Real Effects of Markets on Politics: Evidence from U.S. Presidential Elections

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Online Appendix

A.I Additional data sources

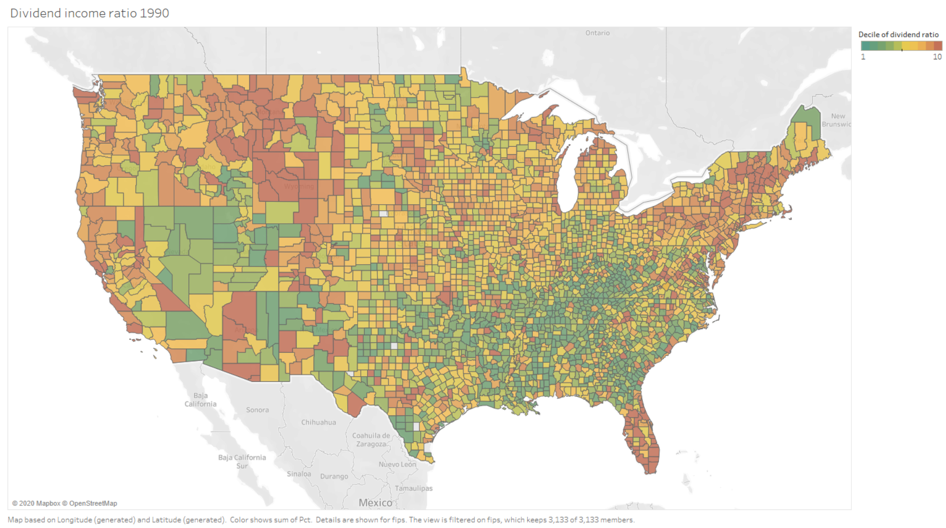
Annual income per capita and total population data are from the Bureau of Economic Analysis (2022). Unemployment rates are from the Bureau of Labor Statistics (2022a), and wages and employment by industry are from Bureau of Labor Statistics (2022b). County population data by age and race are from the Census Bureau (2022b). Educational attainment (percent of people 25 years or older who have a bachelor degree or higher) is from the Census Bureau (2010a). And urban population data in 1990 and 2010 are from the Census Bureau (2010b).

We obtain quarterly aggregate earnings from the Bureau of Labor Statistics (2020b) and unemployment data from the Bureau of Labor Statistics (2020c), real GDP from the Bureau of Economic Analysis (2020), federal funds rates from Board of Governors of the Federal Reserve System (2020) and the credit spread defined as the difference between the Moody's Baa and Aaa bond yields from Moody's (2020). Monthly consumer price index data are from the Bureau of Labor Statistics (2020a).

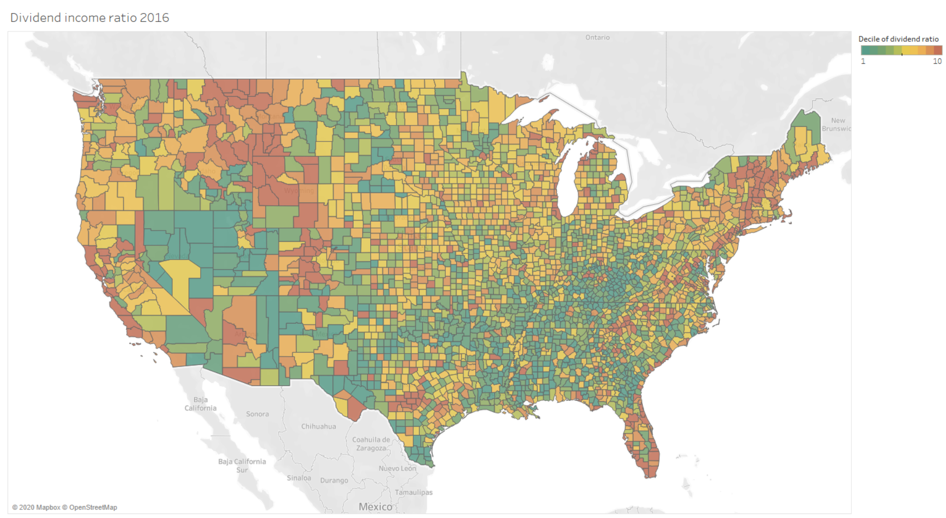
Zip code level tax return data are obtained from the IRS (2021). Daily stock return data are from Center for Research in Security Prices (2021). Corporate headquarters data are from S&P Global (2020). The NAICS and SIC crosswalk data are from the Census Bureau (2022a). Zip code and county cross walk file is obtained from the HUD (2022).

A.II Stock market participation

Figure A.I plots the county-level stock market participation, as measured by the ratio of dividend income over total taxable income, in 1990 and 2016. Table A.I reports the results of regressing the dividend income ratio on various county economic and demographic characteristics, as well as the two instrumental variables discussed in Section A.III.



(a) 1990



(b) 2016

Figure A.I: Stock market participation in 1990 and 2016. This figure shows the decile of the ratio of aggregate dividend income over aggregate taxable income for U.S. counties in 1990 and 2016.

Table A.I: Determinants of stock market participation

The dependent variable is the dividend income ratio (total dividend income in a county relative to total adjusted gross income in that county), measured in percentage points. *Ipc* and *Pop* are income per capita and total population. *White*, *Black*, and *Hispanic* are the fraction of population that is non-Hispanic White, non-Hispanic Black, and Hispanic from Census Bureau's Population Estimates Program. $Under20$ and $Over65$ are the fraction of the population that is under 20, over 65 years old, respectively. $Bachelor_{1990}$ is the fraction of population of age 25 or above with a bachelor's degree or above in 1990. *Headquarters* is an indicator variable equal to one if the county is the headquarters of any publicly traded company, and zero otherwise. Standard errors are clustered by state. P-values are reported in the parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Div_ratio_{1989}	0.743	0.716						
	(0.000)	(0.000)						
$Ln(Ipc)$			1.765	1.739	0.782	0.921	1.700	1.696
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Ln(Pop)$			0.063	0.076	0.024	0.022	0.038	0.058
			(0.126)	(0.063)	(0.412)	(0.481)	(0.364)	(0.160)
$White$			-1.106	-0.989	-0.258	-0.395	-1.074	-0.957
			(0.000)	(0.000)	(0.056)	(0.017)	(0.000)	(0.000)
$Hispanic$			-0.342	-0.141	0.202	0.360	-0.309	-0.127
			(0.004)	(0.070)	(0.063)	(0.008)	(0.006)	(0.100)
$Black$			-0.694	-0.257	0.110	0.195	-0.670	-0.245
			(0.002)	(0.005)	(0.398)	(0.043)	(0.003)	(0.006)
$Under20$			-4.613	-4.851	-1.994	-1.542	-4.530	-4.727
			(0.000)	(0.000)	(0.004)	(0.008)	(0.000)	(0.000)
$Over65$			6.171	5.977	8.761	8.862	6.215	6.019
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Bachelor_{1990}$					0.060	0.053		
					(0.000)	(0.000)		
$Headquarters$							0.160	0.113
							(0.001)	(0.001)
Year FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
State*year FE	No	Yes	No	Yes	No	Yes	No	Yes
R-squared	0.660	0.697	0.353	0.467	0.442	0.521	0.356	0.468
N	24856	24848	24871	24863	24862	24854	24871	24863

A.III IV estimation

In this section we present analysis related to the robustness of the main results presented in the manuscript. We conduct an instrumental variable analysis, instrumenting for participation in two ways. Our first IV is county level education, measured as the fraction of population of age 25 or above with a bachelor's degree or above as of 1990. Because the dependent variable is the *change* in vote shares, using education prior to the beginning of the sample period helps minimize the possibility that the exclusion condition is violated due to reverse causality or omitted time-varying county characteristics. For example, while education levels could be correlated with voters' party affiliation (e.g., Marshall, 2019), it is much less likely to directly affect changes in county vote shares. The exclusion condition, however, can be violated if education is correlated with omitted county characteristics that cause counties to have a differential sensitivity to stock returns other than through stock market participation. For example, education could be correlated with income levels and job types, which may in turn be correlated with exposure to stock market performance through other channels than stock market participation. We therefore continue to control for the interaction of county variables including income levels with stock returns, and on top of that we also further control for the interaction of (lagged) industry employment shares at the country level and stock returns.[1]

Columns (5) and (6) of Table A.I show that county-level stock market participation increases significantly with the education level in 1990. The first two columns of Table A.II report the results where we use the 1990 education as an instrument for dividend income ratio and its interaction with stock returns as an instrument for the interaction between dividend income ratio and stock returns. The point estimates are similar with year effects and with state×year fixed effects and both are much larger than the OLS estimate.

Our second IV is an indicator for whether there are publicly traded firms headquartered within the county, motivated by evidence that investors tend disproportionately to invest in stocks of the companies headquartered in their local communities (Brown,

[1]The ten industries in the QCEW data include natural resources and mining, construction, manufacturing, trade and transportation, information, financial services, professional and business services, education and health services, leisure and hospitality, and other services.

Ivkovic, Smith, and Weisbenner, 2008).[2] The last two columns of Table A.I shows the indicator variable is positively related to stock participation after controlling for local income, population, and demographics, and state×year fixed effects. Columns (3) and (4) of Table A.II show that using headquarters as an IV produces an estimate of 6.64 and 2.79 without and with state×year fixed effects, respectively.[3]

While the substantially larger point estimates of the IV estimation might indicate that the OLS estimate is downward biased, it is also possible that the average effect across all counties is substantially smaller than the effect for counties whose stock market participation is affected by education and headquarters location of publicly traded companies (local average treatment effect). Overall, these IV results support the view that the effect of the stock market is through stock market participation and not some other omitted county characteristics.

[2] We obtain the most recent zip codes of headquarters from Compustat, and historical states of headquarters extracted from the SEC's EDGAR database and from Professor Scott Dyreng. Whenever a company moves its headquarters across state or there is discrepancy in the headquarters states between Compustat and Scott Dyreng's data, we manually collect zip codes of a company's business address. In total, we collected around 3,500 headquarter locations from EDGAR. We then construct an indicator variable at the county year level, which is equal to 1 if a county is the headquarters of any publicly traded company in that year, and zero otherwise.

[3] We obtain similar estimates if we exclude investment companies, which are likely to choose endogenously to locate in areas with high stock participation.

Table A.II: IV estimation

The dependent variable is the change in incumbent vote shares, defined in Table 2 of the manuscript. In the first two columns, the instrument for dividend income ratio is the fraction of population of age 25 or above with a bachelor's degree or above in 1990. In the last two columns, the instrument is an indicator variable for whether a county is the headquarters of any publicly traded company. The instrument for the interaction of dividend income ratio and stock returns is the interaction of the instrument with stock returns. ret is the cumulative stock market return from November of the previous election year to October before the current election. $DemIncum$ is an indicator variable equal to 1 if the incumbent party is Democratic, and 0 otherwise. $\Delta Controls$ denotes the difference in the county economic and demographic variables shown in Table 2 of the manuscript. $Controls * ret$ is the interaction between the level of the control variables as of the previous election and ret. $Occupation * ret$ is the interaction between county-level industry employment share as of the previous election and ret. The levels of these controls are also included. Standard errors are clustered by year. P-values are reported in the parentheses.

	Education		*Headquarter*	
	(1)	(2)	(3)	(4)
$Div\_ratio \times ret$	4.29	4.20	6.64	2.79
	(0.012)	(0.007)	(0.014)	(0.030)
Div_ratio	−2.07	−2.10	−2.57	−0.80
	(0.018)	(0.017)	(0.002)	(0.142)
Year FE	*Yes*	*No*	*Yes*	*No*
ΔControls	*Yes*	*Yes*	*Yes*	*Yes*
ΔControls*DemIncum	*Yes*	*Yes*	*Yes*	*Yes*
Controls*ret	*Yes*	*Yes*	*Yes*	*Yes*
Occupation*ret	*Yes*	*Yes*	*Yes*	*Yes*
State*year FE	*No*	*Yes*	*No*	*Yes*
R-squared	0.125	0.114	0.070	0.145
N	24862	24854	24871	24863

A.IV Alternative measures of market participation

In this section, we address concerns about measurement error in county stock participation discussed in the data section of the manuscript. We adopt three alternative measures of stock participation. First, to address concerns that a county's total dividends can be largely driven by a handful of residents with very high amounts of dividend income, we use a similar measure of dividend income ratio but exclude tax returns from people in the highest income group in a county. Specifically, since 2006, the IRS reports income data by adjusted gross income (AGI) groups, with the top group being those whose AGI exceeds $200,000. Because AGI includes dividend income, by excluding this group of people, the dividend income ratio at the county level will not be driven by a few returns in the far right tail of dividend income. Column (1) of Table A.III reports the results, which show a larger point estimate on the main interaction term than that reported in column (3) of Table 2 of the manuscript.[4]

Second, we measure a county's participation by the fraction of tax returns that report dividend income. Such a measure treats all people with exposure to the stock market equally regardless of their actual investment in the stock market. Column (2) reports the results, which are consistent with what we find when using dividend income ratio to proxy for stock market participation.

Third, we measure a county's participation by its per-capita dividend income. Using this measure assumes that two counties with the same per-capita dividend income have the same sensitivity to stock returns, irrespective of the county's total income levels. Column (3) shows that the interaction between this measure and stock returns is positive and significant.

[4] Dividend income ratio in 2006 is used for the 2008 and prior elections in this regression.

Table A.III: Alternative measures of stock participation

The dependent variable is the change in the incumbent vote share, defined in Table 2 of the manuscript. *Div_ratio_exctop* is the dividend income ratio of residents whose total adjusted gross income is below \$200,000. *ret* is the cumulative stock market return from November of the previous election year to October before the current election. *Participation* is the fraction of income tax returns that report dividend income in a county during the last election year. *Div_pop* is the amount of dividends divided by a county's population. *DemIncum* is an indicator variable equal to 1 if the incumbent party is Democratic, and 0 otherwise. $\Delta Controls$ denotes the difference in the county economic and demographic variables shown in Table 2 of the manuscript. $Controls * ret$ is the interaction between the level of the control variables as of the previous election and *ret*. The levels of these controls are also included. Standard errors are clustered by year. P-values are reported in the parentheses.

	(1)	(2)	(3)
Div_ratio_exctop×*ret*	2.00		
	(0.001)		
Participation×*ret*		0.47	
		(0.003)	
Div_pop×*ret*			0.03
			(0.039)
Div_ratio_exctop	−1.11		
	(0.001)		
Participation		−0.22	
		(0.009)	
Div_pop			−0.01
			(0.089)
Year FE	*Yes*	*Yes*	*Yes*
ΔControls	*Yes*	*Yes*	*Yes*
ΔControls*DemIncum	*Yes*	*Yes*	*Yes*
Controls*ret	*Yes*	*Yes*	*Yes*
R-squared	0.739	0.744	0.736
N	24866	24866	24871

A.V Permutation tests

To examine whether the small number of clusters remains a concern about over-rejection (Cameron, Gelbach, and Miller, 2008), we conduct permutation tests in the spirit of randomization inference commonly used in experimental studies (e.g., Young, 2019, MacKinnon and Webb, 2020).[5] We randomly reassign the eight stock returns to eight elections, while fixing county-level voting, dividend income ratio, and controls. For each permutation of returns, we re-estimate the same models as before and store the estimated coefficients and t-statistics. Taking the specification in column (3) of Table 2 of the manuscript as an example, out of the 10,000 permutations, 134 produce a t-statistic greater than the actual t-statistic of 4.03. The permutation based one-sided p-value is therefore 0.013. This is slightly larger than the p-value 0.005 reported in the table.

A.VI What returns matter to voters?

In this section we extend the analysis of the market's impact on voting by exploring the impact of returns in more detail. We ask whether voters distinguish local stock returns from the nationwide market return. We then examine the timing of returns – the returns early in the incumbent's term versus the returns leading up to the next election at the end of the incumbent's term.

A.VI.1 Local vs. market returns

We explore whether a county's vote is also sensitive to the return of industries or companies that the county is mostly exposed to, which we call "local returns", after controlling for aggregate stock returns. It is not clear ex ante whether and how local returns could affect voting outcomes above and beyond aggregate returns. On the one hand, to the extent that investors exhibit local bias in investing or have greater exposure to local companies' stock performance for other reasons, their stock market wealth would be sensitive to local returns even controlling for overall market performance. On the other hand, if voters that participate in the stock market are better diversified,

[5] These include both field experiments and studies relying on natural experiments (Hsiang and Jina, 2014, Cunningham and Shah, 2018, Gagliarducci, Onorato, Sobbrio, and Tabellini, 2020).

counties with high participation might be less sensitive to the performance of local industries because they have greater national exposure.

We measure local returns in two ways. First, as in Di Maggio, Kermani, Ramcharan, Yao, and Yu (2022), we calculate industry returns at the 4-digit NAICS level by the value-weighted returns of companies in each industry. We then use data from QCEW to calculate a county's employment share at the 4-digit NAICS level and calculate an employment-share-weighted industry return. Second, we measure local returns using the value-weighted return of companies headquartered in the same state. The correlations between the aggregate return and both local returns are around 0.5.

Table A.IV presents the results. Column (1) shows that the interaction between stock participation and local industry returns is not significantly different from zero. Column (2) shows that the interaction between stock participation and returns of locally headquartered public companies is positive and significant at the 10% level, controlling for the effect of aggregate returns. One interpretation of the result is that stock investors have a larger relative exposure to the performance of public companies headquartered locally.[6,7]

A.VI.2 The timing of stock returns

We examine eight returns measured over shorter windows to see if they have additional explanatory power above and beyond the total four-year returns: returns during the first week, month, quarter, and year of the four-year period (returns during and immediately following the election in which the incumbent was elected), and returns during the last week, month, quarter, and year of the four-year period (the returns immediately preceding the election of interest in our tests). Table A.V presents results where we include the interaction between dividend ratio and the four-year total return, as well as the interaction between dividend ratio and one of the shorter-window returns.

[6] Seasholes and Zhu (2010) reports that roughly 30% of the portfolio of the average U.S. household is invested in stocks headquartered within 250 miles of the family's home.

[7] Chodorow-Reich, Nenov, and Simsek (2021) attempts to get more accurate county level exposure to stock returns by using county demographic information and variation in betas across the age distribution. We do not implement this exercise for two reasons. First, Chodorow-Reich et al. (2021) acknowledge that the effect of this adjustment is likely to be small because the county level betas all lie between 0.97 and 1.03. Second, in our estimation we allow voters of different age group to have differential sensitivity to stock returns by directly controlling for the interaction between age and stock returns.

Table A.IV: Presidential elections and local stock returns

The dependent variable is the change in incumbent vote shares, defined in Table 2 of the manuscript. Div_ratio is the county dividend income ratio (total dividend income in a county relative to total adjusted gross income in that county) during the last election year. ret is the cumulative stock market return from November of the previous election year to October before the current election. In column (1), local return is the county-level employment-share-weighted industry returns, where industry returns at the 4-digit NAICS level are the value-weighted returns of companies in each industry. In column (2), local return is the value-weighted return of companies headquartered in the same state. $DemIncum$ is an indicator variable equal to 1 if the incumbent party is Democratic, and 0 otherwise. $\Delta Controls$ denotes the difference in the county economic and demographic variables shown in Table 2 of the manuscript. $Controls * ret$ is the interaction between the level of the control variables as of the previous election and ret. The levels of these controls are also included. Standard errors are clustered by year. P-values are reported in the parentheses.

	County industry	State headquarter
$Div\_ratio \times ret$	1.59	1.35
	(0.005)	(0.010)
Div_ratio	−0.84	−0.93
	(0.014)	(0.005)
$Div\_ratio \times Local\ ret$	0.02	0.50
	(0.886)	(0.056)
$Local\ ret$	0.00	−0.01
	(0.908)	(0.122)
Year FE	Yes	Yes
ΔControls	Yes	Yes
ΔControls*DemIncum	Yes	Yes
Controls*ret	Yes	Yes
R-squared	0.730	0.740
N	23385	24863

None of the other return interactions is statistically significant after controlling for the total four-year return.

Table A.V: Presidential elections and sub-period stock returns

The dependent variable is the change in incumbent vote shares, defined in Table 2 of the manuscript. Div_ratio is the county dividend income ratio (total dividend income in a county relative to total adjusted gross income in that county) during the last election year. ret_{4year} is the cumulative stock market return from November of the previous election year to October before the current election. ret_{other} refers to returns indicated in the table header. For returns at the beginning of the four-year period, the first year return is the cumulative return between November of the previous election year to December of the following year; the first quarter return is cumulative return between November of the previous year to January of the following year; the first month return is the return in November of the previous election year; and the first week return is the weekly return during the week of the previous election. For returns at the end of the four-year period, the last year return is the cumulative return between January and October of the election year; the last quarter return is cumulative return between August and October; the last month return is the return in October; and the last week return is the weekly return during the week right before the election. $DemIncum$ is an indicator variable equal to 1 if the incumbent party is Democratic, and 0 otherwise. $\Delta Controls$ denotes the difference in the county economic and demographic variables shown in Table 2 of the manuscript. Standard errors are clustered by year. P-values are reported in the parentheses.

	ret_{other}							
	First year	First quarter	First month	First week	Last year	Last quarter	Last month	Last week
$Div\_ratio \times ret_{4year}$	1.89	2.11	2.12	2.11	2.00	1.95	2.02	2.24
	(0.020)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Div\_ratio \times ret_{other}$	0.59	0.04	-0.11	0.09	0.49	2.19	1.23	-4.47
	(0.772)	(0.997)	(0.917)	(0.986)	(0.519)	(0.226)	(0.616)	(0.452)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ΔControls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\Delta Controls * DemIncum$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.715	0.715	0.716	0.716	0.716	0.716	0.716	0.716
N	24871	24871	24871	24871	24871	24871	24871	24871

A.VI.3 Is the effect of stock returns linear?

Our model specification in the manuscript assumes that stock holders' propensity to vote for the incumbent party increases linearly with stock returns. In this section, we perform some simple analyses to examine to what extent the results are driven by very positive or very negative returns. Specifically, we create two indicator variables, one for the two elections with the highest preceding 4-year real returns (1996 and 2000), and the other for the two elections with the lowest preceding 4-year real returns (2004 and 2008). We then create interactions between dividend ratios and these two indicators. The first two columns of Table A.VI show that in elections with high (low) returns, high stock participation counties are more (less) likely to vote for the incumbent party. Column (3) shows, when both interaction terms are included, both terms are statistically significant and it cannot be rejected that the two terms have the same (absolute) magnitude. Thus it does not appear that voters react more strongly to positive or negative returns.

A.VII Voter turnout

The increase in incumbent vote share in high participation counties following good stock market performance could be due to voters switching to the incumbent party, or the incumbent party attracting voters who would have otherwise not voted at all. To distinguish these explanations, we examine the effect on voter turnout.[8] In addition, turnout may be an interesting outcome variable in its own right, as it reflects citizens' political and civil engagement and affects societal welfare (Mueller and Stratmann, 2003, Krishna and Morgan, 2011).[9] Prior literature on economic voting produces mixed predictions on turnout, as it has been argued that economic downturns may induce people to mobilize to participate in elections, but it may also lead them to withdraw from the political process (Rosenstone, 1982, Radcliff, 1992).[10]

[8] Turnout is only observed at the aggregate level. Because we do not observe which individuals vote in each election, it is difficult to completely rule out voter composition changes that do not result in large differences in the number of votes.

[9] Additional studies of turnout include, among others, Rosenstone (1982), Gentzkow (2006), Gentzkow, Shapiro, and Sinkinson (2011), and Charles and Stephens (2013).

[10] Recent evidence supports the view that a reduction in wealth due to housing price declines leads to a reduction in voter turnout (McCartney, 2021).

Table A.VI: Is the effect of stock returns on voting linear?

The dependent variable is the change in the incumbent vote share, defined in Table 2 of the manuscript. *Div_ratio* is the county dividend income ratio (total dividend income in a county relative to total adjusted gross income in that county) during the last election year. *high_ret* is an indicator variable for the two elections with the highest preceding 4-year real returns (1996 and 2000). *low_ret* is an indicator variable for the two elections with the lowest preceding 4-year real returns (2004 and 2008). *DemIncum* is an indicator variable equal to 1 if the incumbent party is Democratic, and 0 otherwise. $\Delta Controls$ denotes the difference in the county economic and demographic variables shown in Table 2 of the manuscript. Standard errors are clustered by year. P-values are reported in the parentheses.

	(1)	(2)	(3)
Div_ratio×*high_ret*	1.14		0.78
	(0.018)		(0.086)
Div_ratio×*low_ret*		-1.51	-1.27
		(0.001)	(0.015)
Div_ratio	-0.42	0.17	-0.06
	(0.314)	(0.593)	(0.882)
Year FE	Yes	Yes	Yes
ΔControls	Yes	Yes	Yes
ΔControls*DemIncum	Yes	Yes	Yes
R-squared	0.712	0.714	0.716
N	24871	24871	24871

We estimate a model specification similar to Eq. (1) in the manuscript, where the dependent variable is now the change in turnout defined as the number of votes in a county divided by the county population aged 20 or above, as in Charles and Stephens (2013). Column (1) of Table A.VII shows that recent stock market performance has a negative and marginally statistically insignificant effect on turnout. In column (2), when we further control for state×year fixed effects, the effect on turnout becomes smaller and remains statistically insignificant. Therefore, there is some weak evidence that turnout in high participation counties declines following good stock returns, relative to low participation counties.[11]

We next examine whether the stock market's effect on vote share varies with changes

[11] Charles and Stephens (2013) find that higher local wages and employment lower turnout in almost all other elections but the presidential elections. The authors view their findings being consistent with information-based models of voting. Specifically, better labor market conditions raise the time costs of voters, which is much higher for local and congressional elections since the information for presidential candidates is more ubiquitous.

in turnout. The triple interaction term is negative and statistically significant in column (3), and is close to zero and insignificant in column (4) when state$\times$year fixed effects are included in the estimation. The point estimates of the main interaction terms, measuring the effect when there is no change in turnout (which is close to the sample mean), are close to those reported in Table 2 of the manuscript. Overall, we conclude that while returns have a small effect on turnout, this appears to be distinct from the effect on incumbent vote share, suggesting that returns affect vote share mostly through the intensive margin.

Table A.VII: Stock returns and voter turnout

The dependent variable is the change in voter turnout in the first two columns, defined as the number of total votes divided by the population aged 20 or older in a county. The dependent variable in columns (3) and (4) is the change in incumbent vote share. *Div_ratio* is the county dividend income ratio (total dividend income in a county relative to total adjusted gross income in that county) during the last election year. *ret* is the cumulative stock market return from November of the previous election year to October before the current election. *DemIncum* is an indicator variable equal to 1 if the incumbent party is Democratic, and 0 otherwise. $\Delta Controls$ denotes the difference in the county economic and demographic variables shown in Table 2 of the manuscript. $Controls * ret$ is the interaction between the level of the control variables as of the previous election and *ret*. The levels of these controls are also included. Standard errors are clustered by year. P-values are reported in the parentheses.

	ΔTurnout		ΔIncumbent vote share	
	(1)	(2)	(3)	(4)
$Div\_ratio \times ret$	−0.38	−0.18	1.88	1.01
	(0.162)	(0.210)	(0.004)	(0.004)
Div_ratio	0.06	−0.01	−0.98	−0.47
	(0.638)	(0.870)	(0.004)	(0.070)
$Div\_ratio \times ret \times \Delta turnout$			−12.97	−0.75
			(0.045)	(0.854)
$Div\_ratio \times \Delta turnout$			3.30	−0.50
			(0.303)	(0.827)
$ret \times \Delta turnout$			0.45	0.27
			(0.008)	(0.012)
Year FE	*Yes*	*No*	*Yes*	*No*
ΔControls	*Yes*	*Yes*	*Yes*	*Yes*
ΔControls*DemIncum	*Yes*	*Yes*	*Yes*	*Yes*
Controls*ret	*Yes*	*Yes*	*Yes*	*Yes*
State*year FE	*No*	*Yes*	*No*	*Yes*
R-squared	0.600	0.738	0.737	0.865
N	24871	24863	24871	24863

A.VIII County characteristics

Because the overall effect of the interaction between market returns and participation on voting outcomes is largely driven by party switching, one might expect the magnitude of the effect to be directly related to factors that determine how likely voters are to switch parties. We begin by examining whether the effect of stock returns varies with county-level partisanship and ideology. One might expect economic conditions to be less important in partisan counties because their voters are more likely to identify strongly with one party and thus are less likely to switch parties as a result of economic performance. The effect of economic conditions could also be weaker because partisan voters tend to have biased assessments of current and expected future economic performance (Gerber and Huber, 2009, Mian, Sufi, and Khoshkhou, 2021, Meeuwis, Parker, Schoar, and Simester, 2022). There is also evidence that voter evaluation of government policy varies with ideology (i.e., conservative vs liberal, see, e.g., Kriner and Reeves, 2012). We test for heterogeneous effects by performing the estimation using sub-samples of counties with varying levels of partisanship and political affiliation.

We start by estimating the effect of the main interaction term within subsets of counties sorted by the average Democratic vote share. Figure A.II plots the point estimates of the main interaction term by decile of county Democratic vote share. It appears that the effect is stronger among more Democratic leaning counties. But we still see a significantly positive effect even among the most partisan counties (top and bottom tercile). This visual evidence is consistent with the results shown in Panel A of Table A.VIII, where we split counties by partisanship (identified as those in the top and bottom decile of average Democratic share of the two-party vote), and the tendency to vote for the Democratic party. The point estimates are very close between the most partisan counties and other counties. On the other hand, the effect is substantially larger in more Democratic-leaning counties.[12] These results suggest that Republican voters are relatively less likely to be swayed at the ballot box by stock market returns.

We next examine whether the effect we document varies with political activeness. Greater political engagement is generally associated with greater media consumption and political knowledge, which could influence the impact of economic conditions on voting (Alt, Lassen, and Marshall, 2016) or the informational value of stock market performance. The sign or the intensity of the influence, however, is not a priori clear. On the one hand, politically active voters maybe less influenced by economic issues because there could be many other more important factors influencing their voting decisions. On the other hand, in politically active areas, greater media consumption and greater exposure to political campaigns could make economic issues more salient

[12] Untabulated test results show that the difference is statistically significant at the 1% level without state×year fixed effects, and is significant at the 10% level with state×year fixed effects.

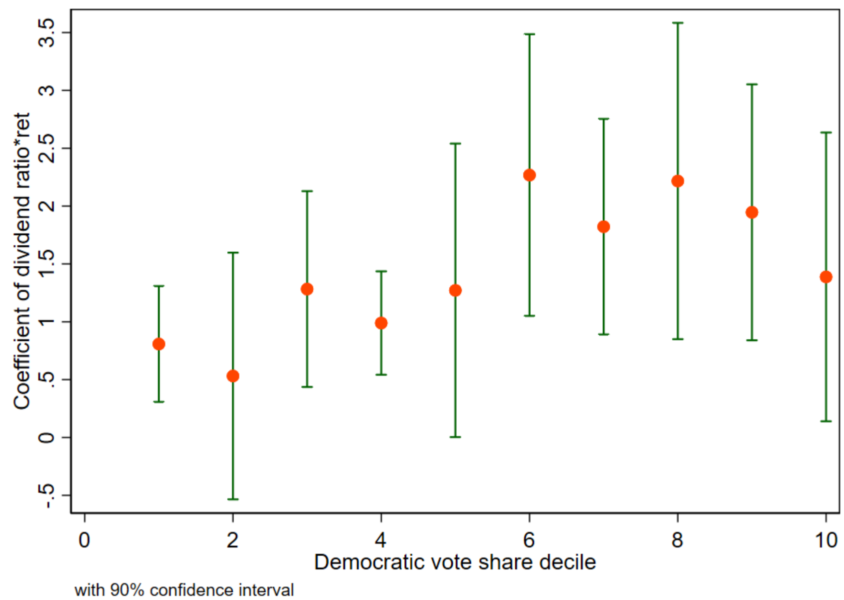


Figure A.II: Point estimate of dividend ratio-return interaction by decile of Democratic share of the two-party vote. For each decile of Democratic share of the two-party vote, we estimate Eq. (1) from the manuscript using the same controls as those in column (3) of Table 2 of the manuscript. The 90% confidence intervals are based on standard errors clustered by year and the T distribution with 7 degrees of freedom.

among voters and thus enhance the impact of stock market performance.

Political activeness is measured by whether a county is located in a swing state and by voter turnout. In particular, counties are considered to be politically active if they are located in swing states (Kriner and Reeves, 2012, Bonaparte and Kumar, 2013) or they had above-median voter turnout in the previous election (Powell, 1986, Bonaparte and Kumar, 2013).[13] Following Geruso, Spears, and Talesara (2022), our list of swing states include Colorado, Florida, Iowa, Michigan, Minnesota, Ohio, Nevada, New Hampshire, North Carolina, Pennsylvania, Virginia, and Wisconsin. Panel B shows that the point estimate is not substantially different between swing states and non-swing states, but is substantially smaller in counties with high turnout.[14]

[13]Note that here we use variation across counties in the level of turnout in the prior election. In prior tests of the extensive margin impacts of the market, we tested for changes in turnout in a given county. This within-county measure removes any persistent differences in turnout levels, which controls for these differences in activism.

[14]The difference between high-turnout and low-turnout counties is statistically significant at the 1% level without state×year fixed effects, and is significant at the 5% level with state×year fixed effects..

Overall, the heterogeneity tests reveal that the effect of stock returns appears to be stronger in Democratic-leaning counties and in areas that are less political active as indicated by low voter turnout. But we do not find that the effect varies with partisanship or swing state status. These results could have implications for how elected officials might set policies to cater to certain constituents in an effort to mitigate or accentuate the heterogeneous effects of market returns.

Table A.VIII: Stock returns and presidential elections: differences across constituent characteristics

The dependent variable is the change in incumbent vote shares, defined in Table 2 of the manuscript. Div_ratio is the county dividend income ratio (total dividend income in a county relative to total adjusted gross income in that county) during the last election year. ret is the cumulative stock market return from November of the previous election year to October before the current election. Partisan counties are those in the top and bottom decile of average Democratic share of the two-party vote. Democratic-leaning counties are those in the top half of average Democratic share of the two-party vote. Swing states include Colorado, Florida, Iowa, Michigan, Minnesota, Ohio, Nevada, New Hampshire, North Carolina, Pennsylvania, Virginia, and Wisconsin. Low and high turnout counties are those with voter turnout below and above the median during the previous election. $DemIncum$ is an indicator variable equal to 1 if the incumbent party is Democratic, and 0 otherwise. $\Delta Controls$ denotes the difference in the county economic and demographic variables shown in Table 2 of the manuscript. $Controls * ret$ is the interaction between the level of the control variables as of the previous election and ret. The levels of these controls are also included. Standard errors are clustered by year. P-values are reported in the parentheses.

Panel A: Ideology								
	Partisan				Dem-leaning			
	Yes	No	Yes	No	Yes	No	Yes	No
$Div\_ratio \times ret$	1.63	1.61	1.14	1.06	2.06	1.07	1.29	0.66
	(0.003)	(0.010)	(0.020)	(0.004)	(0.004)	(0.009)	(0.013)	(0.037)
Div_ratio	−0.92	−0.84	−0.50	−0.50	−0.86	−0.79	−0.48	−0.40
	(0.002)	(0.008)	(0.080)	(0.037)	(0.016)	(0.004)	(0.106)	(0.076)
R-squared	0.692	0.759	0.840	0.879	0.729	0.771	0.863	0.883
N	4973	19898	4941	19898	12432	12439	12424	12439

Panel B: Political activeness								
	Swing states				Turnout			
	Yes	No	Yes	No	High	Low	High	Low
$Div\_ratio \times ret$	1.18	1.64	1.13	0.93	1.18	2.03	0.77	1.31
	(0.008)	(0.010)	(0.007)	(0.024)	(0.009)	(0.002)	(0.048)	(0.001)
Div_ratio	−0.40	−0.95	−0.42	−0.48	−0.77	−0.95	−0.39	−0.57
	(0.167)	(0.003)	(0.135)	(0.057)	(0.009)	(0.004)	(0.091)	(0.020)
R-squared	0.799	0.731	0.878	0.859	0.742	0.751	0.868	0.870
N	7093	17778	7093	17770	12435	12436	12428	12409
Year FE	*Yes*	*Yes*	*No*	*No*	*Yes*	*Yes*	*No*	*No*
ΔControls	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
ΔControls*DemIncum	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Controls*ret	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
State*year FE	*No*	*No*	*Yes*	*Yes*	*No*	*No*	*Yes*	*Yes*

A.IX Election characteristics

In this subsection, we examine potential variation in the effect of the stock market across elections. Because we have only eight elections in the sample, tests using subsamples of elections may have lower power, particularly when there is little variation in returns within the subsamples. Nevertheless, we first examine whether the estimated effects differ depending on whether an incumbent president is running for reelection. One might expect the attribution effect and thus the economic voting channel to be stronger when the incumbent president is up for reelection. The first two columns of Table A.IX, Panel A show that the point estimate of the interaction term is substantially larger in the 1992, 1996, 2004, 2012, and 2020 elections during which the incumbent president ran for reelection.[15] However, columns (3) and (4) show that when we look at within state variation, the two point estimates are almost identical.

Second, we split the sample by whether the Democratic or the Republican party won the election. This test aims to shed light on whether our results can be partially explained by the theory of Pástor and Veronesi (2020), to the extent that their mechanism of changing risk aversion is stronger for stock owners. For example, stock owners might have become more risk averse in 2008 and thus were more likely to vote for the Democratic party, as opposed to a case in which stock owners vote against the incumbent party, which happened to be Republican. Of course, while this is plausible in theory, it does not explain the patterns we observe in other elections such as 2000 or 2016, where a Republican president was elected after good returns (consistent with Pástor and Veronesi (2020)'s theory) but people who own more stocks were more likely to vote for the Democratic candidate. In essence, this alternative explanation would predict that stock market participants always vote more favorably for the winning party, whereas our results show that stock market participants tend to vote more favorably for the incumbent party that "delivers" good returns. Panel B shows that stock returns impact voting even among the subsample of elections where the same party wins, although the tests generally have low power.

[15] The difference, however, is not statistically significant, which may not be surprising given that we generally have low power in the split-election tests.

Table A.IX: Stock returns and presidential elections: differences across election characteristics

The dependent variable is the change in incumbent vote shares, defined in Table 2 of the manuscript. *Div_ratio* is the county dividend income ratio (total dividend income in a county relative to total adjusted gross income in that county) during the last election year. *ret* is the cumulative stock market return from November of the previous election year to October before the current election. Columns (1) and (3) of Panel A use the subsample of elections of 1992, 1996, 2004, 2012, and 2020, columns (2) and (4) of Panel A 2000, 2008, and 2016, columns (1) and (3) of Panel B 1992, 1996, 2008, 2012, and 2020, and columns (2) and (4) of Panel B 2000, 2004, and 2016. *DemIncum* is an indicator variable equal to 1 if the incumbent party is Democratic, and 0 otherwise. $\Delta Controls$ denotes the difference in the county economic and demographic variables shown in Table 2 of the manuscript. $Controls * ret$ is the interaction between the level of the control variables as of the previous election and ret. The levels of these controls are also included. Standard errors are clustered by year. P-values are reported in the parentheses.

Panel A: Incumbent president running				
	Yes	No	Yes	No
$Div\_ratio \times ret$	2.18	1.35	1.04	1.06
	(0.013)	(0.283)	(0.002)	(0.256)
Div_ratio	−1.32	−0.44	−0.83	−0.00
	(0.003)	(0.480)	(0.000)	(0.988)
Year FE	Yes	Yes	No	No
$\Delta Controls$	Yes	Yes	Yes	Yes
ΔControls*DemIncum	Yes	Yes	Yes	Yes
Controls*ret	Yes	Yes	Yes	Yes
State*year FE	No	No	Yes	Yes
R-squared	0.833	0.316	0.905	0.693
N	15543	9328	15538	9325

Panel B: Democrat won				
	Yes	No	Yes	No
$Div\_ratio \times ret$	1.73	1.59	0.36	1.55
	(0.032)	(0.244)	(0.142)	(0.177)
Div_ratio	−1.08	−0.64	−0.46	−0.38
	(0.006)	(0.387)	(0.003)	(0.373)
Year FE	Yes	Yes	No	No
$\Delta Controls$	Yes	Yes	Yes	Yes
ΔControls*DemIncum	Yes	Yes	Yes	Yes
Controls*ret	Yes	Yes	Yes	Yes
State*year FE	No	No	Yes	Yes
R-squared	0.790	0.651	0.893	0.820
N	15542	9329	15537	9326

A.X Stock returns and macroeconomic shocks.

Table A.X reports the coefficients of dividend income ratio interacted with stock returns while controlling for dividend income ratio interacted with various aggregate shocks between elections.

Table A.X: Stock participation and other aggregate shocks

This table reports the estimation results when controlling for dividend income ratio interacted with other aggregate shocks between elections. These aggregate shocks, indicated in the table header, include real GDP growth, real wage growth, change in unemployment rate, change in effective federal funds rates, and change in credit spread. The dependent variable is the change in incumbent vote shares, defined in Table 2 of the manuscript. *Div_ratio* is the county dividend income ratio (total dividend income in a county relative to total adjusted gross income in that county) during the last election year. *ret* is the cumulative stock market return from November of the previous election year to October before the current election. *DemIncum* is an indicator variable equal to 1 if the incumbent party is Democratic, and 0 otherwise. $\Delta Controls$ denotes the difference in the county economic and demographic variables shown in Table 2 of the manuscript. Standard errors are clustered by year. P-values are reported in the parentheses.

	ΔGDP	$\Delta Wage$	$\Delta Unemp\,rate$	$\Delta FF\,rate$	$\Delta Cre\,spread$
	(1)	(2)	(3)	(4)	(5)
$Div\_ratio \times ret$	1.73	2.06	1.15	1.58	2.23
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Div_ratio	−1.47	−0.99	−0.62	−0.67	−1.03
	(0.009)	(0.001)	(0.000)	(0.049)	(0.001)
Year FE	Yes	Yes	Yes	Yes	Yes
ΔControls	Yes	Yes	Yes	Yes	Yes
ΔControls*DemIncum	Yes	Yes	Yes	Yes	Yes
Div_ratio*Header var	Yes	Yes	Yes	Yes	Yes
R-squared	0.716	0.716	0.720	0.716	0.716
N	24871	24871	24871	24871	24871

A.XI Comprehensive specification analysis

In this section, we use a permutation-based approach following Simonsohn, Simmons, and Nelson (2020) to examines the robustness of our main finding to a variety of different empirical specifications and samples. We estimate the incumbent vote share as a function of market returns and stock market participation using a randomly chosen sample and specification. We repeat this one thousand times, and analyze the resulting series of coefficients of interest. The size of the sample in terms of elections used is randomly determined. Specifically, we randomly drop elections from our sample, where each election is equally likely to be dropped, and we randomly choose to drop either two, one, or no elections. At each iteration, we also randomly select 75% of the counties. The control variables included in each regression are also randomized. In particular, we include a randomly chosen alternative interaction control variable, varying either the macro variable (in addition to the market return) or the cross-sectional variable (in addition to participation) with equal probability. The alternative macro variables are the same as those considered in Table 3 of the manuscript: change in aggregate wages, change in unemployment rate, change in federal funds rate, GDP growth, and change in credit spread. The alternative cross-sectional variables are: income per capita, population, county unemployment rate, fraction of population that is Caucasian, black population fraction, Hispanic population fraction, fraction of population under 20 years old, and fraction above 65 years old.

We then estimate the coefficient on $Div\_ratio \times ret$ for each of the one thousand permutations and present the results in Figure A.III. The coefficients are sorted by magnitude, and presented in order with the smallest estimated relationship on the left to highest on the right. The median estimate is 2.07, which is similar to many estimates throughout our paper. Out of all one thousand estimates, 997 are positive and only three are negative.

To compare these findings to what is expected under the null, we randomly assign stock market participation to counties and then repeat the permutation approach described above which generates 1,000 estimates. Finally, we repeat this process 1,000 times, each time reshuffling stock market participation across counties and estimating 1,000 coefficients. Randomly assigning stock market participation constructs the distribution under the null, and requires no assumptions regarding dependence. Instead, we only assume that participation is exchangeable, i.e., any county could have the participation of any other county.

We can use these bootstrapped estimates constructed under the null to test the significance of any given estimate, or of the estimates jointly. Regarding the significance of individual estimates, all of our 1,000 coefficients estimated using the actual data are statistically significant (three negative and 997 positive). Regarding the joint significance implied by the entire specification curve, we follow Simonsohn et al. (2020) and compare the fraction of estimates with a positive sign among the actual data to that in the bootstrapped samples. Among the 1,000 runs of 1,000 bootstrapped estimates, none have at least 997 positive estimates, resulting in a p-value of 0.00 for the joint significance test. In general, these results provide strong support for the view that our findings are robust to various specification and sampling choices.

While our evidence overwhelmingly indicates that the effect is positive and significant, it may still be useful to understand which, if any, choices affect estimated magnitudes. At the bottom of Figure A.III we plot the characteristics of each specification. The first eight rows report instances in which that year's election was dropped from the sample.[16] There are no easily discernible patterns—results are not highly sensitive to which elections are included in the sample. The bottom two rows indicate instances in which certain interaction controls were included. Here it is clear that including a control for the interaction between Div_ratio and a randomly selected macro-economic variable produces estimates of lower magnitudes. However, these magnitudes are still large, with an average estimate of 1.65 among this sample. Controlling for an interaction between stock returns and a randomly selected county-level variable tends to produce estimates of higher magnitudes, in particular higher than the baseline specification. This suggests that important differences across counties may actually be biasing the coefficients downward. No matter which additional interactions are included, the main effect is statistically and economically important.

[16] A more detailed presentation of these instances is presented in Figure A.IV.

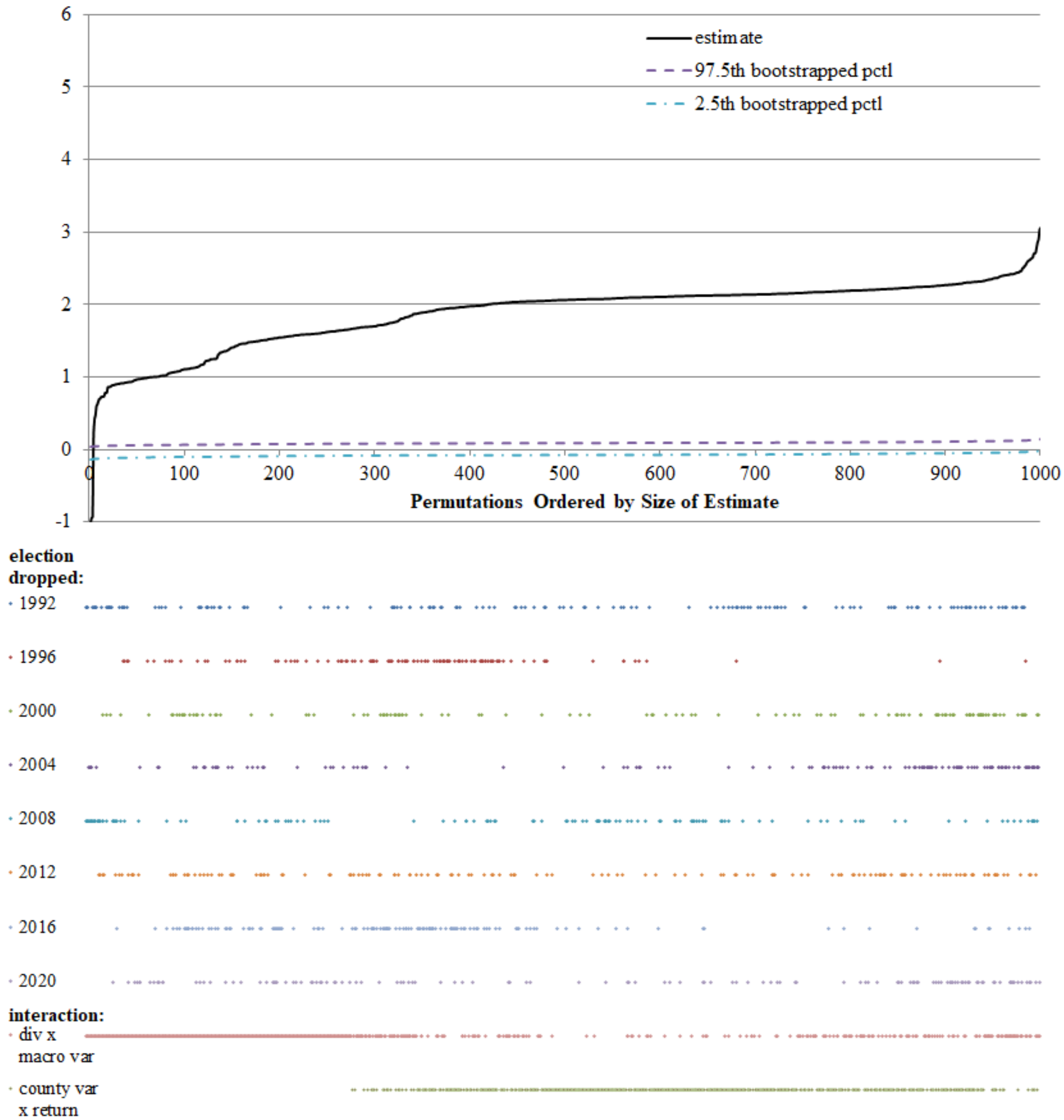


Figure A.III: Specification curve. The figure above plots point estimates and 95% confidence intervals of the coefficient on $Div\_ratio \times ret$ for 1,000 permutations of randomly selected regression samples and control variables. Each permutation is estimated over a random subsample of elections and counties. Controls are also selected randomly. The resulting 1,000 estimates are plotted in the solid line in order from the smallest sized effect to the largest. At the bottom we plot the characteristics of each specification.

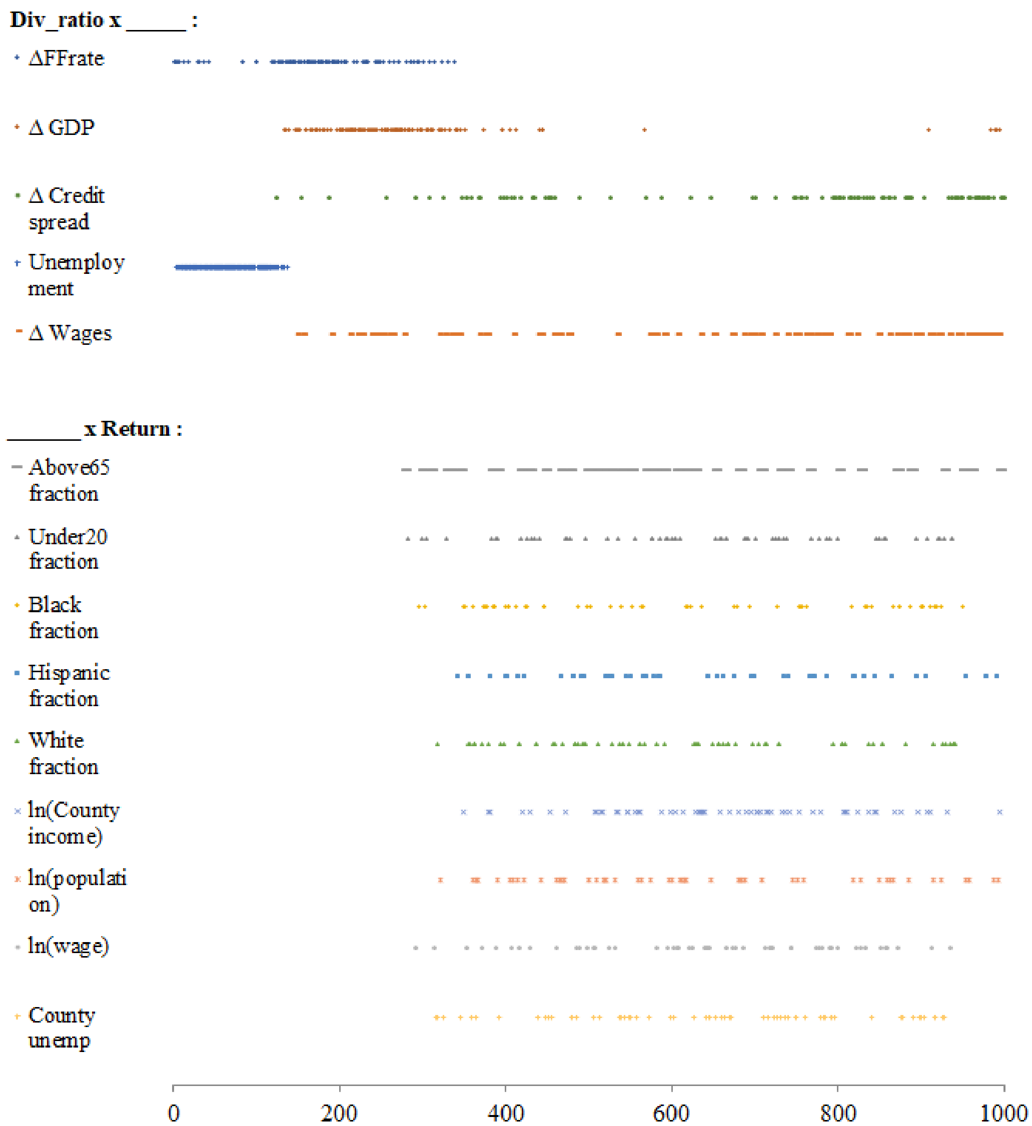


Figure A.IV: Specification Curve Control Details. The figure above plots the characteristics of each specification from the specification curve in Figure A.III. In each specification, we include a randomly selected control interaction term. The top five rows indicate the specifications in which *Div_ratio* is interacted with a macroeconomic variable. The remaining rows indicate specifications in which *ret* is interacted with a county-level variable.

References

Alt, J. E., D. D. Lassen, and J. Marshall (2016). Credible sources and sophisticated voters: When does new information induce economic voting? *The Journal of Politics 78*(2), 327–342.

Board of Governors of the Federal Reserve System (2020). Federal funds effective rate [fedfunds]. Retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/FEDFUNDS (accessed December 2022).

Bonaparte, Y. and A. Kumar (2013). Political activism, information costs, and stock market participation. *Journal of Financial Economics 107*(3), 760 – 786.

Brown, J. R., Z. Ivkovic, P. A. Smith, and S. Weisbenner (2008). Neighbors matter: Causal community effects and stock market participation. *The Journal of Finance 63*(3), 1509–1531.

Bureau of Economic Analysis (2020). Real gross domestic product [a191rl1q225sbea]. Retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/A191RL1Q225SBEA (accessed December 2022).

Bureau of Economic Analysis (2022). Personal income by county, 1988-2020. Available on the BEA website, https://www.bea.gov/itable/regional-gdp-and-personal-income, Interactive Tables: Personal income by county and MSA (accessed September 2022).

Bureau of Labor Statistics (2020a). Consumer price index for all urban consumers: All items in u.s. city average [cpiaucsl]. Retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/CPIAUCSL (accessed April 2021).

Bureau of Labor Statistics (2020b). Employed full time: Median usual weekly real earnings: Wage and salary workers: 16 years and over [les1252881600q]. Retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/LES1252881600Q (accessed December 2022).

Bureau of Labor Statistics (2020c). Unemployment rate [unrate]. Retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/UNRATE (accessed December 2022).

Bureau of Labor Statistics (2022a). Local area unemployment statistics, 1990-2020. Available on the BLS website, https://www.bls.gov/lau/tables.htm (accessed September 2022).

Bureau of Labor Statistics (2022b). Quarterly census of employment and wages, 1988-2020. Available on the BLS website, https://www.bls.gov/cew/downloadable-data-files.htm (accessed September 2022).

Cameron, A. C., J. B. Gelbach, and D. L. Miller (2008). Bootstrap-based improvements for inference with clustered errors. *The Review of Economics and Statistics 90*(3), 414–427.

Census Bureau (1990,2010a). Educational attainment. Data in 1990 are obtained through the USDA https://www.ers.usda.gov/data-products/county-level-data-sets/county-level-data-sets-download-data/ Dataset used: Educational attainment for adults age 25 and older for the U.S., States, and counties, 1970–2020 (accessed January 2021). Data in 2010 are obtained from the 2010 American Community Survey 5-year estimates, https://data.census.gov/all?q=education Under data series S1501 - 2010: ACS 5-Year Estimates Subject Tables; Geography: All counties within United States and Puerto Rico (accessed January 2021).

Census Bureau (1990,2010b). Urban and rural classification and urban area criteria. Data in 1990 are obtained through the CDC https://www2.cdc.gov/nceh/lead/census90/house11/download.htm Dataset used: cnty.dbf (accessed September 2017). Data in 2010 are obtained from the Census website, https://www.census.gov/programs-surveys/geography/guidance/geo-areas/urban-rural/2010-urban-rural.html Dataset used: Percent Urban and Rural In 2010 by State and County (accessed January 2021).

Census Bureau (2022a). Census naics and sic codes concordances. https://www.census.gov/naics/?68967 Dataset used: 2002 NAICS to 1987 SIC (Accessed December 2022).

Census Bureau (2022b). County population by characteristics, 1990-2020. Data from 1990 to 2010 are obtained from the NBER https://www.nber.org/research/data/us-intercensal-county-population-data-age-sex-race-and-hispanic-origin. (accessed May 2017). Data from 2011 to 2020 are obained from the Census website, https://www2.census.gov/programs-surveys/popest/datasets/2010-2020/counties/asrh/ Dataset used: CC-EST2020-ALLDATA.csv (accessed September 2022).

Center for Research in Security Prices (2021). Crsp indexes (daily & monthly), 1988-2020. Technical report. Available to the University of Pittsburgh through Wharton Research Data Services (WRDS), https://wrds-www.wharton.upenn.edu/pages/about/data-vendors/center-for-research-in-security-prices-crsp/ (accessed May 2021).

Charles, K. K. and J. Stephens, Melvin (2013). Employment, wages, and voter turnout. *American Economic Journal: Applied Economics 5*(4), 111–43.

Chodorow-Reich, G., P. T. Nenov, and A. Simsek (2021). Stock market wealth and the real economy: A local labor market approach. *American Economic Review 111*(5), 1613–57.

Cunningham, S. and M. Shah (2018). Decriminalizing indoor prostitution: Implications for sexual violence and public health. *The Review of Economic Studies 85*(3), 1683–1715.

Di Maggio, M., A. Kermani, R. Ramcharan, V. Yao, and E. Yu (2022). The pass-through of uncertainty shocks to households. *Journal of Financial Economics 145*(1), 85–104.

Gagliarducci, S., M. G. Onorato, F. Sobbrio, and G. Tabellini (2020, October). War of the waves: Radio and resistance during world war II. *American Economic Journal: Applied Economics 12*(4), 1–38.

Gentzkow, M. (2006). Television and Voter Turnout. *The Quarterly Journal of Economics 121*(3), 931–972.

Gentzkow, M., J. M. Shapiro, and M. Sinkinson (2011). The effect of newspaper entry and exit on electoral politics. *American Economic Review 101*(7).

Gerber, A. S. and G. A. Huber (2009). Partisanship and economic behavior: Do partisan differences in economic forecasts predict real economic behavior? *American Political Science Review* (3), 407–426.

Geruso, M., D. Spears, and I. Talesara (2022). Inversions in us presidential elections: 1836–2016. *American Economic Journal: Applied Economics 14*(1), 327–57.

Hsiang, S. M. and A. S. Jina (2014). The causal effect of environmental catastrophe on long-run economic growth: Evidence from 6,700 cyclones. Working Paper 20352, National Bureau of Economic Research.

HUD (2022). Usps zip code crosswalk files. https://www.huduser.gov/portal/datasets/usps_crosswalk.html Data year and quarter: 2010 Q1 (Accessed June 2020).

IRS (2021). Individual income tax zip code data. Technical report. Available on the IRS website https://www.irs.gov/statistics/soi-tax-stats-individual-income-tax-statistics-zip-code-data-soi (accessed April 2021).

Kriner, D. L. and A. Reeves (2012). The influence of federal spending on presidential elections. *American Political Science Review 106*, 348–366.

Krishna, V. and J. Morgan (2011). Overcoming ideological bias in elections. *Journal of Political Economy 119*(2), 183–211.

MacKinnon, J. G. and M. D. Webb (2020). Randomization inference for difference-in-differences with few treated clusters. *Journal of Econometrics 218*(2), 435–450.

Marshall, J. (2019). The anti-democrat diploma: How high school education decreases support for the democratic party. *American Journal of Political Science 63*(1), 67–83.

McCartney, W. B. (2021). Does household finance affect the political process? evidence from voter turnout during a housing crisis. *The Review of Financial Studies 34*(2), 949–984.

Meeuwis, M., J. A. Parker, A. Schoar, and D. Simester (2022). Belief disagreement and portfolio choice. *forthcoming, The Journal of Finance*.

Mian, A., A. Sufi, and N. Khoshkhou (2021). Partisan bias, economic expectations, and household spending. *The Review of Economics and Statistics*, 1–46.

Moody's (2020). Moody's seasoned baa corporate bond yield [baa aaa]. Retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/BAA and https://fred.stlouisfed.org/series/AAA (accessed December 2022).

Mueller, D. C. and T. Stratmann (2003). The economic effects of democratic participation. *Journal of Public Economics 87*(9), 2129 – 2155.

Pástor, L. and P. Veronesi (2020). Political cycles and stock returns. *Journal of Political Economy 128*(11), 4011–4045.

Powell, G. B. (1986). American voter turnout in comparative perspective. *The American Political Science Review 80*(1), 17–43.

Radcliff, B. (1992). The welfare state, turnout, and the economy: A comparative analysis. *The American Political Science Review 86*(2), 444–454.

Rosenstone, S. J. (1982). Economic adversity and voter turnout. *American Journal of Political Science*, 25–46.

Seasholes, M. S. and N. Zhu (2010). Individual investors and local bias. *The Journal of Finance 65*(5), 1987–2010.

Simonsohn, U., J. P. Simmons, and L. D. Nelson (2020). Specification curve analysis. *Nature Human Behaviour 4*(11), 1208–1214.

S&P Global (2020). Compustat, 1988-2020. Technical report. Available to the University of Pittsburgh through Wharton Research Data Services (WRDS), https://wrds-www.wharton.upenn.edu/pages/get-data/compustat-capital-iq-standard-poors/ (accessed December 2020).

Young, A. (2019). Channeling Fisher: Randomization Tests and the Statistical Insignificance of Seemingly Significant Experimental Results. *The Quarterly Journal of Economics 134*(2), 557–598.