It follows from this premise that the tone of economic news should reflect change in the incomes of every resident *equally*, irrespective of where the resident lies in the income distribution. Where we are observing gains and losses for *groups* of residents, a further implication is that *equal-sized* groups (i.e., those containing equal numbers of individuals) should receive equal weight in news assessments. We can formalize this normative baseline, for the setup in this paper, as a model of quarterly economic news tone:

$$Tone_t = \alpha + \sum_{k=1}^{K}(\beta_k \times \delta Inc_t^k) + \epsilon_t \ , \beta_{k=j} = \beta_{k \neq j} \ \forall \ k, \tag{1}$$

where $Tone_t$ is the quarterly average of economic news tone; δInc_t^k is average quarterly income growth for quantile k at t, where the set of K quantiles is exhaustive and mutually exclusive and each quantile contains $\frac{1}{K}$ of the distribution; α is the intercept; the β_k's are parameters to be estimated; and ϵ_t is an idiosyncratic error term.[6] These expressions imply that the partial correlation of quarterly income growth with economic tone is equal for any given income quantile (where all quantiles are equal in population size).

Where the groups being compared are of *unequal* size—for instance, when we are comparing a small group of rich residents with larger groups of non-rich residents—the normative baseline weights must be adjusted accordingly. In particular, equal weighting of individuals implies that larger groups should receive greater weight in the economic news than smaller groups, in proportion to their sizes.

To see why, intuitively, consider a deviation from that baseline in which we observed that the economic news was roughly as well correlated with welfare changes for the top 1% as with welfare changes for the bottom 20%. On a *per capita* basis, the welfare of rich individuals

[5] One could imagine alternative premises, such as that the welfare of those with more modest resources should receive greater weight. We note that this alternative premise would generate even larger estimates of the scale of class bias in economic news by setting a normative baseline in which gains and losses for the non-rich should be accorded more-than-equal weight.

[6] For simplicity, we assume contemporaneous relationships.

would, then, be being more strongly reflected in the economic news than the welfare of poor individuals. We would thus consider this pattern as an instance of bias in the economic news in favor of the top 1% relative to the bottom fifth. We emphasize that this characterization is a descriptive conceptualization of the relationships, independent of what may have caused the pattern.

Here we formally derive from our normative premise the relative magnitudes of the partial correlations between income growth and economic tone that represent *unbiased* economic news, in models that identify *unequally* sized income groups (i.e., where all income groups do not contain $\frac{1}{K}$ of the distribution). In turn, we can specify the implied ratio of any pair of income-group-specific income-growth coefficients, provided that the statistical model, consistent with equation 1, includes an exhaustive, mutually exclusive set of income groups. These ratios are the basis of the statistical tests reported in Section of the paper.

Consider models of the following form:

$$Tone_t = \alpha + \beta_1 \times \delta Inc_t^{P0-q} + \beta_2 \times \delta Inc_t^{P(q+1)-100} \quad , \tag{2}$$

where the superscripts on the income growth variables are defined as in the paper and q is a percentile. For instance, if $q = 90$, then β_1 and β_2 capture the partial correlation of economic tone with average income growth from, respectively, the first to the 90^{th} percentile and from the 91^{st} to the 100^{th} percentile. First, we rewrite the equation in terms of percentile-level growth. Given that, by definition, each percentile contains an equal number of citizens, growth in each income group is simply the average of growth across its constituent percentiles.[7] So, for instance, the group average growth rate δInc_t^{P0-q} from above becomes $\left(\frac{\sum_{k=1}^{q} \delta Inc_t^{Pk}}{q}\right)$, expressed as a simple average of the constituent percentiles' growth rates. This substitution gives us:

$$Tone_t = \alpha + \beta_1 \times \left(\frac{\sum_{k=1}^{q} \delta Inc_t^{Pk}}{q}\right) + \beta_2 \times \left(\frac{\sum_{k=q+1}^{100} \delta Inc_t^{Pk}}{100-q}\right). \tag{3}$$

Next, we rearrange the right side of the equation to isolate the percentile-level coefficients:

$$Tone_t = \alpha + \frac{\beta_1}{q} \times \sum_{k=1}^{q} \delta Inc_t^{Pk} + \frac{\beta_2}{100-q} \times \sum_{k=q+1}^{100} \delta Inc_t^{Pk}. \tag{4}$$

[7] Expressing income growth in terms of individuals, i, nested within (equal-sized) quantiles, k, average income growth for a population is equal to $\frac{\sum_k \sum_i \delta Inc_t^{i,k}}{Kn}$, where K is the number of quantiles and n is the number of individuals *per* quantile. Given the properties of the summation operator, we can also express this average as $\frac{1}{K} \times \frac{\sum_k \sum_i \delta Inc_t^{i,k}}{n}$.

By assumption, given the normative model, the percentile-level income growth coefficients must be equal; that is,

$$\frac{\beta_1}{q} = \frac{\beta_2}{100 - q}. \tag{5}$$

Therefore,

$$\beta_1 = \beta_2 \times \frac{q}{100 - q}. \tag{6}$$

This implies that the ratio of β_1 to β_2 is $\frac{q}{100-q}$. For example, if $q = 90$, then β_1 (the coefficient on income growth at or below the 90^{th} percentile) would be 9 times the coefficient on β_2 (the coefficient on income growth above the 90^{th} percentile)[8].

When conducting the coefficient ratio tests, we use the `testnl` function in `Stata` to calculate standard errors and confidence intervals using the delta method.

A5 State-Level Robustness Tests

As we estimate models using national-level economic indicators, one potential concern might be a form of ecological fallacy. To see the concern, consider two groups of states. Suppose that the states in Group A represent a larger share of the national economy than do the states in Group B. Suppose further that Group A experiences rapid income growth only among top-earners and that newspapers located in Group A states report negatively on that development. Meanwhile, suppose Group B states experience disproportionately strong income growth at the bottom of the income scale and that Group B newspapers report positively on this development. Finally, suppose that Group B's newspapers weigh more heavily in our tone measure because we happen to have more Group B newspapers in the sample. In this situation, newspapers in both groups are reporting in a manner sensitive to the interests of non-rich households. Yet we would observe in our data a national-level news bias toward the interests of the affluent: growing inequality nationally accompanied by more positive news. Compositional effects could thus lead national-level inferences astray if we operate only with aggregate economic measures.

We address this possibility by modeling each newspaper's economic news tone as a function of economic developments at the newspaper's state level. We match each newspaper to the state in which it operates, and then merge state-level distributional income-growth data that have

[8]As noted, our normative model does not take account of the *ex ante* distribution of income in society. A more strongly egalitarian logic might, for example, require greater responsiveness to change in the welfare of those at the bottom, implying that the required ratio of β_1 to β_2 would be strictly greater than $\frac{q}{100-q}$.

been calculated using the same methodology as employed for our national data (Sommeiller et al. 2016). Data limitations at the state level mean that we are unable to measure non-rich income growth at any aggregation less than the bottom 90 percent. Given that, we cannot directly mimic the specifications that underlie Figure 4 as we cannot separate out the bottom quintile. Therefore, the specification that we adopt for these state-level income data contains income growth for each of the: the top-X% and the bottom-$(100 - X)$%. As in the national income growth models, we use $X \in \{10, 5, 1, 0.1\}$.

Figure A2 presents estimated coefficient ratios from these models using state-level income growth data. It shows a remarkably similar pattern to that in Figure 4, which is based on the national-level income growth measures. Note that we, again, do not plot the normative baseline for the top-0.1% model (which is 999) as it would distort the x-axis scale. In short, we find clear evidence of an acute pro-rich bias in news–income associations at the state level.

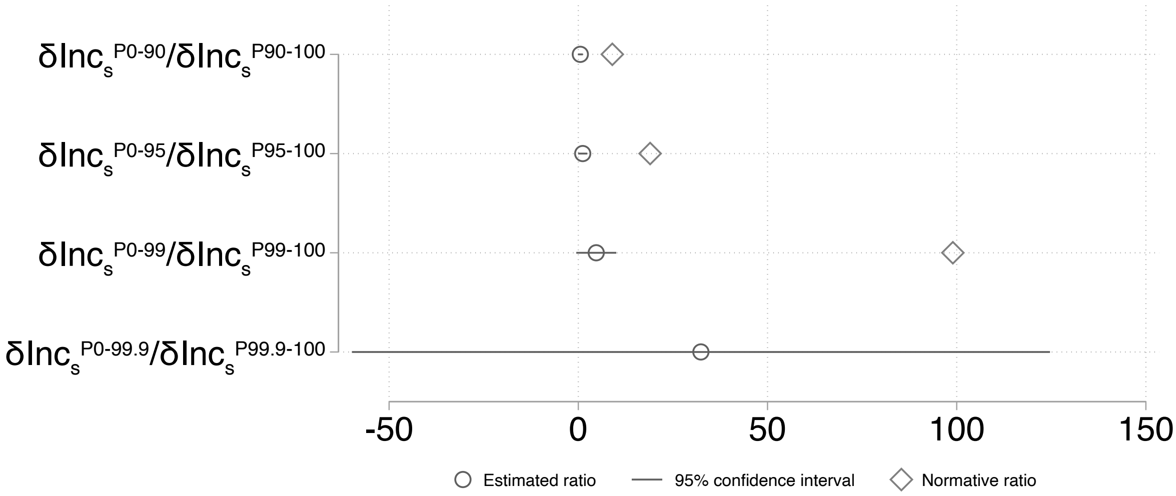


Figure A2: Estimated coefficient ratios from models predicting economic news tone with income growth for different parts of the income distribution, measured at the state level. Diamonds indicate normative baseline for each coefficient ratio, assuming the normative standard of an equal per capita association with news tone for all income groups. The normative baseline for the top-0.1% model is 999 (not plotted). Underlying regression results shown in Supplementary Table B17.

We can also assess whether our argument about the drivers of news tone finds empirical support when using these state-level income growth data. To that end, Table A13 presents the results from a set of models that are analogous to those in Table 1. Model 1 gives the basic descriptive pattern at the state level. Here we are modeling news tone for each newspaper as a function of income growth among the richest 1 percent in the state and of income growth among the bottom 90 percent in the state (as well as newspaper and seasonal fixed effects, newspaper trends, and four lags of the dependent variable, as in our national-level models). We find here an association of newspaper-level news tone with income growth both among the bottom 90 percent and among the top 1 percent in the newspaper's state, each conditional on the other. The results further suggest that income growth for the bottom 90 percent in a state may be associated with a somewhat greater change in state-level news tone than is income growth for the top 1 percent, though the standard errors do not allow us to confidently distinguish between these point estimates. The roughly similar coefficients for rich and non-rich state-level growth rates must be assessed in light of the fact that the latter group is *90 times larger* than the former.[9] That the economic news is roughly as responsive to the fortunes of the two groups implies a dramatic upward class bias in the response to the state-level distribution of gains and losses. We can observe this bias even more simply in Model 2, where we model news tone as a function of state-level top-income shares, and observe the same strong positive association between news tone and top-end inequality at the state level that we report at the national level in Section .

In Models 3–5, as summarized in Section , we then examine whether there is evidence that a "covering the business cycle" mechanism operates at the state level. In Model 3, we enter mean income growth as a measure of aggregate growth,[10] alongside top-income share. We find a moderately significant positive association between mean-income growth and news tone, while the coefficient on top-income share is reduced substantially as compared to the estimate in Model 2. In Model 4, we include the first-difference of the state-level unemployment rate, observing a strong, precisely estimated negative effect on news tone and, again, a similarly reduced top-share coefficient. Finally, the pattern in Model 5 – with top-income share, unemployment, and mean income all included – is remarkably similar to the national-level pattern reported in the equivalent national-level model (Model 5, Table 1), with unemployment emerging as the dominant predictor of news tone. We also note that, unsurprisingly, the effects of the state-level aggregates on newspaper-specific tone are considerably more precisely estimated than are the effects of national-level aggregates that we see in Table 1 in the main text.

These results make clear that the class-biased patterns observed at the national level are not a compositional artifact arising from unbiased state-level dynamics. Newspapers' economic reporting likely responds to some combination of national- and state-level economic developments, and developments at the two levels will mutually influence one another. What is clear, however, is that citizens are more likely to read good economic news as economic gains be-

[9] We also note that these results are not directly comparable to the national-level results in Section , insofar as those analyses divide the non-rich into quintiles, as permitted by the national-level data. When we group the bottom 90 percent together at the national level, we find a weaker relationship between bottom 90-percent income gains and news tone (p=0.24) as reported in Table B20.

[10] State GDP is not available prior to 1997. We thus use mean adjusted gross income for each state, as calculated by the Census Bureau.

come more sharply concentrated among the very rich within their state, a pattern strikingly parallel to that observed for national-level distributional outcomes. Further, the state-level evidence reinforces the national-level evidence on the role of macro-economic aggregates in driving this correlation. The results suggest that journalistic portraits of the state-level economy are strongly driven by state-level growth and (even more directly) employment, with implicit class bias emerging from the inequality-inducing sources of growth.

	(1)			(2)			(3)			(4)			(5)		
	b	se	p	b	se	p	b	se	p	b	se	p	b	se	p
$\delta Inc_{s,t}^{P99-100}$	0.60	0.25	0.02												
$\Delta IncShare_{s,t}^{P99-100}$				5.63	1.40	0.00	4.34	2.15	0.04	3.45	1.45	0.02	2.76	2.15	0.20
$\delta Inc_{s,t}^{P0-99}$	2.84	0.78	0.00												
$\delta Inc_{s,t}^{M}$							0.01	0.01	0.32				0.00	0.01	0.56
$\Delta Unemp_{s,t}$										-0.25	0.07	0.00	-0.24	0.07	0.00
Newspaper FE	Yes			Yes			Yes			Yes			Yes		
Newspaper Trends	Yes			Yes			Yes			Yes			Yes		
Seasonal FE	Yes			Yes			Yes			Yes			Yes		
4 lags of DV	Yes			Yes			Yes			Yes			Yes		
R^2	0.35			0.33			0.32			0.34			0.34		
N	2775			2775			2515			2680			2515		
N newspapers	32			32			31			31			31		
Mean T_i	86.7			86.7			81.1			86.5			81.1		
Min T_i	56			56			55			56			55		
Max T_i	127			127			95			127			95		
Min $Year_{i,t}$	1982			1982			1990			1982			1990		
Max $Year_{i,t}$	2013			2013			2013			2013			2013		
Corr.	psar1			psar1			psar1			psar1			psar1		
AR1-p	0.91			0.77			0.74			0.71			0.74		

Table A13: Estimates of the association between the tone of economic news reporting across newspapers ($Tone_{i,t}$) and state-level predictors. All models estimated by OLS with Beck and Katz (1995) panel corrected standard errors.

Finally, in analyses reported in Table A14, we examine whether responsiveness to financial markets might partially explain state-level associations between inequality and news tone. We do this by repeating the financial-market analysis but with the state-level inequality and macroeconomic predictors employed in Section A5. While the baseline state-level specification is replicated in Model 1, in Model 2 we add quarterly NYSE growth on the righthand side. A comparison of the Model 1 and Model 2 results suggests that stock-market gains and losses indeed account for part of the state-level bias, as the size of the top-share coefficient drops by a third when the financial-market indicator is added to the model. In Models 3 and 4, we add state-level aggregate measures, changes in mean adjusted personal income and unemployment, successively to the model. In the full specification, unemployment is again a substantial negative driver of news tone, with mean-income's positive effect being somewhat smaller and less-precisely estimated. Interestingly, financial market movements still emerge as by far the strongest predictor of state-specific news tone even with state-level economic predictors included in the model. We note, finally, that *all* of the unconditional association between state-level inequality and state-level news tone disappears when stock movements and macroeconomic aggregates are included.

	(1)			(2)			(3)			(4)		
	b	se	p	b	se	p	b	se	p	b	se	p
$\Delta IncShare^{P99-100}_{s,t}$	5.63	1.40	0.00	3.63	1.22	0.00	0.80	1.83	0.66	0.04	1.82	0.98
$\delta NYSE_t$				0.02	0.00	0.00	0.02	0.00	0.00	0.02	0.00	0.00
$\delta Inc^M_{s,t}$							0.01	0.01	0.03	0.01	0.01	0.07
$\Delta Unemp_{s,t}$										-0.16	0.06	0.01
Newspaper FE	Yes			Yes			Yes			Yes		
Newspaper Trends	Yes			Yes			Yes			Yes		
Seasonal FE	Yes			Yes			Yes			Yes		
4 lags of DV	Yes			Yes			Yes			Yes		
R^2	0.33			0.36			0.36			0.36		
N	2775			2775			2515			2515		
N newspapers	32			32			31			31		
Mean T_i	86.7			86.7			81.1			81.1		
Min T_i	56			56			55			55		
Max T_i	127			127			95			95		
Min $Year_{i,t}$	1982			1982			1990			1990		
Max $Year_{i,t}$	2013			2013			2013			2013		
Corr.	psar1			psar1			psar1			psar1		
AR1-p	0.77			0.50			0.23			0.61		

Table A14: Estimates of the association between the tone of economic news reporting across newspapers ($Tone_{i,t}$), income growth at various points of the income distribution, and growth in various financial market indices. All models estimated by OLS with Beck and Katz (1995) panel corrected standard errors.

A6 Details of Coding Procedures for Topic Salience Analysis

For the topic salience analysis presented in Section , we had human coders code the topics mentioned in a sample of news articles. We devised a 17-category coding scheme that covered a relatively broad range of economic developments, including the main economic phenomena associated with aggregate growth and those with a close connection to the distribution of gains and losses. The coding scheme, as used by the coders that conducted the coding, is set out in Table A15.

Any given article could contain reference to any, all, or none of these categories. We asked the coders to code for presence, presence in the lede (or headline), or absence of each category, although the lede-relevant categories were too sparse to be usefully analyzed separately.

Note that, in the graph presented in Section , we combine the "Aggregated corporations: Income," "Aggregated corporations: Value," "Specific corporations: Income," and "Specific corporations: Value" into a single "Corporate" category that, at the article level, is equal to "Yes" (1) if any of the four sub-categories are coded this way, and "No" (0) otherwise.

One research assistant coded a random sub-sample of 2,000 articles from our full (economically-relevant) sample. A second research assistant independently coded a random sub-sub-sample of 200 of those 2,000 articles to allow evaluation of reliability. Intercoder reliability – e.g. as measured by Krippendorff's α – is not of particular importance for the present analysis, given the way in which we are using the measures. In particular, we are interested in evaluating the prevalence of various economic categories in the data in the aggregate. Article-level variance– and, thus, whether two coders might agree on the coding of a particular article–is of little importance for the analysis (in the way it would be if, for instance, we were entering the coded variables into a regression model). As such, satisfactory agreement between the two coders on the overall *prevalence* of the various categories is the key metric for our needs, rather than agreement on an article-by-article basis. Moreover, it is clear that some of our categories are, in fact, very rare in the data (e.g. inequality), and it is well understood that measures of intercoder reliability that "correct" for chance agreement (e.g., Krippendorff's α) are not well suited for evaluating the reliability of such lopsided data.

Table A16 reports various diagnostic measures of our research-assistant-coded data, with a focus on measures of overall prevalence. For completeness, we also show Krippendorff's α values. We note that measures of prevalence of each category in the sample are highly similar across coders. We further see, at the article level, that we achieve reasonably good values for Krippendorff's α for the more balanced categories

Category	Coding Rule
Specific corporations: Income	Income received by specific corporations, e.g., the quarterly earnings/losses of a specific company or changes thereof). Mentions of decline or increase in a specific company's profit .
Specific corporations: Value	Some form of market valuation of a specific corporation. (i.e., the market valuation of a specific company or its share price or changes thereof). Expansion and contraction of specific corporations.
Aggregated corporations: Income	Income received by some aggregated group of corporations, e.g., the quarterly earnings/losses of a specific company or changes thereof. Mentions of decline or increase in aggregate corporate profits.
Aggregated corporations: Value	Some form of market valuation of some group of corporations. That is, the market valuation of corporations, share prices, stock market indices, or changes thereof. Expansion and contraction of corporations at aggregate level.
Average/median earnings	Average or median wages, salaries, or earnings; includes also wages, salaries, or earnings of any group that is clearly not-rich – e.g., manual workers, low-end service-sector workers, etc. Includes mentions of non-wage compensation, including pensions.
(Un)Employment rates/levels/changes	Unemployment and employment rates/levels (including reports on job creation or loss/layoffs).
Inequality (income/wealth)	Mention of inequalities or disparities in wages, income, or wealth, or mention of the shares of income or wealth received or held by particular income/wealth groups. An article that mentions inequality at the bottom – say differences between what the poor earn and what the median earns, or small shares of the poor – was coded for both "inequality" and "poverty"
Poverty (need of non-rich)	Poverty and other forms of unmet or difficult-to-meet material need among the non-rich. This includes low income, housing unaffordabllity, health or nursing care inaccessibility or unaffordability, lack of savings or wealth accumulation. Public student loan and need-based scholarships, Social Security, Medicaid, Welfare payments.
Executive compensation	Including salary, benefits, stock options – for corporate executives.
Aggregated economy	Any mention of the economy as an aggregated phenomenon, including mentions of economic growth, expansion, recession, contraction or references to "the economy" as an undifferentiated whole
Further Definitions for Corporate Categories	
Specific corporations	A reference to one or more named firms. Includes all sorts of firms, including, e.g., real-estate holding companies, manufacturers, service providers; publicly listed and privately held.
Aggregated corporations	A reference to corporations aggregated at some level above that of individual named firms. Could be an industry or sector, a region, the corporate sector as a whole. Includes all sorts of firms, including, e.g., real-estate holding companies, manufacturers, service providers; publicly listed and privately held).

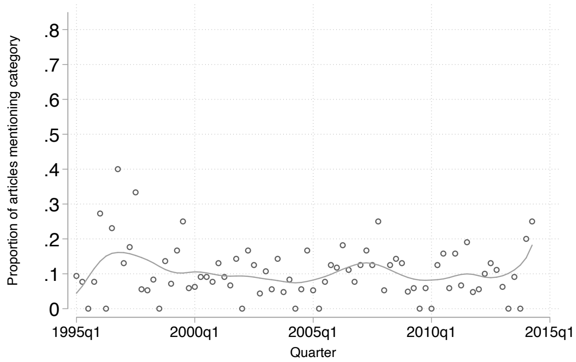
Table A15: Article coding rules for the economic categories that were evaluated by RAs.

Category	Coder 1 Prevalence (N=2000)	Coder 1 Prevalence (N=200)	Coder 2 Prevalence (N=200)	Agreement	Krippendorff's α
Employment	0.22	0.19	0.23	0.92	0.74
Corporate	0.33	0.32	0.27	0.80	0.52
Inequality	0.05*	0.07	0.09	0.90	0.32
Aggregated Economy	0.51	0.49	0.41	0.77	0.60
Executive Compensation	0.02	0.03	0.02	0.97	0.24
Poverty	0.18	0.16	0.14	0.90	0.61
Average Earnings	0.10	0.12	0.12	0.90	0.51

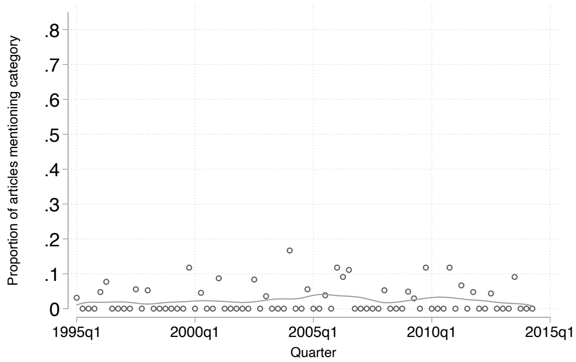
Table A16: Diagnostics of RA codings of economic newspaper articles into economic topic categories. (* N=1580.)

A6.1 Additional topic prevalence plots

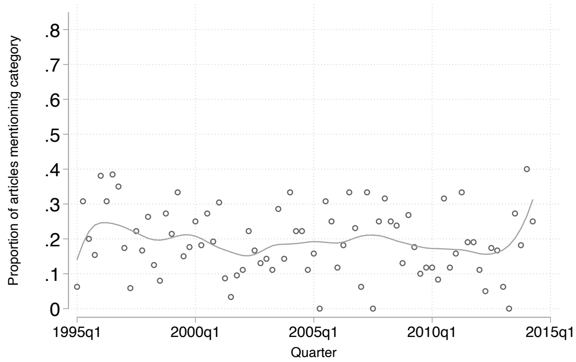
We show here plots of the prevalence of three additional economic topics (beyond those displayed in the main text) with clear distributional implications.



(a) Average Earnings



(b) Executive Compensation



(c) Poverty

Figure A3: Scatter plots of the proportion of newspaper articles mentioning various topics, as categorized by a human coder, by quarter. Lowess curves are shown to smooth noise in the series.

A7 Alternative Mechanisms: Details of Analyses and Results

As discussed in Section , skewed patterns of economic reporting might derive from more explicit interest in or attentiveness to the welfare of the rich, whether arising from the socioeconomic composition of the journalistic profession or from the distributional interests of wealthy owners. We lack micro-level measures of the distributional preferences of either owners or reporters that would allow for direct tests of these mechanisms. A reasonable proxy for those preferences, however, might be found in the measure of newspaper "slant" developed by Gentzkow and Shapiro (2010). Gentzkow and Shapiro (2010) estimate the similarity between the language used by a news outlet and the language employed by Republican as compared to Democratic lawmakers as captured in the Congressional Record. To the extent that the news reflects owners', editors', or reporters' distributional preferences – whatever the source of those preferences – those preferences should also be reflected in partisan alignments, given the two parties' widely differing stances on distributional issues. (A large share of the most partisan phrases from the Congressional Record in Gentzkow and Shapiro's sample relate to economic issues like Social Security, the estate tax, and the budget.) Put differently, if class-biased news derives from less-egalitarian motives or attitudes among those who direct or produce the news, that class bias should be stronger among more Republican-aligned newspapers than among more Democratic-aligned newspapers.

We test this proposition by estimating models interacting each newspaper's partisan slant with change in inequality (top-1% income share).[11] The results are reported in Table A17.[12] $Slant_i$ is coded such that higher values indicate closer alignment with Republicans and the predicted interaction would be positive. Models 1 and 3 report results for national- and state-level inequality, respectively, and indicate that Republican-leaning newspapers are no more likely to deliver class-biased economic news than are Democratic-leaning outlets. Since the *Slant* measure constitutes a snapshot from 2005, we repeat the analysis for a tighter period around this year (2001–2014) in Models 2 and 4, for national- and state-level inequality, respectively. We again find no support for a preference-based mechanism.[13]

As noted in the paper, one variant of our "covering the business cycle" mechanism might focus more on the costs of news production than on pervasive and deep-seated understandings

[11] $Slant_i$ is not time-indexed because it is measured only in 2005.

[12] Gentzkow and Shapiro (2010) provide no slant measure for the *San Jose Mercury News*, an outlet in our sample. Thus, this newspaper is omitted from the present analyses.

[13] It is also worth noting that Gentzkow and Shapiro (2010) find evidence that partisan slant in news content is driven more strongly by reader ideology than by owners' or reporters' ideology. The results in Table A17, however, also cut against the possibility that class-biased news is driven by readers' distributional interests or preferences as these would then also be expected to show up in a newspaper's overall partisan orientation.

	(1)			(2)			(3)			(4)		
	b	se	p	b	se	p	b	se	p	b	se	p
$\Delta IncShare_t^{P99-100}$	8.50	14.97	0.57	-15.80	15.96	0.32						
$\Delta IncShare_{s,t}^{P99-100}$							1.03	7.24	0.89	-5.07	7.45	0.50
$\Delta IncShare_t^{P99-100} \times Slant_i$	13.33	36.91	0.72	64.30	41.70	0.12						
$\Delta IncShare_{s,t}^{P99-100} \times Slant_i$							10.33	16.58	0.53	23.31	17.01	0.17
Newspaper FE	Yes			Yes			Yes			Yes		
Newspaper Trends	Yes			Yes			Yes			Yes		
Seasonal FE	Yes			Yes			Yes			Yes		
4 lags of DV	Yes			Yes			Yes			Yes		
R^2	0.33			0.37			0.33			0.37		
N	2763			1571			2700			1504		
N newspapers	31			31			31			31		
Mean T_i	89.1			50.7			87.1			48.5		
Min T_i	60			25			56			21		
Max T_i	128			55			127			51		
Min $Year_{i,t}$	1982			2001			1982			2001		
Max $Year_{i,t}$	2014			2014			2013			2013		
Corr.	psar1			psar1			psar1			psar1		
AR1-p	1.00			0.00			0.82			0.00		

Table A17: Estimates of the association between the tone of economic news reporting across newspapers ($Tone_{i,t}$) and the change in top-1% income share at national (models 1 and 2) and state (models 3 and 4) level, with moderation by newspaper slant based on data from Gentzkow and Shapiro (2010). Models 1 and 3 estimated on all available observations. Models 2 and 4 estimated on all available observations after 2000. All models estimated by OLS with Beck and Katz (1995) panel corrected standard errors.

of the economy. Growth-oriented reporting might emerge from editors' and reporters' need to economize on time and other resources. Just as Dunaway and Lawrence (2015, 45) argue that "game frame" campaign reporting is less costly than issue-oriented reporting, it may be easier and cheaper for news rooms to track aggregate developments than to dig in to distributional dynamics unfolding beneath the surface. Reporters may, thus, operate on a "covering the business cycle" model not because of its strong postwar track record or deep cognitive embeddedness, but because it is a low-cost (even if misleading) method of summarizing economic complexity.

We test for this possibility by exploiting variation in the strength of economizing pressures both across newspapers in our sample and over time. Dunaway (2008) and Dunaway and Lawrence (2015) argue that news organizations that are owned by publicly traded corporations – under pressure to meet quarterly earnings targets and boost share values – face stronger short-run profit-seeking imperatives than outlets that are privately held. Moreover, they find that newspapers owned by public companies produce more "game frame" and less substantive coverage of issues than the privately held papers. Along similar lines, if class-biased reporting emerges from a focus on aggregates as a cost-cutting news-production model, then we should expect this bias to be stronger for newspapers owned by publicly traded companies than for privately held companies. We should further expect the bias, and the conditioning effect of ownership, to be stronger after 2000, when the sector as a whole saw a reversal of fortune as print revenues began to plunge.

We report the results of tests of these propositions in Tables A18 and A19. In constructing the ownership measures, we began with data shared by Johanna Dunaway from Dunaway and Lawrence (2015) and extended it across newspapers and over time using coding procedures described in Supplementary Materials Section B3.

	(1)			(2)			(3)			(4)		
	b	se	p	b	se	p	b	se	p	b	se	p
δGDP_t	0.06	0.06	0.36	0.09	0.06	0.16						
$\delta Inc^M_{s,t}$							0.01	0.01	0.33	-0.01	0.01	0.42
$\Delta Unemp_t$	-0.30	0.13	0.03	-0.19	0.13	0.14						
$\Delta Unemp_{s,t}$							-0.31	0.08	0.00	-0.34	0.08	0.00
Private	0.00	.	.	0.00	.	.	0.00	.	.	0.00	.	.
Public	-0.10	0.10	0.32	0.06	0.10	0.57	-0.09	0.08	0.24	0.12	0.09	0.20
Private × δGDP_t	0.00	.	.	0.00	.	.						
Public × δGDP_t	0.04	0.05	0.38	0.06	0.06	0.30						
Private × $\Delta Unemp_t$	0.00	.	.	0.00	.	.						
Public × $\Delta Unemp_t$	-0.01	0.11	0.90	0.02	0.12	0.86						
Private × $\Delta Unemp_{s,t}$							0.00	.	.	0.00	.	.
Public × $\Delta Unemp_{s,t}$							0.09	0.07	0.24	0.08	0.08	0.30
Private × $\delta Inc^M_{s,t}$							0.00	.	.	0.00	.	.
Public × $\delta Inc^M_{s,t}$							0.02	0.01	0.01	0.01	0.01	0.08
Newspaper FE	Yes			Yes			Yes			Yes		
Newspaper Trends	Yes			Yes			Yes			Yes		
Seasonal FE	Yes			Yes			Yes			Yes		
4 lags of DV	Yes			Yes			Yes			Yes		
R^2	0.34			0.38			0.34			0.38		
N	2824			1604			2562			1551		
N newspapers	32			32			31			31		
Mean T_i	88.2			50.1			82.6			50.0		
Min T_i	58			23			56			23		
Max T_i	129			55			97			55		
Min $Year_{i,t}$	1982			2001			1990			2001		
Max $Year_{i,t}$	2014			2014			2014			2014		
Corr.	psar1			psar1			psar1			psar1		
AR1-p	0.86			0.00			0.78			0.00		

Table A18: Estimates of the association between the tone of economic news reporting across newspapers ($Tone_{i,t}$) and (a) national-level GDP growth and unemployment rate first difference (models 1 and 2) and state-level mean-income growth and unemployment rate first difference (models 3 and 4) level, with moderation by ownership-type for each newspaper based on data (updated to 2014) from Dunaway (2008). Models 1 and 3 estimated on all available observations. Models 2 and 4 estimated on all available observations after 2000. All models estimated by OLS with Beck and Katz (1995) panel corrected standard errors.

We first examine whether newspapers owned by public corporations generate economic news that is more responsive to aggregates than do other newspapers. In Models 1 and 2 in Table A18, we show national-level results for models with an interaction between ownership type and GDP and an interaction between ownership type and unemployment for the 1982–2014 period and for the period of falling print revenues (2001–2014), respectively. In Models 3 and 4, we show the same for state-level measures. Across the four models, we see only modest evidence of a stronger focus on state-level mean income growth among newspapers at publicly owned companies.

We then examine whether newspapers owned by public corporations generate economic

	(1)			(2)			(3)			(4)		
	b	se	p	b	se	p	b	se	p	b	se	p
$\Delta IncShare_t^{P99-100}$	11.49	5.35	0.03	10.11	4.66	0.03						
$\Delta IncShare_{s,t}^{P99-100}$							5.39	1.54	0.00	4.73	1.59	0.00
Private	0.00	.	.	0.00	.	.	0.00	.	.	0.00	.	.
Public	0.00	0.08	0.99	0.24	0.09	0.01	-0.02	0.08	0.82	0.25	0.09	0.01
Private × $\Delta IncShare_t^{P99-100}$	0.00	.	.	0.00	.	.						
Public × $\Delta IncShare_t^{P99-100}$	6.92	4.24	0.10	4.12	4.30	0.34						
Private × $\Delta IncShare_{s,t}^{P99-100}$							0.00	.	.	0.00	.	.
Public × $\Delta IncShare_{s,t}^{P99-100}$							0.57	1.30	0.66	-0.04	1.57	0.98
Newspaper FE	Yes			Yes			Yes			Yes		
Newspaper Trends	Yes			Yes			Yes			Yes		
Seasonal FE	Yes			Yes			Yes			Yes		
4 lags of DV	Yes			Yes			Yes			Yes		
R^2	0.33			0.37			0.33			0.37		
N	2820			1604			2775			1555		
N newspapers	32			32			32			32		
Mean T_i	88.1			50.1			86.7			48.6		
Min T_i	58			23			56			21		
Max T_i	127			55			127			51		
Min $Year_{i,t}$	1982			2001			1982			2001		
Max $Year_{i,t}$	2014			2014			2013			2013		
Corr.	psar1			psar1			psar1			psar1		
AR1-p	0.93			0.00			0.79			0.00		

Table A19: Estimates of the association between the tone of economic news reporting across newspapers ($Tone_{i,t}$) and the change in top-1% income share at national (models 1 and 2) and state (models 3 and 4) level, with moderation by ownership-type for each newspaper based on data (updated to 2014) from Dunaway (2008). Models 1 and 3 estimated on all available observations. Models 2 and 4 estimated on all available observations after 2000. All models estimated by OLS with Beck and Katz (1995) panel corrected standard errors.

news that is more class-biased. In Table A19, we show results for models with interactions between ownership type and top-income shares. We see little evidence here that upwardly biased news tone is concentrated among newspapers owned by public companies, with just a hint of an interaction apparent in Model 1 (national level, entire period). Notably, though the significant interactions between ownership type and mean-income growth appeared in the state-level models, the state-level models display no significant interaction for class bias itself.

While the public-private distinction may not fully capture the presence of profit-maximization pressures, these results on the whole provide little support for the notion that class-biased news emerges from cost-cutting journalistic methods.

References

Alvaredo, Facundo, Lucas Chancel, Thomas Piketty, Emmanuel Saez, and Gabriel Zucman. 2017. *Global Inequality Dynamics: New Findings from WID.world*. Working Paper 23119. National Bureau of Economic Research.

Beck, Nathaniel, and Jonathan N. Katz. 1995. "What to do (and not to do) with Time-Series Cross-Section Data". *American Political Science Review* 89 (3): 634–647.

Blood, Deborah J., and Peter C. B. Phillips. 1995. "Recession Headline News, Consumer Sentiment, The State of the Economy and Presidential Popularity: A Time Series Analysis 1989–1993". *International Journal of Public Opinion Research* 7 (1): 2–22.

Boydstun, Amber E., Benjamin Highton, and Suzanna Linn. 2018. "Assessing the Relationship between Economic News Coverage and Mass Economic Attitudes". *Political Research Quarterly* 71 (4): 989–1000.

Curtin, Richard, Stanley Presser, and Eleanor Singer. 2002. "The impact of nonresponse bias on the index of consumer sentiment", ed. by Günter Poser and Daniel Bloesch, 307–23.

De Boef, Suzanna, and Paul M. Kellstedt. 2004. "The political (and economic) origins of consumer confidence". *American Journal of Political Science* 48 (4): 633–649.

Dunaway, Johanna. 2008. "Markets, Ownership, and the Quality of Campaign News Coverage". *Journal of Politics* 70 (4): 1193–1202.

Dunaway, Johanna, and Regina G. Lawrence. 2015. "What Predicts the Game Frame? Media Ownership, Electoral Context, and Campaign News". *Political Communication* 32 (1): 43–60.

Garz, Marcel, and Gregory J. Martin. 2020. "Media Influence on Vote Choices: Unemployment News and Incumbents' Electoral Prospects". *American Journal of Political Science*. Forthcoming.

Gentzkow, Matthew, and Jesse M. Shapiro. 2010. "What Drives Media Slant? Evidence From U.S. Daily Newspapers". *Econometrica* 78 (1): 35–71.

Goidel, Kirby, Stephen Procopio, Dek Terrell, and H. Denis Wu. 2010. "Sources of Economic News and Economic Expectations". *American Politics Research* 38 (4): 759–777.

Hollanders, David, and Rens Vliegenthart. 2011. "The influence of negative newspaper coverage on consumer confidence: The Dutch case". *Journal of Economic Psychology* 32 (3): 367–373.

Hopkins, Daniel J., Eunji Kim, and Soojong Kim. 2017. "Does newspaper coverage influence or reflect public perceptions of the economy?" *Research & Politics* 4 (4).

Nadeau, Richard, Richard G. Niemi, David P. Fan, and Timothy Amato. 1999. "Elite Economic Forecasts, Economic News, Mass Economic Judgments, and Presidential Approval". *Journal of Politics* 61 (1): 109–135.

Sommeiller, Estelle, Mark Price, and Ellis Wazeter. 2016. "Income inequality in the U.S. by state, metropolitan area, and county". Economic Policy Institute. Visited on 10/27/2017. `http://www.epi.org/publication/income-inequality-in-the-us/`.

Wlezien, Christopher, Stuart Soroka, and Dominik Stecula. 2017. "A Cross-National Analysis of the Causes and Consequences of Economic News". *Social Science Quarterly* 98 (3): 1010–1025.