Appendix

A. Additional Information on Variables

Table 2 gives a descriptive overview of the continous variables used in the analysis and their source (see Dahlberg et al., 2020; Döring & Manow, 2019; Visser, 2019; Volkens et al., 2020). Three (sets of) variables require further elaboration as their compilation was more complex: the dependent variable; the government position variables; and the corporatism index.

Table 2: Descriptive statistics for the main variables

	Mean	SD	Min	Max	Source
Active Labor Market Spending/GDP	0.005	0.004	0.000	0.039	OECD
Corporatism Index	−0.006	0.606	−1.109	1.339	ICTWSS (Visser 2019)
Cyclically Adjusted Deficit	−0.185	3.031	−25.868	10.230	CPDS
Deindustrialization	63.163	12.404	0.000	90.343	OECD
Education Spending/GDP	0.056	0.015	0.011	0.107	OECD and Unesco
Employment Rate	66.804	6.319	48.475	80.475	OECD
Growth	2.861	3.047	−14.839	25.176	OECD
Inflation	6.714	36.776	−4.478	1020.621	OECD
Investment Priorities	14.068	5.816	0.000	36.530	CMP (Volkens et al. 2020) and ParlGov (Döring and Manow 2019)
Political Constraints Index	0.767	0.118	0.000	0.894	QoG (Dahlberg et al. 2020)
R&D Spending/GDP	0.006	0.002	0.001	0.017	OECD
Share 65+	0.141	0.036	0.031	0.291	OECD
Social Democratic Seat Share	28.578	37.171	0.000	100.000	ParlGov (Döring and Manow 2019)
Trade Openess	80.969	49.179	10.757	380.104	OECD
Unemployment Rate	7.375	4.171	0.556	27.466	OECD

A1. Dependent Variable: Knowledge Investment Index

The knowledge investment index comprises three subindicators, which were operationalized as follows:

Investments in education were measured as the share of GDP spend on primary, secondary and tertiary education. To obtain that measure with as few missing values as possible, I combined the OECD's COFOG (Classification of the Functions of Government) spending data with UNESCO data on education expenditure. For the COFOG data I selected the subcategory of total education spending. I also included the social protection subcategory family and children for both substantive reasons and to make the data more compatible with the UNESCO data. This is because COFOG data are based on ISCED-97 while the UNESCO data use ISCED-2011. One of two main differences between the datasets is that the UNESCO data include education expenditure that COFOG classifies according to its main purpose as child care services under social protection, not under education expenditure.

The other main difference is that the UNESCO data include in education expenditure any research conducted in tertiary educational institutions. On the other hand, COFOG classifies R&D expenditure conducted in tertiary educational institutions to the respective functions (e.g. 01.4 basic research, 07.5 R&D health), and only includes R&D spending on education directly, i.e. pedagogy broadly conceived. The measures are thus highly but not perfectly correlated, which poses problems if data are not missing at random. I decided to prioritize data availability over potential bias (especially because data for some countries are entirely missing), but not only retained the individual measures for robustness checks but also averaged values when values from both measures were available.

Investments in R&D were measured using the OECD's GBARD (Government budget allocations for R&D) data. The index captures overall spending on R&D as this almost per definition is meant to create knowledge-based capital. I also crated an alternative measurement that only measures spending on specific categories directly relevant for the knowledge economy - but this not only comes at the cost of data availability for some countries but might also be seen as substantively questionable.

Investments on active labor market policies were measured using the OECD's LMPEXP dataset. Included was only spending on active (as opposed to passive) spending. In addition, administrative spending was excluded. Included was thus spending on training, job rotation and job sharing, employment incentives, sheltered and supported employment and rehabilitation, direct job creation, and start-up incentives. These categories measure investments that foster the creation and maintenance of both individually and collectively-held knowledge-based capital. The categories were just added up but results do not change if we weight the components in a number of ways that roughly reflect their absolute size.

A2. Government Positions

Government positions are measured either indirectly as the share of social-democratic parties in government or directly through their expressed preferences (Garritzmann & Seng, 2016; Schmitt, 2016). In the latter case, the emphasis of party manifestos on either of the following four categories were summed up: per404 (favorable mentions of long-standing economic planning by the government); per410 (need for government to encourage or facilitate greater production and to take measures to aid economic growth); per411 (importance of science and technological developments in industry and need for training and research within the economy as well as calls for public infrastructure spending); per506 (need to expand and/or improve educational provision at all levels). Additionally, category per507 (limiting state expenditure on education) was subtracted. These categories capture, respectively, whether parties see room for an active and leading role of the state in the economy (Mazzucato, 2013) and the importance they assign to the public provision of (knowledge-based) public goods (R&D, infrastructure, and education).

To do this, I used data from the Comparative Manifesto Project (CMP) (Volkens et al., 2020) as well as data on the partisan composition of cabinets from the ParlGov database (data for the United States, which is missing from the ParlGov database, were added manually) (Döring & Manow, 2019). This allowed me to calculate the relative share of different party families in cabinets and to then weigh them by the number of days they were in office in a given year. The relative issue emphasis parties put on, or the relative importance parties they assign to, different categories - a more reasonable conceptualization of the CMP data (Gemenis, 2013, p. 19) - was calculated for each government by combining the relative emphasis of the governing parties weighted by their seat share. In years with multiple cabinets, values were taken from whichever cabinet was in office for more days.

A3. Corporatism Index

The corporatism index used in the study is a reconstruction of Jahn's (2016) index of corporatism, which is itself based on data from the ICTWSS database complied by Visser (2019). Jahn's index stands out among other conceptions of corporatism not only because it uses variables that are available over many decades and for many capitalist countries; but also because it offers a parsimonious or narrow definition of corporatism that does not contain what it might be used to explain, i.e. things like small open economies, consensual or even consociational political tradition, dominance of a unified social democratic party, high level of social expenditure, and successful economic performance (Jahn, 2016, p. 51). Rather, it focuses on the structural aspects of corporatism, i.e., the hierarchical centralization of collective bargaining; its functional aspect, i.e., "the role these organizations play vis-à-vis the state" and the "style of interest mediation by the state" (Jahn, 2016, p. 51); and the scope of corporatism which focuses on the output side and captures who is actually affected by corporatist arrangements. The robustness checks in Appendix include a version of the corporatism variable that only takes its functional dimension into account.

I additionally included variables that cover whether in a given year a (tripartite) social pact or a (nation-wide) agreement was signed. Somewhat confusingly, they are part of the do-file made available by the Jahn but are explicitly excluded from the index because there are no data on their long-term effects and because including them might lead to double counting similar effects (Jahn, 2016, p. 56). I nonetheless included them because, as Jahn himself notes, they are meaningful indicators of corporatism and also play an important role in Ornston's (2012) conception of corporatism. The inclusion of such variables, however, does not result in noticeable differences in the index itself. Table 3 summarizes this conceptualization and shows how the three aspects of corporatism - structure, function, scope - are operationalized.

The reason why I had to reconstruct Jahn's index in the first place is that the original index provided by Jahn only goes until 2010. Next to the inclusion of social pacts and collective agreements (which are, however, also part of Jahn's do-file), there are two additional differences between Jahn's original index and my reconstruction. First, the linear interpolation of missing data led to implausible values at least when done in R, so I was more conservative than Jahn here and only interpolated values when the maximum number of missing values was less than 4. Second, because of small differences in the normalization of the variables, my index has somewhat less variance than Jahn's, i.e. it compresses values somewhat more to their mean, which however, should only lead to conservative estimates. Figure 4 plots Jahn's original index next to my reconstruction and clearly shows that all remaining differences are very small. Both indices clearly capture the same phenomenon.

Table 3: Corporatism Index

Aspect	Description	Operationalization
Structure	Degree of hierarchical centralization	Organizational structure of collective actors (measure of centralization of wage bargaining) (CENT variable), Structure of work council representation (WC_struct variable, Rights of work councils (WC_rights variable
Function	Degree of concertation with the state	Government intervention in wage bargaining (Govint variable), Dominant level of wage bargaining (Level variable), routine involvement of unions and employers in government decisions (RI variable), social pact or collective agreement signed (Pactsign and AgrSign variables)
Scope	Degree to which agreements encompass broader segments of society	Coordination of wage bargaining (measure of bindingness of norms regarding maximum or minimum wage rates or wage increases) (Coord variable), Mandatory extension of collective agreements (Ext variable)

B. Additional Information on Emprical Strategy

B1. Missing Data

Missing data are a perennial problem of quantitative comparative political research. Most statistical methods assume the absence of missing values, that is, they require rectangular datasets. However, 'rectangularizing' a dataset by dropping all partially observed observations from the analysis can lead to biases, inefficient use of the existing information, and incorrect uncertainty estimates. For this reason, multiple imputation techniques are widely considered the royal road to handling missing data. The idea is to extract as much information as possible from the available data, to use that information to construct multiple, complete datasets where the observed values are the same and the imputations vary depending on the estimated uncertainty in predicting each missing value, and to then combine the results (Honaker & King, 2010, p. 561).

I used Amelia, a multiple imputation technique and package specifically designed to handle missing data in time-series-cross-sectional datasets by allowing to impose smoothness over time-series variables (by including q-order polynomials), shifts over cross sectional variables, and interactions between the two where the time-trends can vary across cross-sectional units (Honaker et al., 2019; Honaker & King, 2010). Since imputations are predictive and not causal, I included all available

Figure 4: Comparing Jahn's original to my own corporatism index

variables as well as their lags and leads. I also included a degree one polynomial indicating linear time effects. Because some variables are strongly correlated (the investment index and its subcategories), I applied a ridge prior of 1 percent of the rows of the data to shrink the covariances and aid the stability of the EM algorithm, basically trading an increase in bias for an increase in efficiency (Honaker et al., 2019, p. 23).

Overall, only around 10% of all used cells were missing. Data rarely had to be imputed over more than a few years and in these cases imputation uncertainty is reflected in the standard errors of the regression models.

There are a number of tools to evaluate the imputations. One is to visually inspect the mean and variances of the imputations across time and over countries and compare them to the observed values. Figure 5 does just that for a number of countries and for R&D investment. Figure 6 does the same for deindustrialization (for the sake of transparency, I plotted countries with rather many missing values next to those with no missing values to illustrate the plausibility of the imputations). What we can gather from this (as well as from doing the same for other variables) is that imputations are quite sensible. The range of imputed values falls well within what we would find plausible. Moreover, the imputation take into account uncertainty when imputation takes place over several missing values, which is reflected in the models themselves.

Another thing we can do is to overimpute, that is, to "sequentially treat each of the observed values as if they had actually been missing" (Honaker et al., 2019, p. 31). We can then multiply impute these values and thus construct a confidence interval of what the imputed values would have been had the actually observed data been missing. This allows us to evaluate whether the observed data "fall within the region where it would have been imputed had it been missing" (Honaker et al., 2019, p. 31). Figure 7 shows the results for the investment index, Figure 8 does the same for the corporatism index. For those as well as for the other variables, the vast majority of confidence intervals fall on the $x = y$ line, and for all variables most of them do. This gives us confidence in the predictive validity of the imputation model (Honaker et al., 2019, p. 31).

A final way to evaluate the imputations is to compare the distribution of imputed values to the distribution of observed values. Figure 9 and Figure 10 are examples of such density plots, assuring us at least that the most imputations fall within the known bounds (the density distributions can also 'correctly' differ if there is a systematic reason why values for certain observations are missing). For the corporatism index, the imputed values a somewhat more centered than the observed ones, which would is less problematic as it decreases variance in a conservative manner and without a directional bias.

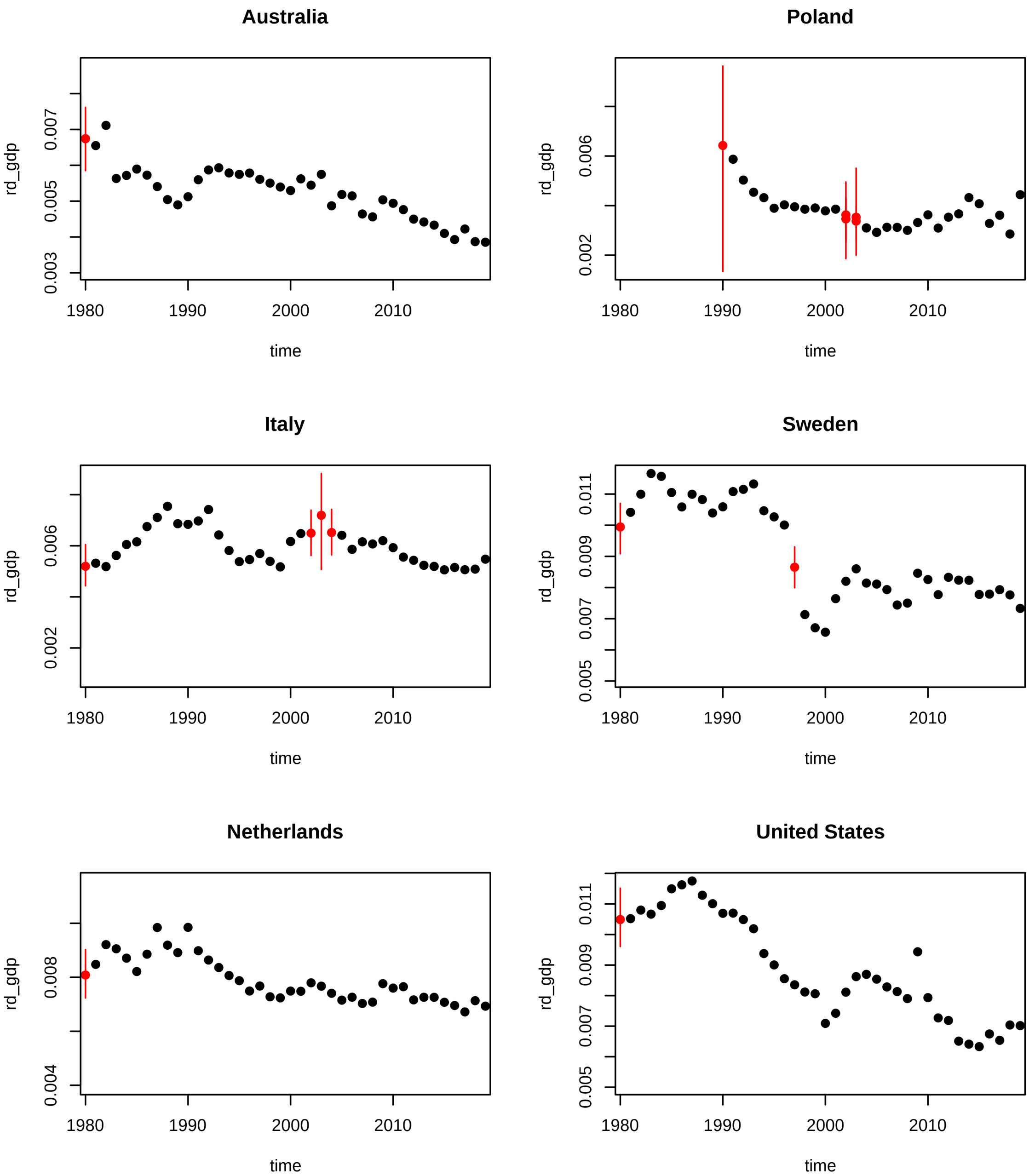

Figure 5: TSCS Plot for R&D Investment. The black points represent observed values, the red represent the mean of the imputations, the red lines represent 95% confidence bands of the imputation distribution

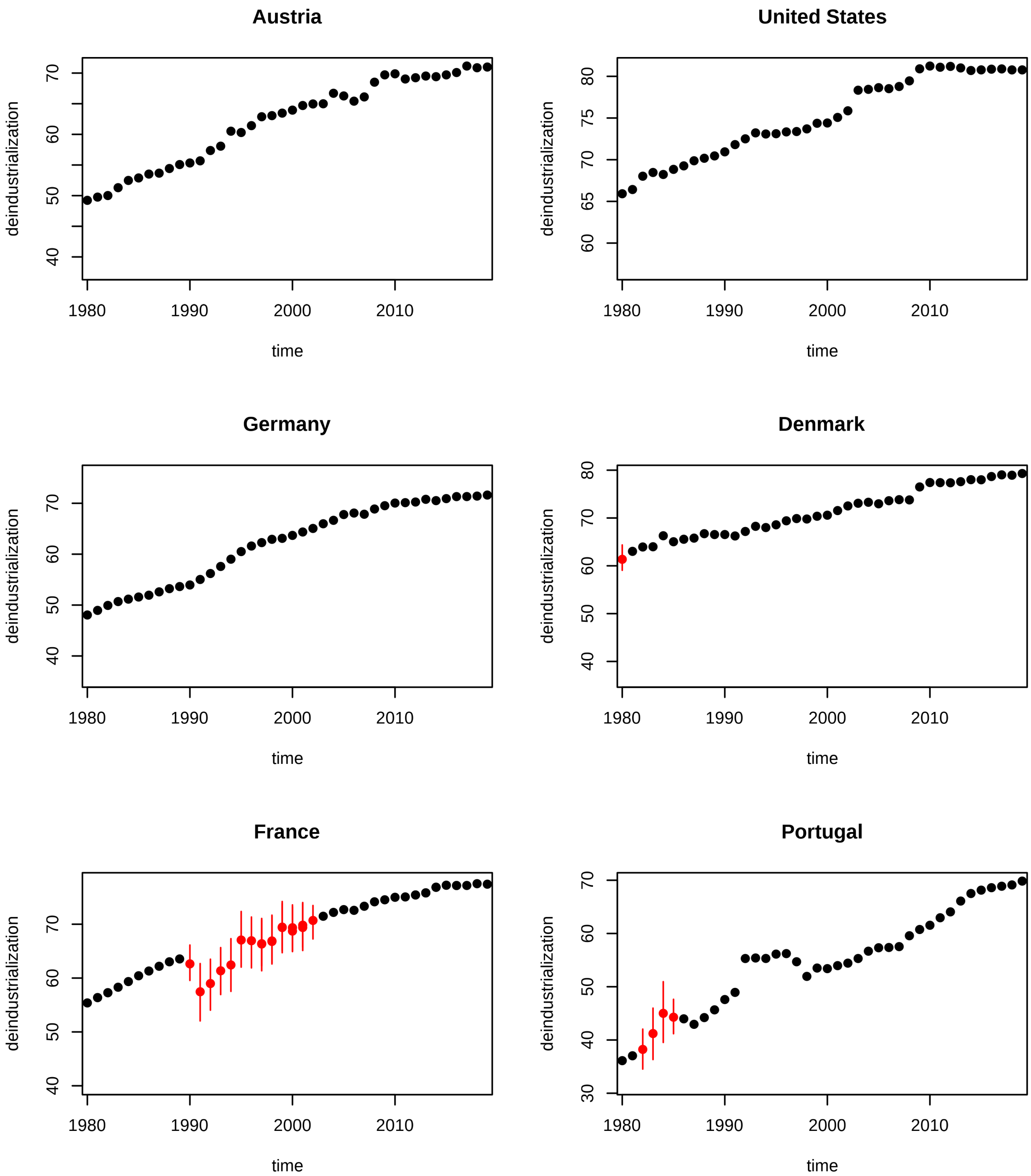

Figure 6: TSCS Plot for Deindustrialization. The black points represent observed values, the red represent the mean of the imputations, the red lines represent 95% confidence bands of the imputation distribution

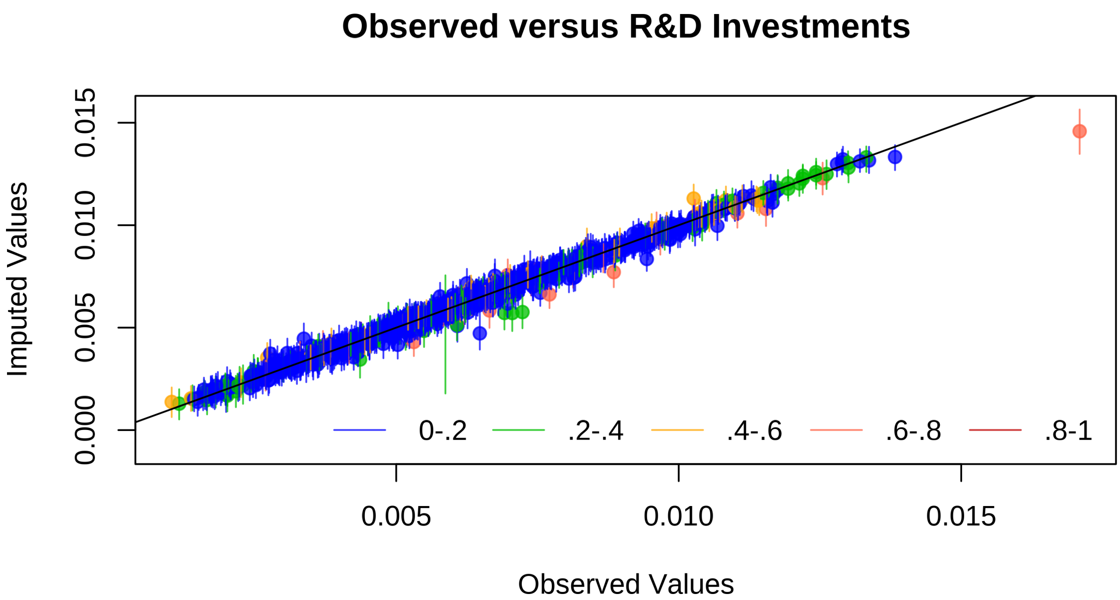

Figure 7: Overimputation Diagnostic Graph. If all imputed values fall on the x = y line, the imputation model would be a perfect predictor of the true value. If most confidence intervals (>90%) fall on this line, this gives us confidence in the imputation model. The colors of the line represent the fraction of missing observations in the pattern of missingness for that observation

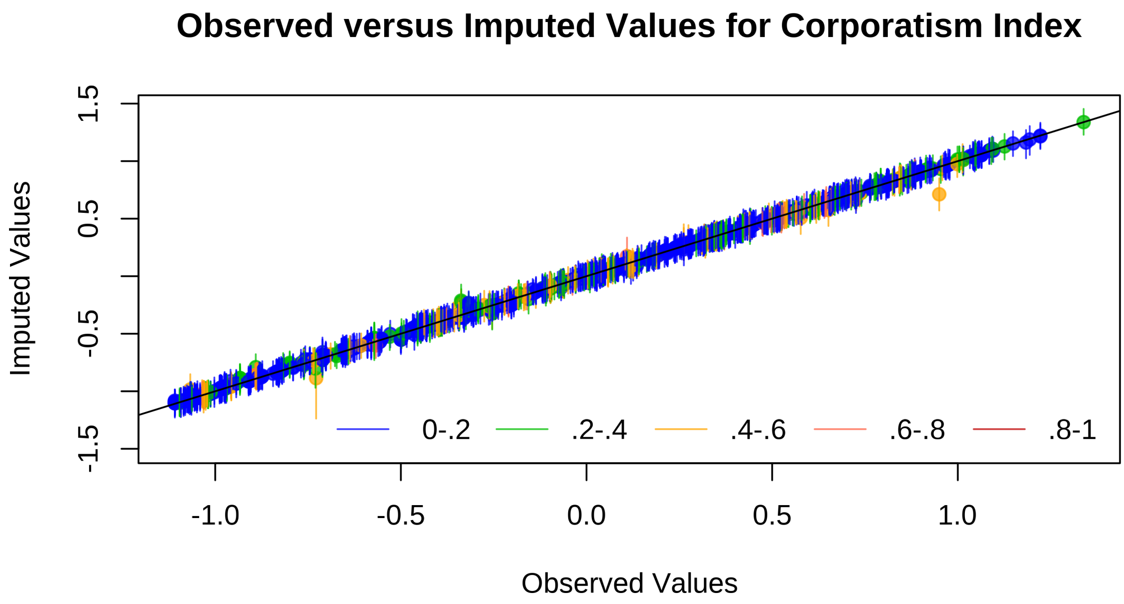

Figure 8: Overimputation Diagnostic Graph. If all imputed values fall on the x = y line, the imputation model would be a perfect predictor of the true value. If most confidence intervals (>90%) fall on this line, this gives us confidence in the imputation model. The colors of the line represent the fraction of missing observations in the pattern of missingness for that observation

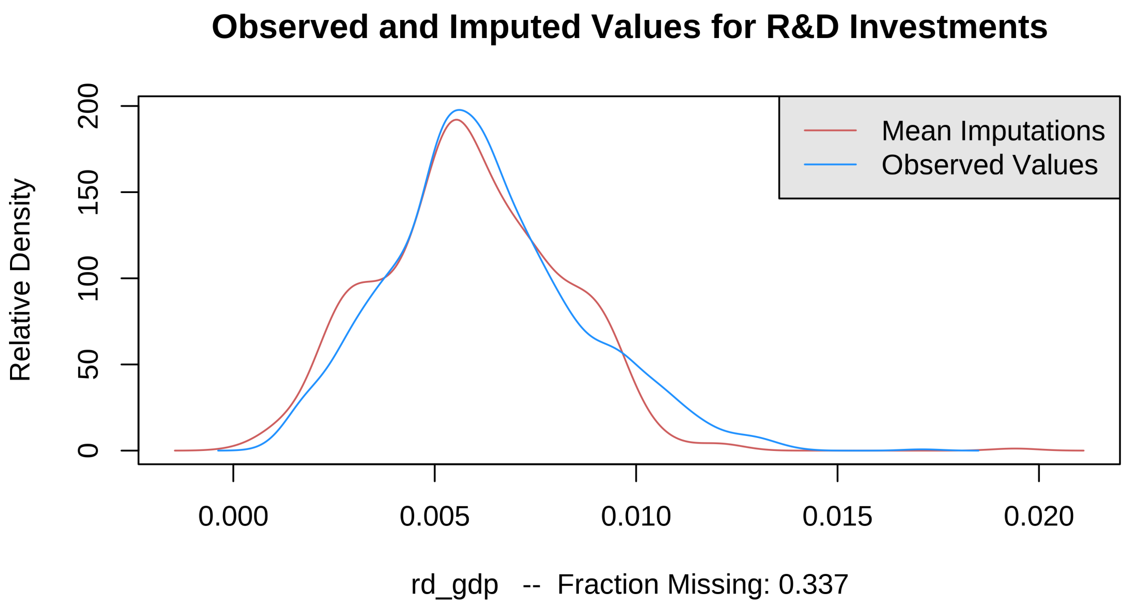

Figure 9: Density Plot. The distribution of mean imputations is shown in red, the distribution of observed values is shown in blue

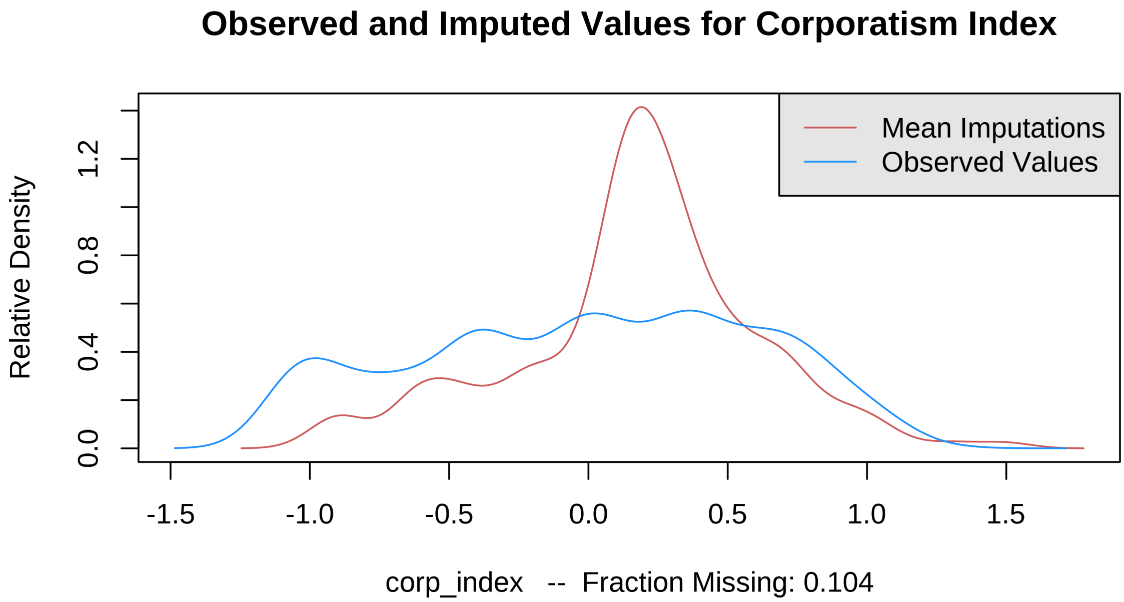

Figure 10: Density Plot. The distribution of mean imputations is shown in red, the distribution of observed values is shown in blue

B2. Model Assumptions

There are a few model assumptions that require discussion. First, in fixed-effects regressions of time-series-cross-sectional data, heteroskedasticity (unequal error variance across countries) and contemporaneous error correlation (due to common shocks, etc.) are often a problem as they bias estimates (Beck & Katz, 1995). However, because they already partition the error into within- and between-country error components, this should be less of a problem for within-between models. Bartels (2015) shows that this is indeed the case and the estimates from within-between models are quite similar to those from fixed-effects models with panel-corrected standard errors.

Second, even though mixed models assume that higher-level entities are drawn from an Normal distribution, Beck & Katz (2007) show that they handle even highly non-normal distributions very well.

Third, the within-between model thus offers a substantive solution to a central objection to random-effects model, namely that they assume that lower-level (here occasion-level) covariates are uncorrelated with the random effects term such that $cov(x_{tgc}, u_{0gc}) = 0$ (Bartels, 2015; Bell & Jones, 2015). Not only do simulations show that "even in the presence of rather extreme violations of this assumption, the random-effects estimator can still be preferable to (or at least no worse than) the fixed-effects estimator" (Clark & Linzer, 2015, p. 407). It also the case that the within-between specification prevents biased lower-level coefficients due to omitted variables at the higher level. This is because "there can be no correlation between level 1 variables included in the model and the level 2 random effects – such biases are absorbed into the between effect" (Bell et al., 2019, p. 1059). This is also why the Hausmann test, a positive result of which is commonly taken as a reason to prefer a fixed- over a random-effect specification, is insufficient to decide between the two (Clark & Linzer, 2015, p. 403). In fact, "a negative result in a Hausmann test tells us only that the between effect is not significantly biasing an estimate of the within effect"; the explicit modeling of the difference between those effects thus "makes the Hausmann test, as a test of FE against RE, redundant" (Bell & Jones, 2015, p. 138). There can of course still be bias in the between effects and the effects of higher-level variables due to unmeasured higher-level characteristics. But this is a problem mainly if we want to know the direct causal effect of a higher-level variable. If we instead interpret these coefficients as "proxies for a range of unmeasured social processes" (Bell et al., 2019, p. 1059) the coefficient estimates can still be valuable provided their interpretation is theoretically sound.

Fourth, although Stegmueller (2013) has influentially argued that maximum-likelihood estimators produce severely overconfident estimates when there are fewer than 15-20 higher-level entities (and has recommended using a Bayesian approach instead), recent follow-up work has identified flaws in Stegmueller's simulation study (Elff et al., 2020). The authors find that maximum-likelihood estimators generally provide unbiased coefficient estimates in linear multilevel models even with few higher-level entities. Moreover, restricted maximum-likelihood estimators, together with using a heavier-tailed t distribution with limited degrees of freedom instead of the standard normal distribution, provide much-improved estimators of variance parameters (over standard maximum-likelihood estimates), especially for very small cluster sizes (5-10 higher level entities).

Finally, if variables have a unit-root, coefficient estimates can be spurious. While an Augmented Dickey-Fuller test for the country-averaged investment index rejects the null hypothesis of a unit root (p-value = 0.38), visual inspection reveals an upward trend in the data. I included cubic splines to account for time trends (cf. Garritzmann & Seng, 2020) and I also run additional robustness checks that model time differently, including with a third-order polynomial of time [as suggested by Kelvyn Jones here]. But I cannot fully exclude the possibility of non-stationarity – not least because it is unclear how well standard tests for stationarity perform for time-series-cross sectional data with relatively low numbers of annual observations. Transforming variables to their first differences could be a technical fix to eliminate potential non-stationarity. However, this would come at a theoretical cost as we lose the ability to estimate meaningful between-effects (which are all about levels, not change). There are also theoretical considerations following from the structure of time-series-cross-sectional data (Beck & Katz, 2011, pp. 342–344). In particular, stationarity is constrained because of natural bounds. For example, the share of conservative parties in government is constrained between 0-100, and spending variables as a share of GDP can realistically only go so high, which also bounds their variances. This also implies that political economy data that show an increasing trend cannot continue this trend indefinitely. That is, data that are non-stationary in a certain time-period may not be so be over a longer (or shorter) period. Given all this, I'm reasonable confident to have correctly modeled the data.

B3. Model Diagnostics

As all models, mixed effects models rely on a number of assumptions that need to be met or approximated to get unbiased estimates. Here, I present a number of such model diagnostics - all values being averaged across the multiply imputed datasets.

B31. Multicollinearity To detect multicollinearity, I calculated the variance inflation factor (VIF) for the different variables in the imputed models to estimate how much the variance of a regression coefficient is inflated due to multicollinearity in the respective models. Table 4 shows the averaged values for the different variables in the respective models. It shows that the VIF are very low (around 1) to moderate (for the deindustrialization and share of elderly people variables). None of the VIFs is very high, which gives us confidence that multicollinearity does not bias the results (common rules of thumb argue for excluding variables with VIF of 4 or higher, or even 10 or higher). However, including GDP per capita as a control leads to relatively high VIFs for this variable as well as the deindustrialization variable (VIFs of between 4 and 6). I therefore excluded it as a control variable. Importantly, as the next section shows, including GDP per capita does not change any of the main findings.

Table 4: Variance Inflation Factors

Variable	Variance Inflation Factor
Deindustrialization (within)	1.678966
Trade Openness	1.410212
EU Member	1.234968
Debt Rule	1.166376
Unemployment	1.147798
Institutional Contraints	1.099673
Adjusted Deficit	1.095275
Social Democratic Party	1.060313
Corporatism (within)	1.044121
Corporatism (between)	1.029282
Corporatism (between)*Deindustrialization (within)	1.025481
Small State	1.022393
Deindustrialization (between)	1.011625

B32. Distribution of Residuals Figure 11 and Figure 12 show that the residuals - again averaged across models - are homoscedastic and approximately normally distributed.

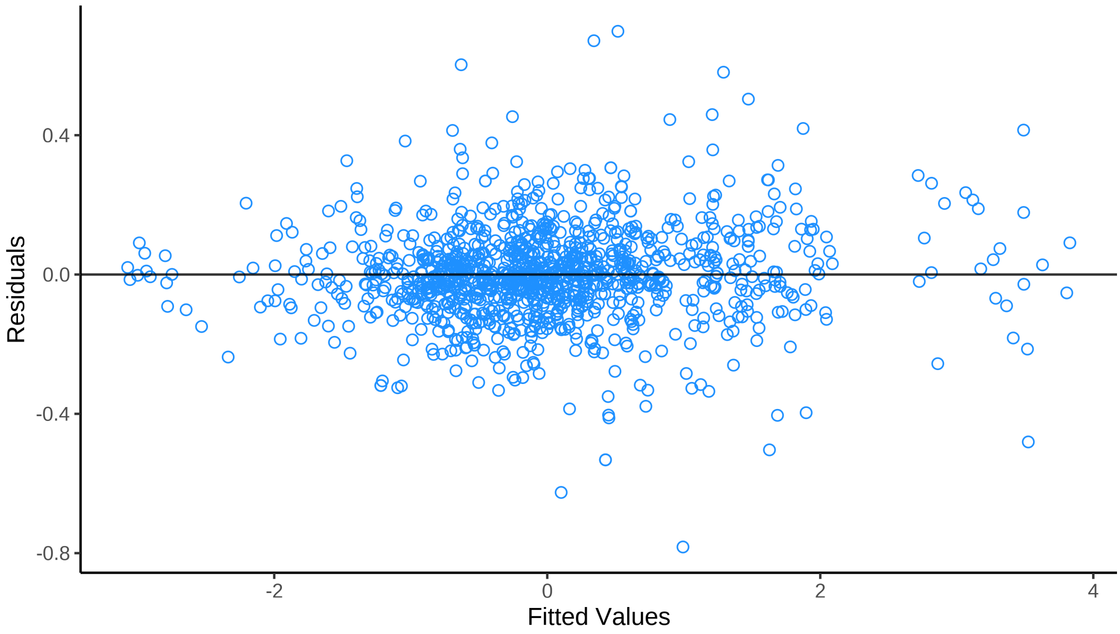

Figure 11: Residuals versus fitted values

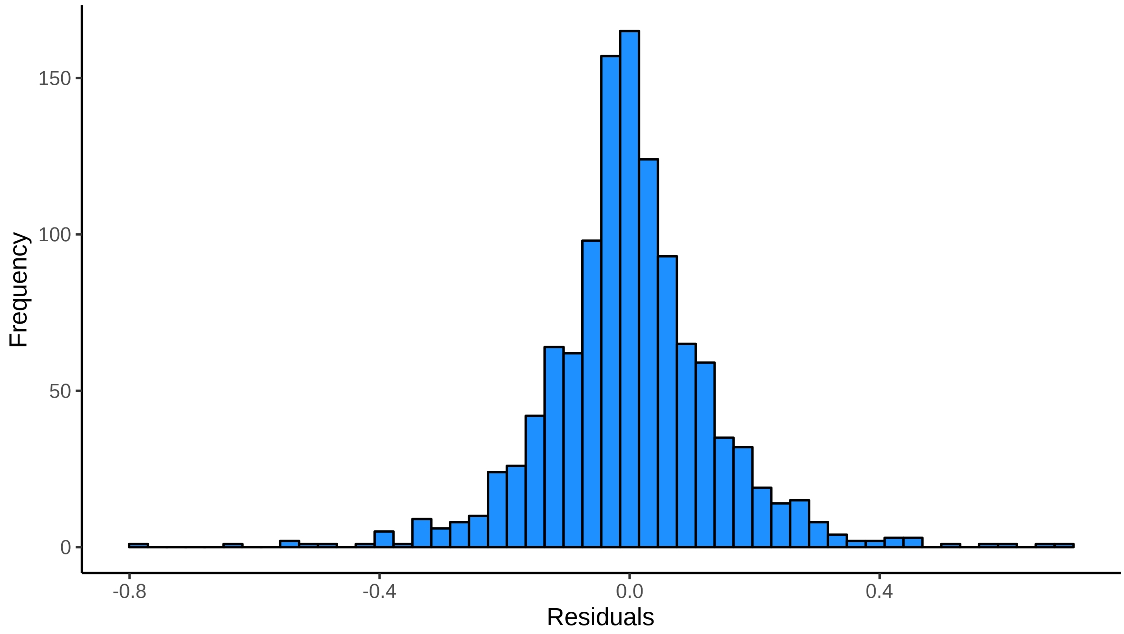

Figure 12: Histogramm of Residuals

B4. Robustness Checks & Alternative Specifications

I ran a number of alternative model specifications to ensure the robustness of my main findings. The first model in Table 5 is equivalent to Model 3 in the main paper but uses a direct measure of partisan preferences instead of the share of social democratic parties. The results remain the same: at least in recent years and decades, the partisan composition of government and the positions of governing parties had no significant influence on investment spending. The second model includes a GDP per capita variable as an additional control variable, which was excluded from the main model because of potential multicollinearity issues. As we can see, however, including it does not substantially alter any of the main results, although it is interesting that richer countries seem invest less rather than more in knowledge-based capital - all else being equal. The third model includes a lagged dependent variable. While this comes with many issues of its own, some argue that this might help avoid anti-conservative estimates of the error terms due to autocorrelation while producing good estimates even in the presence of minor residual autocorrelation (Keele & Kelly, 2006; cf. Beck & Katz, 2011). Naturally, including the LDV absorbs a lot of variance and reduces effect sizes and pushes the interaction effect of corporatism and deindustrialization to the 0.1 significance level. However, even this does not affect the main findings of the paper, in particular the one on the effect of corporatism. Model 4 uses a version of the investment index that only uses education data from UNESCO - instead of the version where education data are combined with COFOG data from the OECD (see Appendix). Again, the main results hold.

The first model in Table 6 includes a measure of foreign direct investment (FDI) as it is plausible to assume that countries invest in knowledge-based capital to remain attractive to foreign investors. This is measured as inflowing FDI as a share of GDP. However, I do not find any effect in either direction. The second model changes the corporatism variable by only including its functional elements, i.e. those that pertain to the role social partners play vis-à-vis the state, such as the involvement of unions and employers in government decisions. We find that this more parsimonious operationalization yields very similar results, crucially corroborating the main argument. Interestingly, if we include employment instead of unemployment levels, we find a significant negative effect of employment on investments. Like the effect of unemployment, this is purely a within effect. This suggests that while countries increase investments in especially individually-held knowledge-based capital when unemployment increases, they may decrease spending as employment levels get higher controlling for everything else, especially fiscal capacity. One explanation is that as countries increase their employment levels, there is less pressure on governments to further invest in knowledge-based capital while countries with increasing unemployment levels are pressured to step up their investments in order to ensure the viability of their tax base and contribution systems.

This, however, should be further explored in future studies. Finally, including debt levels instead of deficit does not change any of the main results either, although debt levels instead of deficits remain not significant.

The first model in table 7 shows the results of using an alternative measure of institutional constraints (also from Henisz (2002)), which does not have an effect on investments either. The second model shows that there is also no effect if we separate the within and between effects of the (original) institutional constraints variable. The between effect is - as we would expect - positive but not significant. Table 7 also shows results when using alternative specifications of the small state variable (third and fourth model). They show that the strong and significant positive effect is limited to countries with fewer than 6 million inhabitants. There is no such effect for countries with less than 10 million inhabitants (third model) or for those with between 6 and 20 million inhabitants (in the fourth which takes large states as a baseline category). The last model Table 7 includes an additional control variable that measures the share of the population over 65, which seems to have a positive effect on investment but does not influence any of the main results.

Finally, table 8, shows the results when using only selected categories of R&D investment or only the subcomponents of the knowledge investment index as dependent variables. Again the results are robust even if we only use the subcomponents, although there are some small but relevant differences, especially with regard to the within effect of deindustrialization and its interaction with corporatism. Moreover, R&D (and ALMP) investments are not affect by the smallness of a state, but rather by fiscal capacity, including the existence of a debt rule. This points to some heterogeneity in the determinants of investment spending for different categories of (knowledge) investments, which future research should explore further.

	Direct Measure	With GDP/Capita	With Lagged DV	Alterantive DV
(Intercept)	**−0.88*****	**−1.51*****	**−0.30*****	**−0.55***
	(0.20)	(0.22)	(0.08)	(0.22)
Lagged Dependent Variable			**0.77*****	
			(0.03)	
Social Democratic Party		−0.01	0.01	−0.02
		(0.02)	(0.01)	(0.02)
Weighted Emphasis Investment	−0.00			
	(0.02)			
Corporatism (within)	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Corporatism (between)	**0.35****	**0.46*****	**0.09***	**0.33***
	(0.13)	(0.14)	(0.04)	(0.13)
Institutional Contraints	−0.01	−0.01	0.02	0.02
	(0.03)	(0.03)	(0.02)	(0.04)
Adjusted Deficit	**−0.10*****	**−0.10*****	**−0.06*****	**−0.09*****
	(0.02)	(0.02)	(0.01)	(0.02)
Deindustrialization (within)	**0.14***	**0.14***	0.03	0.08
	(0.06)	(0.07)	(0.03)	(0.06)
Deindustrialization (between)	**0.50*****	**0.73*****	**0.12*****	**0.53*****
	(0.12)	(0.13)	(0.04)	(0.12)
Trade Openness	**−0.23*****	**−0.15****	**−0.09****	**−0.16***
	(0.05)	(0.05)	(0.03)	(0.07)
Unemployment	**0.12*****	**0.07*****	0.01	**0.16*****
	(0.02)	(0.02)	(0.01)	(0.02)
Small State	**0.81*****	**0.71****	**0.24*****	**0.62****
	(0.22)	(0.22)	(0.07)	(0.24)
Debt Rule	−0.02	−0.01	−0.00	−0.06
	(0.04)	(0.04)	(0.03)	(0.05)
EU Member	0.09	0.06	0.04	0.05
	(0.06)	(0.06)	(0.03)	(0.08)
Corporatism*Deindustrialization	**0.11***	**0.15****	0.03°	0.09°
	(0.05)	(0.05)	(0.02)	(0.05)
GDP/Capita		**−0.52*****		
		(0.07)		
AIC	482.84	434.17	22.53	734.64
N (Government)	441	441	441	441
N (Country)	32	32	32	32
N (Total)	1167	1167	1166	1167
Variance Government Level	0.09	0.09	0.00	0.09
Variance Country Level	0.48	0.52	0.03	0.51
Residual Variance	0.03	0.03	0.04	0.05
Variance Random Slope	0.06	0.08	0.00	0.06
Covariance Random Slope/Intercept	0.02	0.05	0.00	0.03

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\circ}p < 0.1$

Table 5: Mixed-Effect Models

	With FDI	Corporatism (functional)	Employment	Debt Instead of Deficit
(Intercept)	**−0.87*****	**−0.85*****	**−0.85*****	**−0.79*****
	(0.20)	(0.21)	(0.21)	(0.20)
Social Democratic Party	0.00	−0.00	−0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.02)
Corporatism (within)	0.01		0.01	0.01
	(0.01)		(0.01)	(0.01)
Corporatism (between)	**0.35****		**0.33***	**0.35****
	(0.13)		(0.13)	(0.13)
Corporatism functional (within)		0.00		
		(0.01)		
Corporatism functional (between)		**0.28***		
		(0.14)		
Institutional Contraints	−0.01	−0.01	−0.01	−0.03
	(0.03)	(0.03)	(0.03)	(0.02)
Adjusted Deficit	**−0.10*****	**−0.10*****	**−0.09*****	
	(0.02)	(0.02)	(0.02)	
Debt Level				0.01
				(0.03)
FDI Inflows	−0.01			
	(0.01)			
Deindustrialization (within)	**0.14***	**0.14***	**0.19****	**0.14***
	(0.06)	(0.06)	(0.06)	(0.06)
Deindustrialization (between)	**0.50*****	**0.51*****	**0.51*****	**0.50*****
	(0.12)	(0.13)	(0.12)	(0.12)
Trade Openness	**−0.23*****	**−0.22*****	**−0.24*****	**−0.27*****
	(0.05)	(0.05)	(0.05)	(0.05)
Unemployment	**0.12*****	**0.12*****		**0.11*****
	(0.02)	(0.02)		(0.02)
Employment			**−0.11****	
			(0.04)	
Small State	**0.82*****	**0.79*****	**0.82*****	**0.87*****
	(0.22)	(0.23)	(0.23)	(0.22)
Debt Rule	−0.02	−0.02	−0.02	−0.02
	(0.03)	(0.04)	(0.04)	(0.04)
EU Member	0.09	0.09	0.07	0.09
	(0.06)	(0.06)	(0.06)	(0.06)
Corporatism*Deindustrialization	**0.11***		**0.11***	**0.11***
	(0.05)		(0.05)	(0.05)
Corporatism(functional)*Deindustrialization		**0.11***		
		(0.05)		
AIC	491.44	486.50	503.29	542.74
N (Government)	441	441	441	441
N (Country)	32	32	32	32
N (Total)	1167	1167	1167	1167
Variance Government Level	0.09	0.09	0.10	0.10
Variance Country Level	0.48	0.52	0.49	0.48
Residual Variance	0.03	0.03	0.03	0.03
Variance Random Slope	0.06	0.08	0.06	0.05
Covariance Random Slope/Intercept	0.02	0.05	0.02	0.01

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\circ}p < 0.1$

Table 6: Mixed-Effect Models

	Alt. Contraints	Constraints W-B	Alt. Small State 1	Alt. Small State 2	Includes Share Elderly
(Intercept)	**−0.87*****	**−0.85*****	**−0.57****	**−0.91****	**−0.67****
	(0.20)	(0.20)	(0.20)	(0.31)	(0.21)
Social Democratic Party	−0.00	−0.00	−0.00	−0.00	−0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Corporatism (within)	0.01	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Corporatism (between)	**0.35****	**0.38****	**0.38***	**0.34****	**0.30***
	(0.13)	(0.13)	(0.15)	(0.13)	(0.13)
Institutional Contraints			−0.01	−0.01	−0.01
			(0.03)	(0.03)	(0.03)
Alternative Institutional Contraints	0.00				
	(0.02)				
Institutional Contraints (between)		0.18			
		(0.12)			
Institutional Contraints (within)		−0.01			
		(0.01)			
Adjusted Deficit	**−0.10*****	**−0.10*****	**−0.10*****	**−0.10*****	**−0.10*****
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Deindustrialization (within)	**0.14***	**0.14***	**0.13***	**0.14***	**0.15***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Deindustrialization (between)	**0.50*****	**0.46*****	**0.50*****	**0.50*****	**0.51*****
	(0.12)	(0.12)	(0.14)	(0.12)	(0.12)
Trade Openness	**−0.23*****	**−0.23*****	**−0.22*****	**−0.23*****	**−0.23*****
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Unemployment	**0.12*****	**0.12*****	**0.12*****	**0.12*****	**0.12*****
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Share 65+					**0.18****
					(0.06)
Small State	**0.81*****	**0.80*****			**0.82*****
	(0.22)	(0.22)			(0.22)
Small State (under 10 Mil)			−0.03		
			(0.06)		
Large State (larger than 20 Mil)					
Medium-sized state (between 6-20 Mil)				0.05	
				(0.27)	
Small State (under 6 Mil)				**0.87****	
				(0.32)	
Debt Rule	−0.02	−0.02	−0.02	−0.02	−0.02
	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)
EU Member	0.09	0.09	0.08	0.09	0.08
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Corporatism*Deindustrialization	**0.11***	**0.11***	**0.12***	**0.11***	**0.11***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
AIC	484.35	486.66	502.31	488.85	480.23
N (Government)	441	441	441	441	441
N (Country)	32	32	32	32	32
N (Total)	1167	1167	1167	1167	1167
Variance Government Level	0.09	0.09	0.10	0.09	0.09
Variance Country Level	0.48	0.45	0.66	0.48	0.50
Residual Variance	0.03	0.03	0.03	0.03	0.03
Variance Random Slope	0.06	0.06	0.06	0.06	0.06
Covariance Random Slope/Intercept	0.02	0.02	0.05	0.02	0.04

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\circ}p < 0.1$

Table 7: Mixed-Effect Models

	Only Selected R&D	R&D as DV	Education as DV	ALMP as DV
(Intercept)	**−0.87*****	−0.22	**−0.97*****	−0.29
	(0.20)	(0.21)	(0.20)	(0.27)
Social Democratic Party	−0.00	−0.01	−0.00	−0.00
	(0.01)	(0.02)	(0.02)	(0.02)
Corporatism (within)	0.01	0.00	0.00	0.02°
	(0.01)	(0.01)	(0.01)	(0.01)
Corporatism (between)	**0.35****	**0.27***	0.25°	**0.45****
	(0.13)	(0.12)	(0.13)	(0.14)
Institutional Contraints	−0.01	−0.06°	0.00	−0.01
	(0.03)	(0.04)	(0.03)	(0.03)
Adjusted Deficit	**−0.10*****	**−0.07*****	**−0.09*****	**−0.07*****
	(0.02)	(0.02)	(0.02)	(0.02)
Deindustrialization (within)	**0.13***	0.09	**0.14***	0.01
	(0.06)	(0.10)	(0.06)	(0.08)
Deindustrialization (between)	**0.49*****	**0.40*****	**0.45*****	0.19
	(0.12)	(0.11)	(0.12)	(0.13)
Trade Openness	**−0.22*****	**−0.17***	**−0.28*****	**0.14***
	(0.05)	(0.07)	(0.05)	(0.07)
Unemployment	**0.12*****	0.01	**0.10*****	**0.13*****
	(0.02)	(0.02)	(0.02)	(0.03)
Small State	**0.82*****	−0.16	**0.98*****	0.13
	(0.22)	(0.19)	(0.23)	(0.26)
Debt Rule	−0.02	**−0.11***	0.02	−0.10°
	(0.04)	(0.05)	(0.03)	(0.05)
EU Member	0.09	**0.20***	0.04	0.11
	(0.06)	(0.08)	(0.06)	(0.09)
Corporatism*Deindustrialization	**0.11***	0.15°	**0.10***	0.01
	(0.05)	(0.08)	(0.05)	(0.05)
AIC	488.06	622.15	641.41	1001.31
N (Government)	441	441	441	441
N (Country)	32	32	32	32
N (Total)	1167	1167	1167	1167
Variance Government Level	0.09	0.08	0.11	0.13
Variance Country Level	0.49	0.43	0.50	0.57
Residual Variance	0.03	0.04	0.04	0.06
Variance Random Slope	0.05	0.19	0.06	0.06
Covariance Random Slope/Intercept	0.02	−0.07	0.01	−0.07

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\circ}p < 0.1$

Table 8: Mixed-Effect Models

B5. Descriptive Statistics for Individual Index Components

Figure 13 to Figure 15 show descritpive statistics for the individual subcomponents of the knowledge investment index.

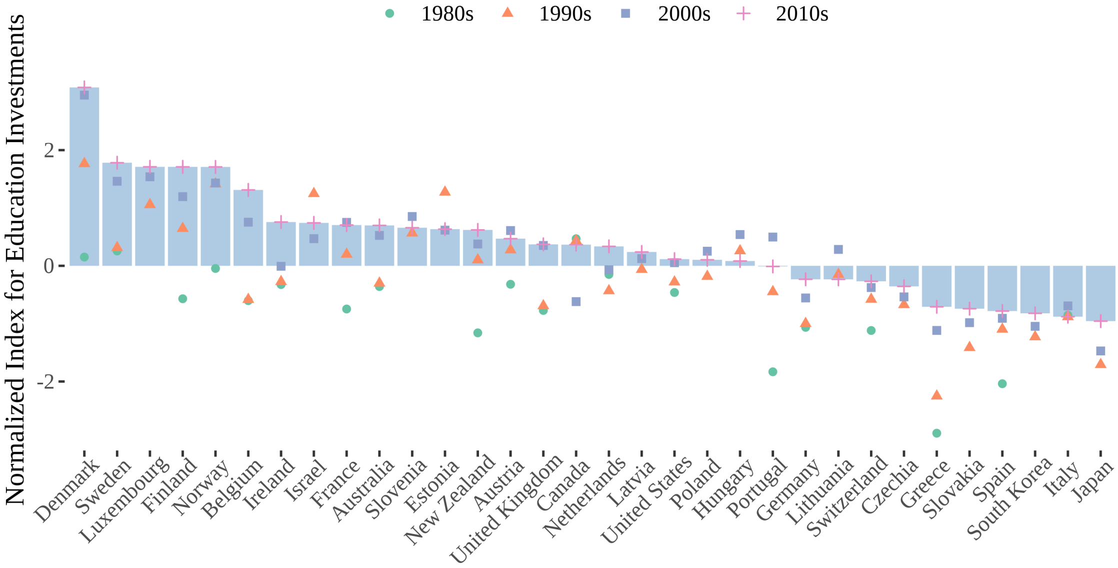

Figure 13: Normalized Investment in Education (1980s-2010s). Values are averaged across multiple imputations.

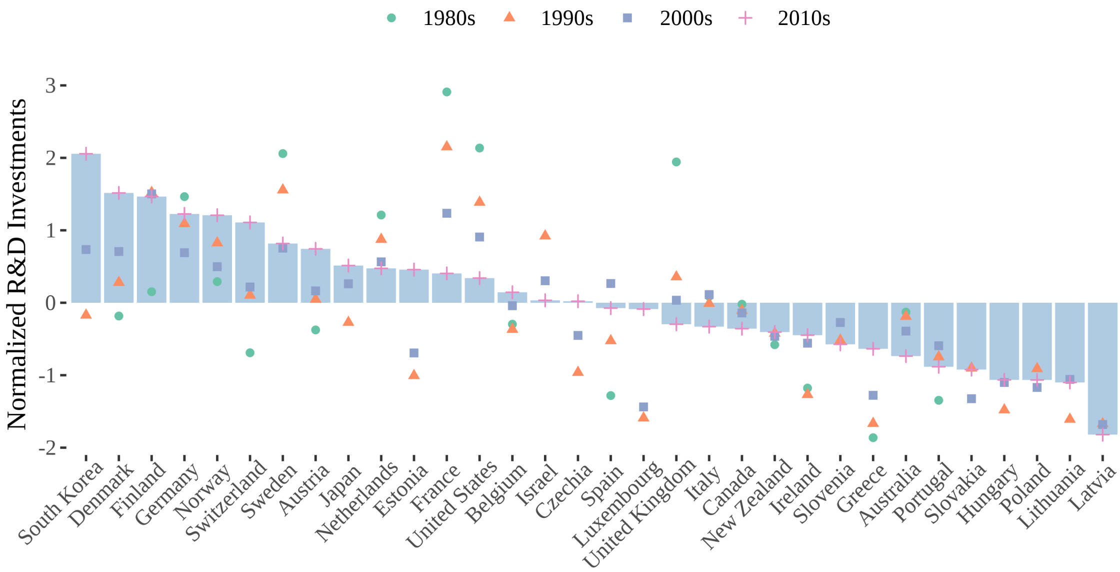

Figure 14: Normalized Investment in Research and Development (1980s-2010s). Values are averaged across multiple imputations.

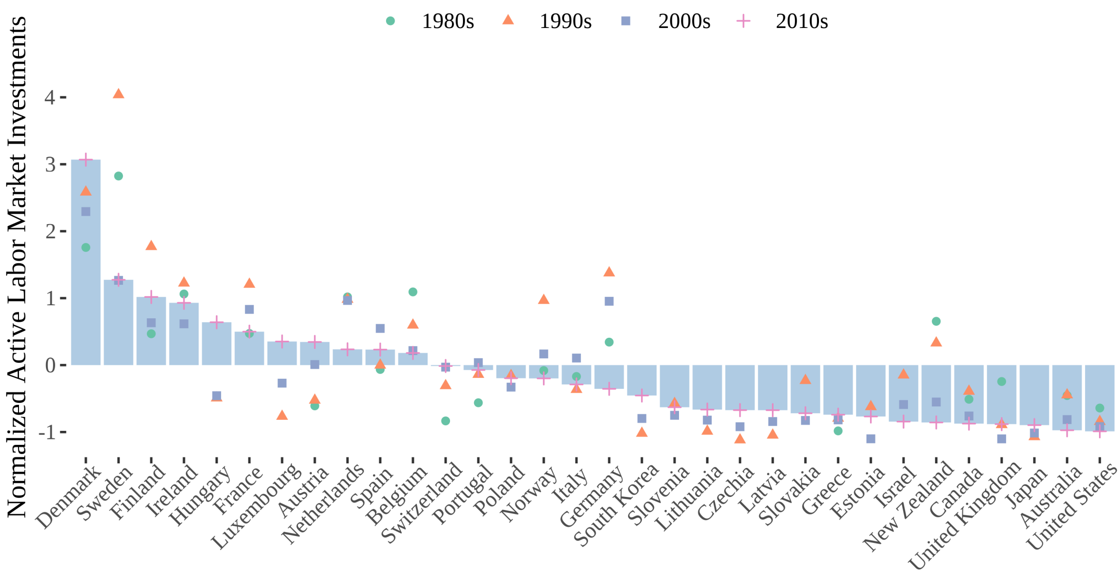

Figure 15: Normalized Investment in Active Labor Market Policies (1980s-2010s). Values are averaged across multiple imputations.

B6. Random Slopes for Individual Index Components

Figure 16 to Figure 19 show the random slopes for deindustrialization for all countries. Figure 16 is based on the main model with the index for investments in knowledge-based capital, the other figures use data from models with the individual sub-components of this index as dependent variables.

Figure 16: Random slopes for deindustrialization across countries. Based on the main model with the full dependent variable

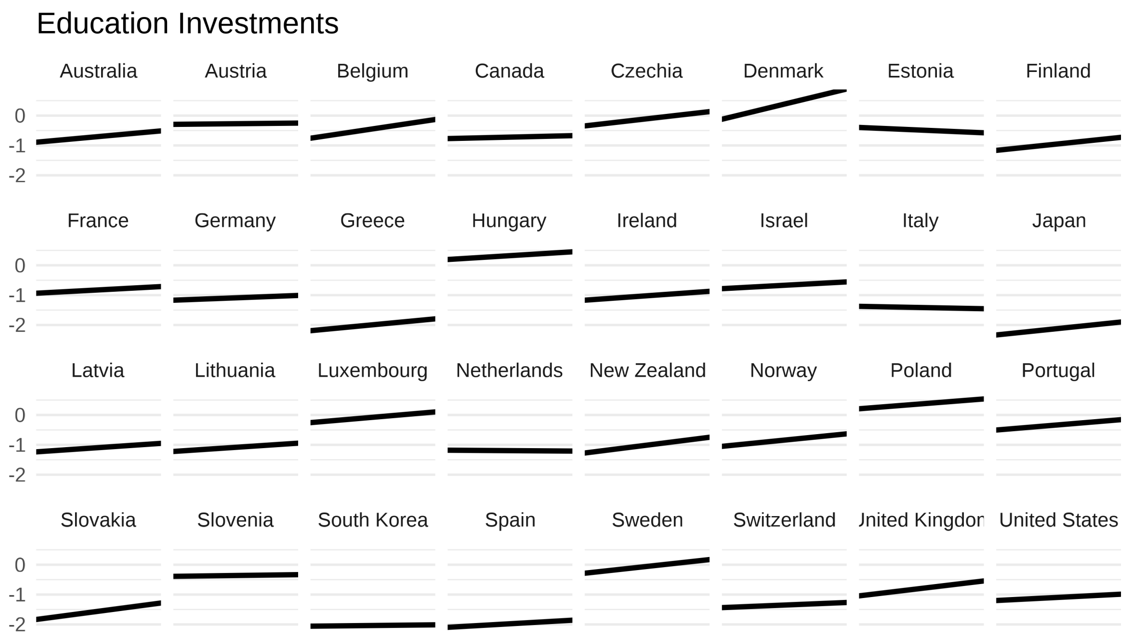

Figure 17: Random slopes for deindustrialization across countries. Based on the main model with the full dependent variable

Figure 18: Random slopes for deindustrialization across countries. Based on the main model with the full dependent variable

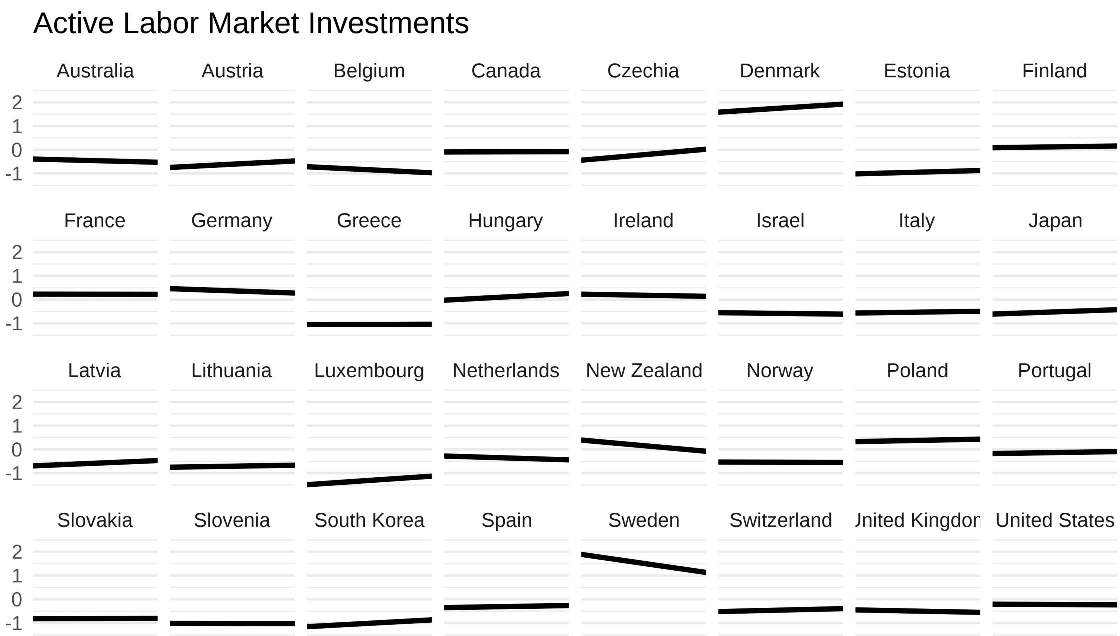

Figure 19: Random slopes for deindustrialization across countries. Based on the main model with the full dependent variable

C. Textual Analysis

As discussed in the main paper, I had originally included an ideational explanation - in addition to the institutional one focusing on corporatism. I report the theory behind it, the data collected, and the analysis here for transparency reasons. While I found some weakly robust support that a more positive discourse on public debt, investments, and technological change might be associated with higher levels of investments in knowledge-based capital, I did not really trust these results. Descriptively plotting the sentiment of discourse, for example, did not provide intuitive results and could have been influenced by all kinds of things that don't really capture state identities or debt cultures. Most importantly, however, garbage-in-garbage-out also and perhaps especially applies to text-as-data methods. And while my textual data were not garbage, they were very broad in what their coverage as the underlying search strings were too broad (they also had to be to get enough articles from each country for most years). Interpreting these results is indeed like 'reading tea leaves' (Chang et al., 2009), and feeling uncomfortable with ones data is a good sign not to use them. If I don't trust them, how can I expect others to? There is, however, much potential, I still believe, in using text-as-data methods in similar designs. It is important however, to get good and relatively precise/narrow data first (Nicholls & Culpepper, 2020)

C1. Theory

Often overlooked, Katzenstein's argument is as much ideational as it is institutional.[5] Here, I want to spin this argument further by more systematically theorizing the role of state identities and politico-economic cultures in mediating the causal chain between challenges and responses. Ideas matter because they help actors understand their interests and coalitional options in a world of uncertainty (Blyth, 2003). "To the extent that economic reality is uncertain - which in real life is nearly always - cognitive elements affect decision making" (Gourevitch, 1986, p. 63). Political actors therefore "experiment into an open horizon, often driven by myopic conceptions of group interests, without anyone's being able to predict today whether the path pursued will actually pay off in the longer run either for (1) the political actors and their constituencies advancing the reforms right now and/or for (2) the macroeconomic performance of the polities (or regions) in which these reforms prevail" (Beramendi et al., 2015, p. 60).

Investment policies are therefore a matter of 'puzzling' as much as of 'powering' (Heclo, 1974, p. 305), of "conflicting identities" as much as of "conflicting interests" (Ziegler, 1997, p. viii). In this

[5] In fact, Katzenstein himself notes that "the impermeability of the field of political economy to considerations of identity persists to date" (Katzenstein, 2003, p. 11).

context, three questions are of particular importance. First, how is the state's role in the economy understood? Second, how is the relationship between public debt or deficits and public investments construed? And third, is technological change seen a threat or an opportunity?

The first question shapes how public investments are viewed. Are they seen as essential and essentially positive in an economy in which markets regularly fail to provide important goods? Can governments legitimately act as investors or even entrepreneurs in their own right (Mazzucato, 2013)? Or are they seen as circumspect, as a symptom of an overreaching government incapable of making the right investments and discontent with limiting itself to administering markets? Mazzucato herself points to the central importance – and self-fulfilling nature – of the 'discursive battles' (Mazzucato, 2013, p. 3) around the proper understanding of government. In the US, for example, the discursive war on the very notion of government has not only produced a large-scale shift in how government is portrayed and talked about (George, 2013); but it has also changed the confidence of, resources allocated to, and therefore effectiveness of the governments, which reinforces the discursive shift (Hacker & Pierson, 2016).

The second question concerns how public debt and public deficits are viewed. Notions of public spending are profoundly intertwined with "contending representations of state virtue" (Dyson, 2014, p. 263), which are themselves anchored in different ideologies of debt and economic cultures. Dyson distinguishes between two ideologies of debt, one that "represents debt as shameful and potentially poisonous to virtue", and one that values debt for its "productive use" (Dyson, 2014, p. 268). In combination with different economic cultures – the culture of elite magnificence, stability culture, consumer culture, social welfare culture, and welfare protection culture – these ideologies give rise to five different representations of state virtue: the dignified state, the ascetic state, the permissive state, the protective state, and the inclusive state (Dyson, 2014, pp. 269–283). While the dignified state mostly belongs to the past, the latter four of these representations of state virtue offer a useful typology of modern state identities.

- The ascetic state is based on a negative view of debt and an economic culture that centers around fiscal stability and prudence. It views debt as inherently suspicious and prioritizes stable finances over investments as the best way to provide justice. Ascetic states are unlikely to pursue investment policies. This is increasingly true even for states that run fiscal surpluses as preceding fiscal consolidations have entrenched a new fiscal regime that makes higher spending increasingly difficult (Haffert & Mertens, 2015)
- The permissive state is a state that boosts consumer culture by incentivizing high levels of private debt, even if this comes at the expense of neglecting public goods, including digital goods. "Longer-term investment in public infrastructure and in building inclusive forms of

social capital took second place to more immediate individual consumer gratification. It was inimical to belief in the virtues of the entrepreneurial state supporting bold and high-risk innovation" (Dyson, 2014, p. 278).

- The protective state also has a sanguine view of public debt but views it not as a means to promote public welfare but as tool of political patronage and clientelism. This, together with the resulting distrust in the state, makes such protective states unlikely to invest in the future.
- The inclusive state grows out of a social welfare culture that "public expenditure as essential to the promotion of social peace and solidarity and to strengthening long-term-growth"; in particular, debt financing is seen as positive due to its "developmental role for the state in supporting fundamental innovations that [are] high cost and uncertain and whose fruits lay fax in the future" (Dyson, 2014, p. 279). Inclusive states can be expected to invest most in knowledge-intensive capital.

The third question relates to how technological change is viewed. Already in Shonfield (1965) we find the notion that states' reactions to technological and economic change depend on the "broad stance that a variety of national actors take to the economy, which in turn is based on culturally specific orientations deeply rooted in national history" (Hall, 1997, p. 185). Dobbin and Ziegler echo this view when they point to the importance of historically rooted 'industrial cultures' (Dobbin, 1994) and the professional identities of administrative and technical elites (Ziegler, 1997) in assimilating novel problems to old ways of thinking, and therefore in shaping political responses to technological and economic change. The Swedish "policy style" (Richardson, 2013), for example, has been characterized as one of 'principled pragmatism' (Heclo & Madsen, 1987) and applied, 'secular rationalism' (Tomasson, 1970, pp. 291–292). Perhaps unsurprisingly, then, the Swedish reactions to recent technological upheavals has been relatively forward-looking, with an emphasis on manageable opportunities rather than threats (Goodman, 2017; Marenco & Seidl, 2021).

How countries answer these three questions may thus depend on their identities and broader politico-economic culture. These ideational forces can be expected to influence how states think about digitalization, and consequently their role in shaping it. What Dyson said about public debt also applies to public investments and technological change: their "relationship [with] political rule remains pre-eminently a realm of subjective knowledge, conveyed by storytelling. Stories perform vital functions. They offer a compass in navigating radical economic and political uncertainty, as well as a sanctuary for retreat in the face of sheer complexity and passionate contestation. Stories also have a moral function. They distribute praise and blame [but] also serve as distorting prisms through which responsibility is evaded" (Dyson, 2014, p. 7). These stories, as Vivien Schmidt has argued, are told in discourse, where visions of what is empirically and morally right are articulated and state identities and politico-economic cultures are reflected and shaped (Schmidt, 2008).

C2. Analysis

C21. Data To test the ideational explanation, I collected 88136 newspaper articles for 30 countries. Newspaper articles were collected via factiva and Nexis Uni based on three sets of search strings.

a search string capturing discourse on technological change with references to *technological change* or *technological progress*

a search string capturing discourse on pubic debt and deficits with references to *public debt* or *government debt* or *public deficit* or *government deficit*

a search string capturing discourse on public investments references to *public investment* or *government investment*

These search strings had to appear at least once in an article within 2 words from each other (i.e. public-sector investment also counted). Translations of these search strings were verified by native speakers of the respective languages, who sometimes also added particular terms that are used in their country's debates on these issues (e.g. Staatsschulden in Germany). All newspaper articles additionally had to contain at least one reference to the country in questions in order to make it less likely to collect articles that a solely about discourses in other countries (although this is not per se problematic as the way in which countries talk about, say, public deficits in another country also reflects the way they think about it themselves). If searches led to a particularly high number of articles (>10000 for one topic in one country), the search strings were made somewhat more restrictive, i.e. they had to contain at least two references to the above-mentioned terms.

For many countries, it was relatively easy to find articles from the countries' main newspapers of the center-left and center-right, i.e. those that can in combination be considered representative of the national discourse. In those cases, it was also possible to collect articles going back to the 1990s and thus have continuous time series over 20 years or so. For some countries, however, it was more difficult to obtain such time series, and for a few others still it was also not possible to get access to the countries main newspapers but only to their English-language versions or to English-language newspapers that specifically cover the region. Thus, while for the United States we have continuous coverage from the New York Times, the Washington Post, and the Wall Street Journal since the 1980s, for Sweden the articles only reach back to the early 2000s. For Greece, I used the English edition of Kathimerini, one of the country's main newspapers. For South Korea, I used some of the main English-speaking outlets such as the Korea Times. Often, newspaper were also complemented by press wires.

However, in all these cases, I manually made sure that only such newspapers or news agencies were included in the sample that reliably conveyed a good picture of the national discourse, i.e. those that were either translations from original-language articles or contained many quotes by national social actors and were thus trying to depict national political debates. Articles that mainly contained technical or economic information (such as the latest unemployment statistics) were excluded. Table 9 gives an overview of the newspaper included in the sample.

Table 9: Newspaper Corpus Overview

Newspaper	Number of Articles
Australia	
Sydney Morning Herald	2752
The Daily Telegraph	380
Canberra Times	14
The Australian	1
Austria	
Austria Presse Agentur	2175
Die Presse	1185
Der Standard	679
Wirtschaftsblatt	522
Salzburger Nachrichten	321
Kurier	74
Belgium	
Agentschap Belga	531
SeeNews Belgium	43
Canada	
The Globe and Mail	5149
The Toronto Star	2741
National Post	2148
La Presse Canadienne	309
The Financial Post	61
Czech Republic	

Table 9: Newspaper Corpus Overview *(continued)*

Newspaper	Number of Articles
Hospodárské Noviny	1124
Lidové Noviny	251
Denmark	
Politiken	1135
Ritzau General News Service	395
ErhvervsBladet	178
Webnews - Danish	178
Jyllands-Posten	107
Estonia	
Baltic Business Daily	472
The Baltic Times	92
Baltic Daily - Political/Social News	76
BNS Baltic Business News	53
Baltic Business Weekly	39
Baltic Business News	23
Finland	
Kauppalehti	529
Suomen Tietotoimisto	192
France	
Le Monde	2811
Le Figaro	1614
L'Humanité	649
La Croix	308
Libération	36
Germany	
Handelsblatt	863
Süddeutsche Zeitung	739
taz, die tageszeitung	313
Der Tagesspiegel	237
WirtschaftsWoche Online	212
Die ZEIT	158

Table 9: Newspaper Corpus Overview *(continued)*

Newspaper	Number of Articles
Greece	
Kathimerini English Edition	472
Greek Reporter	66
Hungary	
Világgazdaság	933
Napi Gazdaság	378
Ireland	
The Irish Times	3608
Irish Independent	1556
Irish Examiner	903
Sunday Business Post	646
Evening Herald	8
Israel	
The Jerusalem Post	620
Globes	548
The Times of Israel	63
Italy	
Corriere della Sera	2027
La Stampa	1786
La Repubblica	1443
Japan	
Jiji Press	1492
The Nikkei	674
The Daily Yomiuri	437
The Japan Times	260
The Japan Economic Journal	197
The Japan News	57
Report From Japan	53
Japanese Business Digest	5
WebNews - Japanese	1

Table 9: Newspaper Corpus Overview *(continued)*

Newspaper	Number of Articles
Latvia	
Baltic Business Daily	914
Baltic Daily - Political/Social News	95
BNS Baltic Business News	73
The Baltic Times	63
Baltic Business News	29
Baltic Business Weekly	19
Lithuania	
Baltic Business Daily	474
BNS Baltic Business News	49
The Baltic Times	43
Baltic Daily - Political/Social News	35
Baltic Business Weekly	29
Baltic Business News	5
Netherlands	
NRC Handelsblad	1066
Het Financieele Dagblad	982
de Volkskrant	532
De Telegraaf	220
Vrij Nederland	34
De Groene Amsterdammer	22
New Zealand	
The New Zealand Herald	1677
The Dominion Post	445
The Press	364
Waikato Times	205
Norway	
Dagens Næringsliv	542
Norsk Telegrambyrå	254
TDN Nyhetsbyrå	94
Aftenposten	35

Table 9: Newspaper Corpus Overview *(continued)*

Newspaper	Number of Articles
Bergens Tidende	17
Stavanger Aftenblad	16
Norsk Telegrambyr	5
Vestnytt	3
Poland	
Rzeczpospolita	1566
Gazeta Wyborcza	857
Gazeta Prawna	718
Gazeta.pl	61
Portugal	
Publico	1811
Jornal de Notícias	501
Correio da Manhã	404
Slovakia	
Slovenska Tlacova Agentura	497
Výber správ zo Slovenska	270
Dennik N	60
Slovenia	
The Slovenia Times	228
Esmerk Slovenia News	21
Slovenia Today	15
M-Brain Slovenia News	11
News Bites - Central and Eastern Europe: Slovenia	5
Spain	
ABC	1334
El Periódico	1323
El Pais	1153
El Mundo	609
La Vanguardia.com	290
El Diario.es	63
Sweden	

Table 9: Newspaper Corpus Overview *(continued)*

Newspaper	Number of Articles
Nyhetsbyrån Direkt	922
Dagens Nyheter	187
Helsingborgs Dagblad	42
Sydsvenskan	18
Switzerland	
NZZ	1192
Tages-Anzeiger	305
Blick	13
United Kingdom	
The Guardian	3696
The Times	2424
The Daily Telegraph (UK)	1479
United States	
The New York Times	4122
The Washington Post	2626
The Wall Street Journal	870

C22. Methods

C221. Sentiment Analysis The paper uses a dictionary-based approach to sentiment analysis but complements it with natural language process in order to account for negators, amplifiers and deamplifiers. I used standard negators, amplifiers and deamplifiers obtained from the lexicon package.

The sentiment scores represent the unweighted average of four different dictionaries:

– the AFINN dictionary developed by (Nielsen, 2011);

– the Bing sentiment lexicon developed by Hu & Liu (2004);

– the NRC Word-Emotion Association Lexicon developed by Mohammad & Turney (2010); and

– the syuzhet dictionary (and accompanying R package) developed by Matthew Jockers and the Nebraska Literary Lab (Jockers, 2017).

While these dictionaries are widely used and relatively general in purpose, I combined them to make sure that the results are not driven by the particularities of any one of these dictionaries. In case of the NRC dictionary, I did not use their emotion-based dictionaries (such as those for anger, fear, or hope) but only those for positive and negative terms. The afinn and syuzhet dictionaries have a higher resolution than bing and nrc by scoring words not just as negative (-1) and positive (+1) but allowing more gradation. I transformed these higher-resolution scales to a binary positive-negative score for both technical reasons and to provide more robust estimates. After all, whether a word is positive or negative is a much more straightforward question than whether a positive word is quite (+3), very (+4) or extremely (+5) positive, especially across different contexts and for machine-translated documents.

C222. Topic Modeling

Preprocessing

The topic models included only articles about public debt/deficit and public investment as they were meant to capture different state identities, which revolve around debt cultures and conceptions of the role of the state in the economy. For pre-processing, I used annotated part-of-speech tags to select nouns, adjectives, and verbs. I discarded punctuation and stopwords as well as semantically less meaningful parts of speech like determiners or names entities like dates. I also included a list of 184 n-grams, which was manually compiled based on the most frequent collocations identified in the text (with log-frequency biased mutual dependency used as the ordering metric). I lowercased but did not stem our document feature matrix as the difference between singular and plural forms can be meaningful while the difference between uppercased and lowercased words is most likely not – at least in the types of policy and newspaper documents I look at. In addition, I removed remaining word trash such as html tags, common untranslated words, as well as country-specific information using the named entity information. This latter removal is meant to ensure that differences in topic prevalence are, as much as possible, the result of substantive differences and not of local vernaculars or parochial word usage. Lastly, I removed words that appeared in more than 50 per cent or less than 0.5 per cent of documents. While this is a somewhat arbitrary (although commonly used) standard, qualitative inspection revealed but proofed to be a useful threshold that removed many very specific and rare terms while still retaining un-common but not unimportant words.

Number of Topics

I chose a topic model with k = 45 topics. This decision was assisted by several metrics. Figure 20 plots four metrics – semantic coherence, exclusivity, residuals, and held-out-likelihood – for models with different ks. The range of k was theoretically decided as topics should be broad enough to be at least potentially relevant in different countries, but narrow enough to capture interesting frames of public debt or public investment. This suggests a number of topics somehwere between 20 and 80. Semantic coherence is a metric that measures how often the most frequent words in a topic actually co-occur in a document. While semantic coherence has been shown to correlate well with human judgments of topic quality, it has been shown to increase when topics are dominated by very common words (Roberts et al., 2018). Exclusivity, by contrast, penalizes models with few dominant top words. It measures the share of top words which are distinct to a given topic, thus creating something of a trade-off with semantic coherence. The residuals capture overdispersion of the variance of the multinomial in stm's data generating process (Roberts et al., 2018). Higher values indicate overdispersed residuals, implying that the latent topics cannot account for the overdispersion and more topics may be needed to use up the extra variance. Held-out likelihood estimates the probability that words appear in a document when these words have been removed before the estimation. It is a measure of predictive performance, with higher values indicating better performance. Hence, we want semantic coherence, exclusivity, and held-out likelihood to be as high and the residuals to be as low as possible. Figure 20 suggest that a topic model with k = 45 should be a good choice, and one that falls squarely within the realm of what we would expect.

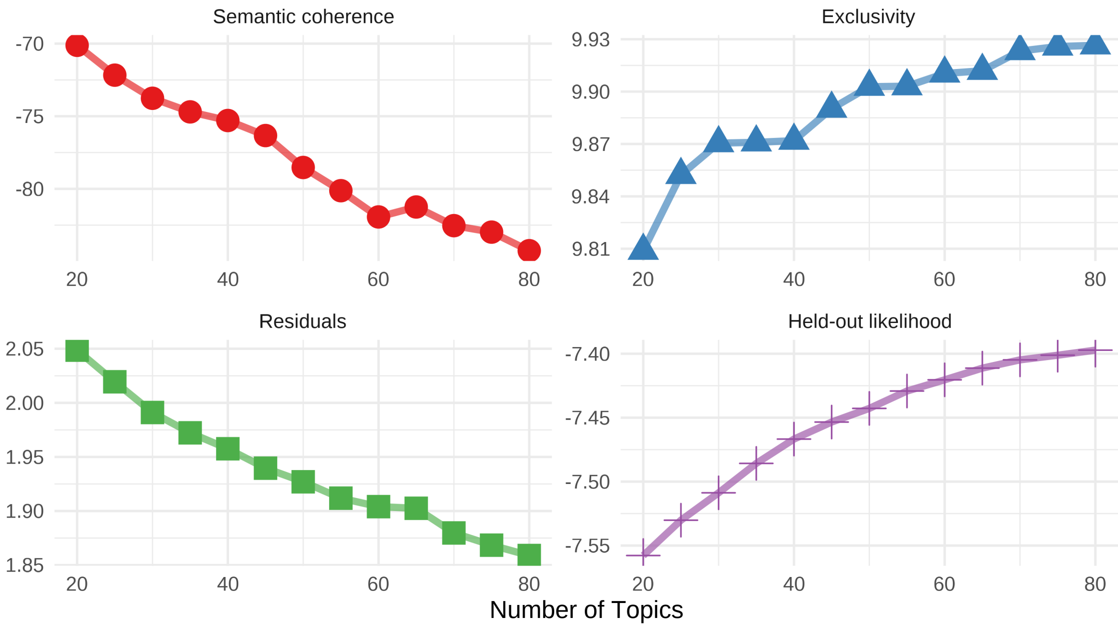

Figure 20: Model diagnostics for different numbers of topics (20 to 80)

Topic Interpretation & Aggregation

I allowed the country variable and the date variable to influence the prevalence of topics. The topics were then labeled based on the most *FR*equent and *EX*clusive Words (FREX). Lastly, topics were assigned to either the ascetic state category or the inclusive state category or they were not assigned at all. Based on Dyson (2014), topics were assigned to the ascetic state category if they were about balanced budgets, credit ratings, structural reforms, or the like. They were assigned the inclusive state category if they were about investments in infrastructure, green technologies, research, education, or worker protection. Figure 21 plots wordclouds with the most common FREX terms for the topics that make up the inclusive state (red) or ascetic state category (blue).

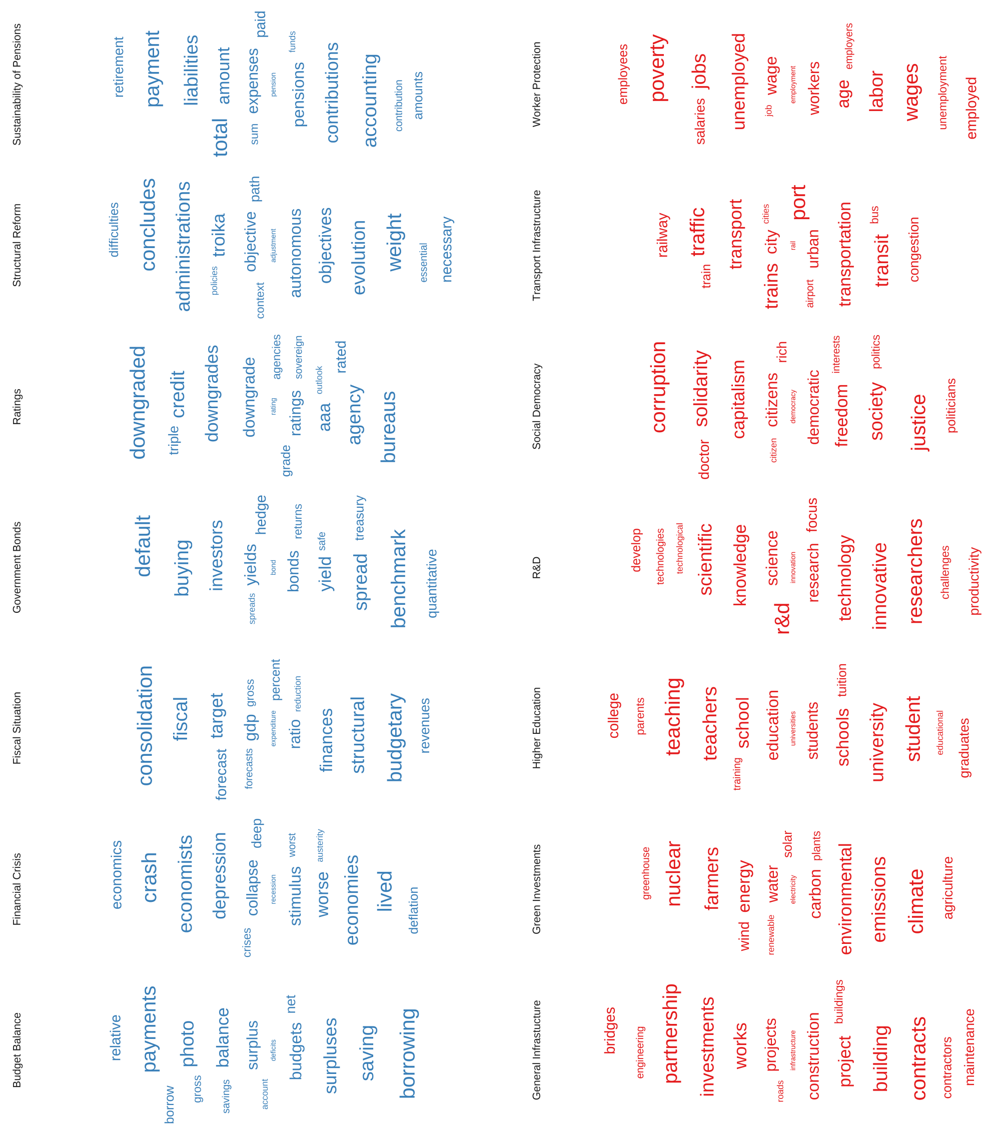

Figure 21: Wordcloud with top FREX terms for topics assigned to the inclusive state (red) or ascetic state category (blue)

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