Financial Development and Fragility

A Clustering Analysis

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Abstract

This paper explores the potential correlations between financial development and state fragility, using a sample of 137 countries observed over the period from 1998–2019. The countries are grouped into clusters that capture the different joint states of financial development and fragility. The paper introduces a new switching methodology to further allow for a qualification of the evolution of countries in terms of fragility scores with and without controlling for other variables. Irrespective of the precise methodology and state fragility measure as used in this paper, the findings indicate a negative correlation between financial development and state fragility, after controlling for several forms of observed and unobserved heterogeneity.
Financial Development and Fragility:  
A Clustering Analysis*

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1 Introduction

State fragility is one of the most pressing development challenges of our time, with an estimated 800 million people living in fragile states. In broadest terms, fragility refers to a situation where the state is unable or unwilling to fulfill the basic needs of its citizens. The definition centers on the potential for adverse outcomes and the absence of fundamental structures that ensure continuity and stability. Countries with higher levels of fragility more often struggle to provide basic services to their citizens, to maintain economic stability, or to implement effective policy (Stewart and Brown, 2009). Political instability in fragile countries is more likely to be linked to armed conflict, civil unrest, and violence (Chami et al., 2021).

In this paper, we examine the relationship between state fragility and financial development to determine which countries are more prone to extended periods of instability, other things being equal. Financial development is the process of development of institutions and markets to overcome the costs associated with the delivery of the key functions of the financial system: mobilizing savings, promoting greater information sharing, improving resource allocation, and facilitating diversification and management of risk (Levine, 2005). Financial development, especially when starting from low levels, plays a pivotal role in promoting efficient resource allocation and fostering entrepreneurship, thereby contributing to economic stability and potentially reducing state fragility. At the same time, however, state fragility can obstruct the process of financial development. Financial markets and, more broadly, financial activity rely critically on well-functioning institutions.
that protect property rights and provide a minimum of certainty; on an envi-
ronment of trust among economic agents; and on the ability of policy-makers
to provide stable macroeconomic conditions. Fragile states, where these ele-
ments are in short supply, can be expected to have less developed financial
institutions and markets—although the evidence on this is mixed (Barajas
et al., 2021).

Numerous studies have empirically investigated the links between finan-
cial development and economic growth, often uncovering positive and signif-
icant correlations (Levine, 1997; Beck et al., 2000; Valickova et al., 2015),
with causality running from finance to growth. Financial development has
also been shown to reduce income inequality and is strongly associated with
poverty alleviation (Beck et al., 2007). However, the relationship between
financial development and state fragility (or its opposite, resilience), which
may be heterogeneous across groups of countries and measures of financial
development, has not been extensively addressed in the existing literature
(Barajas et al., 2021). This leaves a gap that this paper aims to fill.

There are at least two major limitations of the current study that we
want to mention upfront. First, measuring state fragility is not undisputed;
see for instance Grimm et al. (2014). Similarly, proxying financial develop-
ment is a difficult exercise given its multifaceted nature; see, for example,
Svirydzenka (2016). In this paper we use World Bank and IMF measures for
state fragility and financial development, respectively. For state fragility we
use the Country Policy Institutional Assessment (CPIA) score, a widely used
metric to classify fragile countries. This picks up aspects related to the level
of institutional capacity and policy environment of a country. For financial
development, we use the financial development (FD) index, introduced by
Sahay et al. (2015), which is a relative ranking of countries on depth, access,
and efficiency of financial institutions and financial markets.

Second, there is an obvious endogeneity issue with the current analysis.
The relationship between financial development and state fragility may work
both ways. The current data set does not allow us to solve this endogeneity
issue. Though we account for observed and unobserved static and dynamic heterogeneity, we cannot exclude further heterogeneity that might impact the results. Further corrections do not really seem possible given the patterns in the empirical data. Particularly the dynamics of the fragility proxies are quite stale, resulting only in a limited value added of the time-series dimension of the analysis and impeding hopes to seriously address the potential endogeneity biases. To accommodate this concern, we report a number of different robustness checks of the baseline analysis.

We explore the potential link of financial development with the degree of state fragility in a sample of 108 countries from 1998 to 2019 using a variety of methodologies. Our main research question is whether we can distinguish different groups in the data that show different dynamics of CPIA and CPIA-FD correlation over time. In particular, we ask whether countries remain rather stable within their CPIA-FD group for a longer period of time, or whether they can transition for instance from high-fragility to low-fragility groups (see also Safran and Sugiyarto, 2014). For this, we first group countries based on their aggregate CPIA and FD scores using a clustering approach to account for possible heterogeneity. Based on this preliminary analysis, we find two or three stable clusters in the data. Next, we use the approach of Bonhomme and Manresa (2015) to investigate the correlation between CPIA and FD, while controlling for cluster-specific time-varying heterogeneity as well as for a group of observed determinants of fragility, such as growth, inflation, military spending, and natural resource rents. Finally, we extend the methodology of Bonhomme and Manresa (2015) to account for switches of groups over time. We do so in a more generic setting than for instance Lumsdaine et al. (2023), who generalize Bonhomme and Manresa (2015) to a setting with structural breaks. In our approach, we do not enforce ex-ante that changes over time should be of a before-after structural break, but allow for more flexible changes, where patches of observations at different times may belong to the same regime, alternated by a different regime at other times. This is important in our current setting, where countries may
transit from high fragility to low fragility and back again several times over a longer period.

We find a negative association between state fragility as a left-hand side variable and financial development. This association between the two variables remains after controlling for other variables that can determine state fragility, such as growth, military spending and inflation. It also remains if we control for unobserved heterogeneity with or without clustering, and with or without allowing for cluster switches. Finally, the effect remains if we swap the CPIA scores by the Fund for Peace’s Fragile State Index (FSI) scores as a proxy for state fragility.

The remainder of this paper is set up as follows. In Section 2 we present the methodology used to divide the different countries into groups, both in a static and dynamic way. Section 3 describes the data and variables used. Section 4 presents the results, and Section 5 concludes. An appendix gathers additional empirical results and robustness checks not shown in the main paper.

2 Clustering methodologies

2.1 The model

Let \( y_{i,t} \in \mathbb{R}^{G \times 1} \) for \( i = 1, \ldots, I \) and \( t = 1, \ldots, T \) be a vector of multivariate panel data observations. The panel can be unbalanced. In our context, the vector \( y_{i,t} \) may for instance contain different financial development proxies such as the FD index, state fragility proxies such as the CPIA score, and possibly other economic indicators, not all of which may be available at all times or for all countries. We assume that all elements of \( y_{i,t} \) are either observed or missing for a specific unit \( i \) at time \( t \). We also define a matrix of observed covariates \( X_{i,t} \in \mathbb{R}^{G \times M} \).

At each time \( t \), unit \( i \) belongs to one of \( K \) groups or clusters. The corresponding group is indicated as \( k_{i,t} \in \mathcal{K} = \{1, \ldots, K\} \). For each group, we
specify the model for $y_{i,t}$ as
\begin{equation}
    y_{i,t} = \alpha_{k_{i,t},t} + X_{i,t} \beta_{k_{i,t}} + \varepsilon_{i,t}, \quad \varepsilon_{i,t} \overset{\text{iid}}{\sim} q_\varepsilon(\varepsilon_{i,t}; \Sigma_{k_{i,t}}, \psi_{k_{i,t}}),
\end{equation}
for some density $q_\varepsilon(\cdot; \Sigma_k, \psi_k)$ with mean zero, covariance matrix $\Sigma_k$, and shape parameter(s) in the vector $\psi_k$. The parameters $\alpha_k = (\alpha_{k,1}, \ldots, \alpha_{k,T})^\top$, $\beta_k$, $\Sigma_k$, and $\psi_k$, for $k \in K$, are gathered into a parameter vector $\vartheta$ that needs to be estimated from the data together with the cluster assignments $k_{i,t}$.

The set-up in Eq. (1) is quite general and nests a number of specifications from the literature. This includes specifications for $K$-means clustering with time-varying cluster means (by setting $k_{i,t} \equiv k_i$ and $\beta_{k_{i,t}} \equiv 0$) or time-invariant cluster means (by in addition setting $\alpha_{k_{i,t},t} \equiv \alpha_k$). Additionally, the specification covers clustering methods based on group-specific time-varying heterogeneity (by setting $k_{i,t} \equiv k_i$ and taking $y_{i,t}$ as scalar, so $G = 1$) as in Bonhomme and Manresa (2015). In addition, however, Eq. (1) also allows for group-specific time-varying heterogeneity specifications where units are allowed to switch cluster over time.

### 2.2 Static clustering membership

Group membership is defined based on minimizing a membership loss function. For time-invariant or static group membership ($k_{i,t} \equiv k_i$) as in Bonhomme and Manresa (2015), we define
\begin{equation}
    k_{i,t}(\vartheta) \equiv k_i(\vartheta) = \arg\min_{k \in K} \sum_{t=1}^T L(\cdot; \vartheta_{k_{i,t}}, S_{i,t}).
\end{equation}
where $L(\cdot; \vartheta_{k_{i,t}}, S_{i,t})$ is a loss-function, and $\vartheta_{k_{i,t}}$ contains the parameters $\alpha_{k_{i,t}}$, $\beta_k$, $\psi_k$, and $\Sigma_k$ for group $k$ at time $t$. For instance, $L(\cdot; \vartheta_{k_{i,t}}, S_{i,t})$ can be a squared or absolute loss based on the prediction errors $(y_{i,t} - \alpha_k - X_{i,t} \beta_k)$. Alternatively, the loss might be based on the negative log-likelihood, for instance for a Gaussian likelihood $-\log q_\varepsilon(\varepsilon_{i,t}; \Sigma_k, \psi_k)$. Asymmetry in the loss-function is easily allowed for.

As in Bonhomme and Manresa (2015), estimation of $\vartheta$ and the group membership vector $k = (k_1, \ldots, k_I)$ works by alternating the following two
steps. From an initial (random) starting value for $\hat{k}^{(r)}$ for $r = 0$, the parameters $\vartheta$ are estimated as:

$$\hat{\vartheta}^{(r)}(\hat{k}^{(r)}) = \arg\min_{\vartheta \in \Theta} \sum_{t=1}^{T} \sum_{i=1}^{I} L(y_{i,t}; \hat{\vartheta}^{(r)}_{k_i^{(r)}}, t, S_{i,t}).$$

(3)

These optimizations can be carried out separately for each of the tuples $(\alpha_k, \ldots, \alpha_{k,T}, \beta_k, \psi_k, \Sigma_k)$. Next, the group membership vector $\hat{k}^{(r)}$ is updated to $\hat{k}^{(r+1)}$ via Eq. (2) using the value $\hat{\vartheta}^{(r)}(\hat{k}^{(r)})$. This procedure is repeated until convergence, which typically only uses a few iterations. For robustness, a large number of starting values $\hat{k}^{(0)}$ is used, and the estimates $\hat{k}$ and $\hat{\vartheta}$ are retained that give the best overall criterion value in Eq. (3).

### 2.3 Cluster switching

If units are allowed to switch group membership over the period of the sample, different strategies are available. As in Lumsdaine et al. (2023), we can extend the approach of Bonhomme and Manresa (2015) to allow for a structural break. In our current context, however, that may not be desirable. Countries that have transited from a group of high fragility to one of low fragility might find themselves switching back to the former group if the country enters a stressed period due to war, political turmoil, economic distress, or other reasons. We therefore extend both Bonhomme and Manresa (2015) and Lumsdaine et al. (2023) in the following way, while retaining ease of estimation.

Time-varying group membership is determined as follows. First, we group the different time points $t \in \mathcal{T} = \{1, \ldots, T\}$ into $H$ disjoint groups $\mathcal{T}_h$ for $h = 1, \ldots, H$, such that $\cup_{h=1}^{H} \mathcal{T}_h = \mathcal{T}$, and $\mathcal{T}_h \cap \mathcal{T}_{h'} = \emptyset$ for all $1 \leq h < h' \leq H$. We constrain $k_{i,t} = k_{i,t'} = \hat{k}_{i,h}$ for all $t, t' \in \mathcal{T}_h$, while no constraint is imposed if $t \in \mathcal{T}_h$ and $t' \in \mathcal{T}_{h'}$ for $h \neq h'$. This setting allows for much more flexibility of switches in group membership beyond the structural break setting, while

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1 One can also start with an initial guess of $\hat{\vartheta}^{(0)}$ rather than $\hat{k}^{(0)}$. 

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7
still allowing for a structural break to emerge if for instance $H = 2$ and $t < t'$ for all $t \in T_1$ and $t' \in T_2$.

To estimate the parameters $\vartheta$, the time-partitions $\{T_h\}_{h=1}^H$, and the time-varying group memberships $\hat{k} = (\hat{k}_{1,1}, \ldots, \hat{k}_{I,H})$ with $k_{i,t} = \hat{k}_{i,h}$ for $t \in T_h$; compare Bonhomme and Manresa (2015).

1. Set $r = 0$ and start from some some initial random time-partition $\{\hat{T}_h^{(r)}\}_{h=1}^H$ and time-varying group assignments $\hat{k}^{(r)}$, with $\hat{k}_{i,t}^{(r)} = \hat{k}_{i,h}^{(r)}$ for $t \in \hat{T}_h^{(r)}$.

2. Given $\hat{k}^{(r)}$ and $\{\hat{T}_h^{(r)}\}_{h=1}^H$, estimate $\vartheta$ as

$$
\hat{\vartheta}^{(r)} = \arg \min_{\vartheta \in \Theta} \sum_{h=1}^H \sum_{i=1}^I \sum_{t \in \hat{T}_h^{(r)}} L(y_{i,t}; \vartheta, \hat{k}_{i,h}^{(r)}, S_{i,t}).
$$

3. Given the partition $\{\hat{T}_h^{(r)}\}_{h=1}^H$ and the parameter vector $\hat{\vartheta}^{(r)}$, update the time-varying group assignments

$$
\hat{k}_{i,h}^{(r+1)} = \arg \min_{k \in \mathcal{K}} \sum_{t \in \hat{T}_h^{(r)}} L(y_{i,t}; \hat{\vartheta}^{(r)}, S_{i,t})
$$

for every $i$ and $h$ and set $\hat{k}_{i,t}^{(r+1)} = \hat{k}_{i,h}^{(r)}$ for $t \in \hat{T}_h^{(r)}$.

4. Re-estimate the parameter $\hat{\vartheta}^{(r)}$ as in step 2 using the new group assignments.

5. Update the partition as

$$
\hat{T}_h^{(r+1)} = \left\{ t : h = \arg \min_{h \in \{1, \ldots, H\}} \sum_{i=1}^I \sum_{k=1}^K L(y_{i,t}; \hat{\vartheta}^{(r)}, S_{i,t}) \mathbb{1}\{k = \hat{k}_{i,h}^{(r+1)}\} \right\},
$$

i.e., allocate each time point to that subset in the partition that minimizes its total (across units $i$) loss function, given the cluster memberships $\hat{k}_{i,h}$ as estimated in the previous step.

6. Increment $r$ by 1 and repeat steps 2–5 until convergence.

7. Use different random initial starting values and repeat steps 1–6, retaining the estimates that yield the best criterion function value.
2.4 Identification and the number of clusters

So far, the analysis has been based on an assumed number of clusters $K$ and number of subsets $H$ in the partition of time points $T$. To determine these numbers in a data-driven way, different strategies can be followed. First, if the loss function is taken as the negative log-likelihood value, one can use standard model selection criteria, where the number of parameters is given by the length of $\vartheta$, which increases in $K$.

Note that the model specification with dynamic group membership as introduced in Section 2.3 is prone to a standard clustering identification challenge. To illustrate this, consider a setting with $H = 2$ partitions, $K = 2$ groups, and $I = 2$ units, while abstracting from the presence of control variables ($\beta_k \equiv 0$). Let unit 1 and 2 be permanently in cluster 1 and 2, respectively, i.e., $\alpha_{1,t} = \bar{\alpha}_1$, $\alpha_{2,t} = \bar{\alpha}_2$, and $k_{i,t} = i$ for all $t$ and $i = 1, 2$. Then this setting has the same loss value as one where (i) both units switch cluster halfway the sample (i.e., $k_{1,t} = 1$ for $t = 1, \ldots, \lfloor T/2 \rfloor$, and $k_{1,t} = 2$ for $t = \lceil T/2 \rceil + 1, \ldots, T$, and similarly for $k_{2,t}$); and (ii) the cluster means switch at the same time (i.e., $\alpha_{1,t} = \bar{\alpha}_1$ and $\alpha_{2,t} = \bar{\alpha}_2$ for $t = 1, \ldots, \lfloor T/2 \rfloor$, and $\alpha_{1,t} = \bar{\alpha}_2$ and $\alpha_{2,t} = \bar{\alpha}_1$ for $t = \lceil T/2 \rceil + 1, \ldots, T$). There are different solutions to this identification problem. One of these maximize the overlap of the units in cluster $k$ between times $t$ and $t+1$ to identify the cluster identities (see, for instance, Custodio Jo˜ ao et al., 2022). Given the limited number of clusters we find in our empirical application and the clear-cut stability over time, this identification issue does not seem to be a particular challenge in the current application.

3 The data

As our state fragility variable in the baseline analysis, we use the CPIA score, which is a widely accepted proxy for state fragility. The CPIA is a composite index of 16 policies grouped into four different clusters. These clusters relate to economic management; structural policies; policies for social inclusion;
and public sector management and institutions. Individual policy scores are collected from the World Bank through surveys of its staff. For each policy, a score between 1 and 6 is provided, with higher scores indicating higher degrees of policy and institutional effectiveness, making the CPIA actually more a matter of resilience than of fragility. These scores are averaged at both the cluster and country level to provide an overall CPIA score falling between 1 and 6, with an unweighted average score of 3.2 or less generally seen as the threshold of state fragility. However, in our analysis, we treat state fragility as a continuum rather than a binary concept. We, therefore, refer to state fragility more broadly as countries with lower CPIA score without using the 3.2 cutoff point.

CPIA scores are available since 1977 for World Bank client countries though only those for low-income IDA-eligible countries are published. However, in our sample we focus on the period 1998-2019 to ensure comparability of CPIA scores to account for several changes occurred to the methodology over the years (see Gonzalez and Nishiuchi, 2018, for an overview). For the sample, we concentrate on countries without too many missing values for the CPIA. This means we leave out from the sample a number of World Bank client countries that have high-income status. As these countries would typically have high CPIA values, there would be little to explain from the covariates.

As a robustness check later in the paper, we also perform part of the analyses with another measure of fragility, namely the Fund for Peace’s Fragile States Index (FSI). This index consists of five groups of indicators measuring state cohesion, economic conditions, political legitimacy and public service provision, social conditions, and external intervention. The FSI is only available from 2006 onwards. We therefore do not use it in our baseline analysis, which spans a longer timeframe. The FSI also covers more countries than the CPIA in the sense that the latter has missing values for a fair number of developed OECD countries. In our robustness analysis, we therefore discard these countries as well in order to have similar samples for the CPIA and
FSI analyses.

As a proxy for financial development, we use the FD index, a summary measure of how developed financial institutions (banks, insurance companies, mutual funds, and pension funds) and financial markets (stock and bond markets) are in terms of their depth (size and liquidity of markets), access (ability of individuals and companies to access financial services), and efficiency (ability of institutions to provide financial services at low cost and with sustainable revenues, and the level of activity of capital markets). The FD index was developed by Sahay et al. (2015) (see also Svirydzenka, 2016) to overcome the shortcomings of single indicators (such as ratio of private credit to GDP) as proxies of financial development, which is essentially a multidimensional process. To that end, a number of sub-indices are created for financial institutions and markets across depth, access, and efficiency, culminating in the final index of financial development.

We consider four covariates for the analysis where we cluster countries based on unobserved time-varying heterogeneity while controlling for linear effects of other observables. In particular, drawing from the empirical literature on the determinants of state fragility (see, for example, Akanbi et al., 2021; Simon Feeny and Regan-Beasley, 2015; Blomberg et al., 2011; Carment et al., 2008, 2011), we consider GDP growth ($gdpgrowth$), inflation ($inflation_w$, winsorized at 0.5%), military expenditure as a share of GDP ($militarygdp$), and total natural resources rents as a share of GDP ($natresrentgdp$). Other controls were also investigated in earlier preliminary analyses (e.g. gross capital formation as a share of GDP, life expectancy, changes in effective executive of the country), but none of these led to stable results and their coefficients were typically estimated very close to zero.

There are quite some missing values in the data. Depending on what selection mechanism is used, we therefore end up with a different number of countries and time-series observations in the sample. Table 1 summarizes the main differences. Particularly the requirement that the additional controls exist for all time points can cause substantial sample attrition. Therefore,
Table 1: Sample selection and observation numbers

This table summarizes the different numbers of observations used in the different analyses based on the sample selection criteria. In each case, for a particular combination \((i, t)\) the CPIA, FD (or all its constituents), and the controls need to be available. The sample selection relates to the number of countries \(i\) and the number of observations \((i, t)\).

<table>
<thead>
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<th>required</th>
<th>linear clustering</th>
<th>clustering with</th>
<th>clustering with</th>
<th>clustering with</th>
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<td>panel (2-dim)</td>
<td>controls</td>
<td>(7-dim)</td>
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<td>1998–2019</td>
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<td></td>
<td></td>
</tr>
<tr>
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<td>yes</td>
<td></td>
<td></td>
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<tr>
<td>FD consituents</td>
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<td></td>
<td></td>
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</tr>
<tr>
<td>controls</td>
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<tr>
<td>nr. countries</td>
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<tr>
<td>nr. observations</td>
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<td>2750</td>
<td>2236</td>
<td>1078</td>
</tr>
</tbody>
</table>

for our clustering analyses without controls, we only require the CPIA and financial development proxies to exist. Given that clustering is performed with time-varying cluster means, we require the variables to be present for all times. For the panel data analysis, we take all observations into account for which we observe the CPIA, financial development proxies, and the other controls.

Averages of CPIA and FD are presented in Figure 1. The time-series averages per country in Figure 1a show some expected differences, such as higher financial development scores in economies such as for instance the Republic of Korea, Brazil, China, India, and South Africa, and lower scores in most of Sub-Saharan Africa.

The CPIA scores are only partially correlated with the FD scores, at best. Some countries that have relatively low FD scores can at the same time, have relatively high CPIA scores, and the other way around. This result is in line with Barajas et al. (2021). Notably the largest part of Sub-Saharan Africa has low FD scores, but at the same time shows much more variety in the
Figure 1: CPIA and Financial Development (FD) descriptives

Figure 1a shows the time-series averages of the FD index using the full sample period. Figures 1b and 1c show the time-series of the cross-sectional averages of CPIA and FD.

Also when we consider the time-series of cross-sectional averages or the individual series, we see much dispersion across countries. The average CPIA in Figure 1b shows an upward trend during roughly the first half of the sample, followed by a deterioration over the period 2008-2013, after which it flattens out. By contrast, the FD average seems to be either mildly increasing or relatively flat throughout the sample. The overall pattern is not directly
clear and is investigated in more detail in the empirical analysis in the next section.

4 Results

Our results section is split into three parts. In Section 4.1 we provide a standard linear panel data analysis with fixed effects as a benchmark. In that setting, there is a significantly negative relation between financial development and state fragility. To account for omitted heterogeneity beyond the fixed effects, we provide two first clustering analyses in Section 4.2. The cluster assignments in this analysis are static. In Section 4.3 we relax this assumption and allow countries to (repeatedly) switch cluster membership over time. Finally, Section 4.4 presents a number of robustness checks, including disaggregating the FD index into all 6 (institutions and markets-related) constituents or into 3 (institutions-related only), and redoing the core analyses, and a robustness check where we replace the CPIA index by the FSI index as an alternative measure for state fragility.

4.1 Linear model with two-way fixed effects

As a first benchmark, we estimate a two-way panel data model with country-fixed effects and time-fixed effects,

\[ CPIA_{i,t} = \alpha_i + \delta_t + \beta_F D_{i,t} + X_{i,t}\beta + \varepsilon_{i,t}. \]

This first model has no clustering effects, i.e., there are no separate groups. The dependent variable is country \( i \)'s CPIA score at time \( t \), and the regressors include financial development (FD) and our four control variables \( X_{i,t} \) from Section 3.

A graphical representation of the coefficient estimates can be found in Figure 2a. We find that increases in FD and GDP growth are associated with lower fragility (higher CPIA scores), whereas higher inflation is associated
Figure 2: Linear panel-data regression results

This table contains the results of a linear two-way fixed-effects model \( CPIA_{i,t} = \alpha_i + \delta_t + \beta_{FD}FD_{i,t} + X_{i,t}\beta + \epsilon_{i,t} \), where \( X_{i,t} \) contains the control variables GDP growth, Inflation, Military spending as a percentage of GDP, and Natural resource rents as a percentage of GDP; see Section 3.

(a) Coefficient estimates

(b) Time fixed effects

with higher fragility (lower CPIA scores). Military spending and natural resource rents appear insignificant.

Figure 2b shows the evolution of the time-fixed-effects \( \delta_t \). We see that \( \delta_t \) increases swiftly in the first part of the sample, then levels off, and starts decreasing mildly towards the end of the sample. The effects are similar to those in the raw descriptive data in Figure 1b, though the decline in average CPIA sets in much later after accounting for the controls in the linear panel data model. This can partly be explained by the time-series behavior of average FD as shown in Figure 1a, which mildly increases over the last part of the sample. As the CPIA is rather flat on average over the same period, and the regression coefficient of FD is positive, the negative trend in the time-effects \( \delta_t \) off-sets the slightly positive trend in FD.

4.2 Clusters and heterogeneity

The benchmark linear panel data model from Section 4.1 already accounts for some heterogeneity between countries by the inclusion of the time- and country-fixed effects, as well as a number of key control variables. There
might, however, be further heterogeneity. As in Bonhomme and Manresa (2015) we address this by allowing for group or cluster-specific time-varying effects in the model. As a first step in this analysis, we investigate the number of clusters directly using a bivariate location-scale model without regressors and with static cluster compositions, corresponding to equation (1) with \( y_{i,t} = (CPIA_{i,t}, FD_{i,t})' \) and \( \beta_{k,i,t} = 0 \).

Using the algorithm described in Section 2.2, we estimate the model for different numbers of clusters, \( K \in \{2, ..., 6\} \). We note that is quite different from doing bivariate clustering on \((CPIA_{i,t}, FD_{i,t})\) only, as we allow for time-variation in the means. In fact, the clustering takes place in a \(2T\)-dimensional space \((CPIA_{i,1}, ..., CPIA_{i,T}, FD_{i,1}, ..., FD_{i,T})'\). The numbers of observations for the different analyses was presented in Table 1. We account for scale differences between CPIA and FD by using standardized versions of the variables, \( \widetilde{CPIA}_{i,t} = m_{CPIA} + (CPIA_{i,t} - m_{CPIA})/s_{CPIA} \) and \( \widetilde{FD}_{i,t} = m_{FD} + (FD_{i,t} - m_{FD})/s_{FD} \), where \( m_t \) and \( s_t \) are the cross-sectional means and standard deviations of the different variables.

To choose the optimal number of clusters, we compute a variety of cluster-validation indices. The outcome is presented in Figure 3, together with the mean squared error criterion which is used to find the parameters.\(^2\) We find that most indices point towards two clusters. The mean squared error, which is used as the objective function for estimating the parameters, decreases monotonically in the number of clusters by construction and is therefore not useful to select the number of clusters. Given most criteria point to \( K = 2 \) clusters, we use this number as our benchmark in the remainder of our analysis.

The estimated cluster assignments based on the above analysis are shown in Figure 4. Besides most countries in Sub-Saharan Africa and the Middle East and North Africa, Cluster 2 comprises several countries in Central America (El Salvador, Guatemala, Honduras, Nicaragua), South America.

\(^2\)For a more detailed overview of the different cluster indices, see, for instance, De Amorim and Hennig (2015).
Figure 3: Cluster validation indices for $(\text{CPIA}, FD)$

The figure contains the values of 5 cluster validation criteria as well as the mean squared error (MSE) for the bivariate clustering location-scale model without regressors and without cluster switching. Better clustering performance is indicated by higher Calinski Harabasz, Hartigan, Krzanowski-Lai, and Sihouette indices, and by lower Davies-Bouldin index values. The in-sample MSE always decreases in the number of clusters and is therefore not suitable for selecting the number of clusters.

![Figure 3: Cluster validation indices for $(\text{CPIA}, FD)$](image)

(such as Bolivia, Dominican Republic, Ecuador, Guyana, Haiti, Paraguay, the República Bolivariana de Venezuela), Southeast Asia (e.g., Bangladesh, Bhutan, Mongolia, Myanmar, Nepal), and several countries in Eastern Europe (e.g., Belarus, Bosnia and Herzegovina, Moldova, Romania, Ukraine), and Central Asia (e.g., Armenia, Azerbaijan, Georgia, Kyrgyz Republic, Pakistan, Tajikistan, Turkmenistan, Uzbekistan).

The countries allocated to Cluster 2 include many of the relatively larger as well as emerging economies, including Argentina, Brazil, China, India, Indonesia, Mexico, South Africa, Korea, and Türkiye, and several countries in Eastern Europe, such as Bulgaria, Croatia, and Poland.

Next to the cluster membership indicators for each country, our estimation algorithm yields bivariate time-varying group-specific means for each cluster. These are shown in Figure 5. In terms of FD, the clusters appear well separated, with the 90% quantile band hardly overlapping. For CPIA
Given this preliminary analysis, we fix the number of clusters to $K = 2$ and proceed with our model with cluster specific time-varying effects a la Bonhomme and Manresa (2015), including FD as our regressor of interest together with our four controls in a regression with CPIA as the dependent variable. Besides the cluster-specific time-fixed effects, we also include cluster-specific slope coefficients in the model in Eq. (1). This allows for extra flexibility and in particular allows us to investigate whether the association between state fragility (CPIA) and financial development (FD) is different for different groups of countries. The results are given in Figure 6.

Interestingly, the association between FD and CPIA does not seem to be affected by the clustering; see Figure 6a. In both clusters, the association is significantly positive, implying that higher financial development is associated with lower state fragility. There are some other notable differences, however. Particularly military spending is positively associated with state
Figure 5: Population-weighted time-varying cluster mean FD

The figure shows the population-weighted time-varying cluster means of the FD index. The clusters are obtained by clustering the $2T$-dimensional observations $(CPIA_{i,1}, \ldots, CPIA_{i,T}, FD_{i,1}, \ldots, FD_{i,T})$, with static cluster membership. The figure also shows the 90%-quantile bands based on the estimated coefficients, again population weighted.

Fragility (lower CPIA) in the second cluster, whereas no significant association is found for cluster one. This may also explain the insignificant effect with wide standard error bands in Figure 2a: there appear to be two very distinct relations, such that pooling these heterogeneous effects into one coefficient results in a large uncertainty about its precise value. Conversely, more GDP growth is only significantly associated with lower fragility in cluster 1.

The cluster labels, of course, face an identification problem and can be switched around at random (cluster 1 being called 2, and the other way around). The cluster composition, however, is not random. We see some remarkable differences with the clustering assignments without the controls; Figure 6c. Again we observe many of the larger emerging economies in the same cluster, such as Brazil, China, India, Indonesia, South Africa, Korea, and Türkiye. However, in this alternative methodology, they are accompanied by a number of countries which formerly were in the other cluster, such
Figure 6: Panel-data regression results with cluster-specific coefficients

This figure contains the results of a linear two-way fixed-effects model $y_{i,t} = \alpha_{k,i} + X_{i,t} \beta_{k,i} + \epsilon_{i,t}$, where $X_{i,t}$ contains the control variables GDP growth, Inflation, Military spending as a percentage of GDP, and Natural resource rents as a percentage of GDP; see Section 3.

(a) Cluster-specific slope coefficients

(b) Cluster-specific time-effects $\alpha_{k,t}$

(c) Cluster membership

as Chad, the Arab Republic of Egypt, Guatemala, Côte d’Ivoire, Liberia, Niger, Nigeria, Sudan, and the República Bolivariana de Venezuela. Some other countries, by contrast, have fallen out of the cluster, such as Botswana, and, notably, Mexico. A similar phenomenon holds for the other cluster. We conclude that the choice of clustering methodology and in particular
the correction for control variables during clustering can make a substantial difference in the cluster compositions.

In Figure 6b we show the patterns of the estimated time-varying intercepts. These can be compared to the time-varying cluster means without regression controls as shown in Figure 5. Observed and unobserved heterogeneity may thus have substantial effects on the clustering results. As mentioned earlier, however, the association between CPIA and FD remains largely materially unaffected by the cluster the country belongs to; see Figure 6a.

4.3 Allowing for cluster membership switches

In this section, we extend the previous analysis by allowing countries to switch cluster membership over time. In this way, countries are allowed to switch back and forth between for instance a high and low fragility group, depending on their historical development. We stress again that our analysis departs from that of Lumsdaine et al. (2023), who extend Bonhomme and Manresa (2015) to accommodate a structural break. In our setting, we divide up time into $H$ time buckets. The time points in these buckets may be consecutive, such as in the case of a structural break, or not. By allowing for this additional flexibility, a structural break is still possible, but will come out of the analysis endogenously through the estimation procedure laid out in Section 2.3.

We experiment with $K = 2$ or $K = 3$ clusters, and $H = 2$ or $H = 3$ time buckets, based on the preliminary analysis in Section 4.2. Given that we allow for different time buckets, it is also important to be somewhat more lenient on the number of clusters, as the possible cluster transitions of countries may land them in intermediate groups that do not have the properties of either of the former two groups in the clustering results with static cluster membership; see Section 4.2. Figure 7 presents an overview of the number of cluster switches in these four different settings.

There are two main features to notice in Figure 7. First, the time-
Figure 7: Cluster switches

This figure shows the cluster membership switches in terms of numbers of countries. The top panels are for $K = 2$ clusters, whereas the bottom clusters show the results for $K = 3$ clusters. The left-hand and right-hand panels show the results for $H = 2$ versus $H = 3$ time buckets for cluster switches; see Section 2.3 for details.

(a) $K = 2$ clusters, $H = 2$ time buckets
(b) $K = 2$ clusters, $H = 3$ time buckets
(c) $K = 3$ clusters, $H = 2$ time buckets
(d) $K = 3$ clusters, $H = 3$ time buckets

clustering results in adjacent time points put into a time-bucket. Endogenously, the methodology thus converges to a structural break type setting. The break occurs fairly early in the sample (after 5 of the 22 years) for $H = 2$ time buckets, irrespective of whether we consider $K = 2$ or $K = 3$ clusters. For the case of $H = 3$ time buckets, the changes are again in the beginning of the sample, namely after the first 4 years and the next 6 years. A second feature that emerges from Figure 7 is that cluster membership is rather sticky. We identified the cluster identity on the bases of the cluster average of its CPIA score, the highest average CPIA cluster getting identity 1, followed by 2 and 3. For the case of $K = 2$ clusters, there is only a small number of
countries that switch from cluster 1 to 2, or reversely, as indicated by the smaller bands in the figure. This holds for both $H = 2$ and $H = 3$ time buckets. We also see that the number of countries can change over time, as the regression methodology can easily deal with unbalanced panels. For $K = 3$ clusters, we see that the results become somewhat less stable. Particularly the countries in the middle CPIA group (cluster 2) have sizable transitions upward and downward. This might signal that this number of clusters is over-fitting the data. It is interesting to see that for $K = 3$ transitions over two clusters are very rare: only for the setting of $H = 3$ time buckets we see an incidental transition from the lowest CPIA cluster (number 3) to the highest one (number 1).

In Figure 8 we provide the results for the regression parameters for a variety of numbers of clusters $K = 2, 3, 4$ and time partitions $H = 1, 2, 3, 4$. The regression coefficients show quite a consistent picture. In all cases, we see that high financial development (FD) is negatively associated with fragility (low CPIA score). Also GDP growth is associated with higher CPIA scores for all settings considered. Conversely, inflation and natural resource rents have a negative association with CPIA scores. Only military spending seems not robust, the coefficient being sometimes positive, sometimes negative, and sometimes insignificant.

Some of the estimated group-specific time-effects are shown in Figure 9 and in line with those in Figure 9a for static cluster membership, though slightly smoother for all settings considered. Note that the group-specific effects in Figure 9a are based on different sets of countries at different times due to the possible cluster membership switches. This partly explains why the pattern of $\alpha_{k,t}$ is smoother in the latter case. Note that for $K = 2$ the high and low CPIA groups show an increasing trend in fragility (or a negative trend in CPIA scores) in the latter part of the sample after controlling for financial development and the other regressors in the model, irrespective of whether we allow for cluster switches or not. This decline appears much more pronounced after controlling for all these effects than it does in the raw data
This figure contains the results of a linear grouped fixed-effects model with $K = 2, 3, 4$ clusters (indicated by the different colors) and $H = 1, 2, 3, 4$ time partitions (indicated by the horizontal positions in the graphs). The vertical axis holds the value of the regression coefficient for each $(K, H)$ combination. The underlying regression model is $CPIA_{i,t} = \alpha_k + \beta_{FD}FD_{i,t} + X_{i,t}\beta + \varepsilon_{i,t}$, where $X_{i,t}$ contains the control variables GDP growth, Inflation, Military spending as a percentage of GDP, and Natural resource rents as a percentage of GDP; see Section 3.
Figure 9: Panel-data group-specific time-effects with cluster membership switches

This figure contains estimates of $\alpha_{k,t}$ for different values of the number of clusters $K$ and time partitions $H$. The regression model is given by $CPIA_{i,t} = \alpha_{k,i,t} + \beta_{FD}FD_{i,t} + X_{i,t}\beta + \varepsilon_{i,t}$, where $X_{i,t}$ contains the control variables GDP growth, Inflation, Military spending as a percentage of GDP, and Natural resource rents as a percentage of GDP; see Section 3.

(a) $\alpha_{k,t}$ for $K = 2, H = 2$

(b) $\alpha_{k,t}$ for $K = 2, H = 3$

(c) $\alpha_{k,t}$ for $K = 3, H = 2$

(d) $\alpha_{k,t}$ for $K = 3, H = 3$

(compare Figure 1). For $K = 3$ clusters, the picture slightly changes. In that case, the negative trend shows up for the high and to some extent the middle CPIA group, whereas the low CPIA (high fragility) group shows an increase and flat pattern over most of the sample. Note, however, that $K = 3$ was not selected by most of the cluster selection criteria in Figure 3. The negative pattern in CPIA scores in the high CPIA cluster is rather remarkable.

In Figures A.4 and A.5 in the appendix we show the averages of all 6 variables in the analysis. There we see that the average FD, and Inflation
figures are clearly separated throughout the sample, irrespective of the cluster reshuffling from one time-partition to the next. Again, this underlines our earlier finding of a positive association between state fragility on the one hand, and financial development and inflation on the other. The association of the averages is somewhat less clear for the other three variables, with periods of positive and negative association alternating over time.

In Figure 10, we show the cluster membership for $K = 2$ and $H = 2$. Results for the other settings are provided in the appendix. Given that countries may switch cluster, we provide two maps: one for time bucket 1 (top panel, 1998–2002), and one for bucket 2 (bottom panel, 2003–2019). There are some interesting differences with the static clustering results in Figure 6c. For instance, countries like Kazakhstan and Madagascar were allocated to cluster 1 under static cluster membership after controlling for all effects in the analysis. In Figure 10, however, they are allocated to this same group only for the first years in the sample. After that, they switch to cluster 2. The converse also occurs. For instance, countries like Mali and Kenya belong to cluster 1 in the static analysis. In the dynamic analysis, however, they switch from cluster 2 in the first few years of the sample to cluster 1 in the more recent years. The dynamic patterns above thus allow for a much richer characterization of countries in terms of the evolution of their relative degree of fragility and the status of their financial development. A full list of transitions for the case of $K = 2$ clusters and $H = 2$ time buckets is given in Table 2.

4.4 Robustness

Thus far, we have concentrated the analysis on the aggregate FD index. This index, however, is composed out of $2 \times 3$ (or $3 \times 2$) sub-indices. In particular, there are sub-indices on financial markets (FM) and financial institutions (FI), each sub-divided into Access, Depth, and Efficiency as FMA, FMD, FME, and FIA, FID, FIE. In this robustness section we investigate three additional analyses. First, in Section 4.4.1 we use 7 variables: all FD
Figure 10: Cluster membership results under switching

This figure contains the cluster membership results for the analysis with $K = 2$ clusters and $H = 2$ time partitions using the model $CPI_{i,t} = \alpha k_{i,t} + \beta^{FD}D_{i,t} + X_{i,t} \beta + \epsilon_{i,t}$. where $X_{i,t}$ contains the control variables GDP growth, Inflation, Military spending as a percentage of GDP, and Natural resource rents as a percentage of GDP; see Section 3.

(a) 1998 to 2002

(b) 2003 to 2019
components and CPIA. Given that there are many missing values for the market-related FD components (FM), we perform a second robustness check in Section 4.4.2 using CPIA and the institutions related (FI) components of FD, only. Finally, in Section 4.4.3 we replace the CPIA score by the FSI index as an alternative proxy for state fragility and redo the core analysis.

### 4.4.1 Clustering CPIA and all FD components (7 variables)

In this section, we re-trace our steps using these 6 FD constituents in the analysis, rather than FD itself. For instance, in the clustering analysis, this means that we perform clustering with all 6 FD constituents together with CPIA (7 variables in total) over all time periods, i.e., clustering $7T$-dimensional observation vectors. The FD constituents are much less complete in the database, substantially limiting the sample size; see also the observation numbers in Table 1.

Figure 11 shows the cluster validation criteria for the raw clustering analysis. As for the case with aggregate FD, the disaggregated analysis points to at most two clusters. One might even question whether two clusters is appropriate given the much reduced number of observations. For comparability, however, we proceed with allocating countries into two clusters. The result is provided in Figure 12.

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<td>1 Bolivia, Dominican Republic, Hungary, Kazakhstan, Sri Lanka, Madagascar, Malawi, Türkiye</td>
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<tr>
<td>2 Benin, Georgia, Kenya, Korea, Rep., Mali</td>
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The figure contains the values of 5 cluster validation criteria as well as the MSE for the bivariate clustering location-scale model without regressors and without cluster switching using CPIA and the six financial development constituents (FMA, FMD, FME, FIA, FID, FIE). Better clustering performance is indicated by higher Calinski Harabasz, Hartigan, Krzanowski-Lai, and Silhouette indices, and by lower Davies-Bouldin index values. The in-sample mean squared error (MSE) always decreases in the number of clusters and is therefore not suitable for selecting the number of clusters.

Cluster membership reveals much commonality with the previous setting using aggregate FD for clustering. Larger and emerging economies like Brazil, China, India, South Africa, and Türkiye are placed in the same group. However, a country like Mexico is now placed in the other group. The results have to be interpreted with caution, however. As the map already shows, many countries cannot be classified due to a lack of data regarding the FD constituents. As a result, the groups cannot really be compared across analyses: finding two clusters in a sample of around 130 countries is a completely different analysis than finding two clusters in a sample of around 50 countries, and the cluster compositions can be very different as a result.

The cluster averages of the different variables in the cluster analysis together with their confidence bands can be found in Figure 13. We see that most variables’ bands overlap somewhat, leaving much of the distinction be-
between the two clusters to be driven by the CPIA. The clustering analysis hardly distinguishes with respect to financial markets’ access, depth, and efficiency (FMA, FMD, FME). There is quite some overlap between the values of these variables between the two clusters, which is not too surprising given the limited number of countries in the current analysis. Though the averages may be different for variables such as FMD and FME, for all three of these the bands largely overlap. We conclude that some association between higher financial development and lower fragility (higher CPIA) seems to persist, but that the differences are arguably mainly attributable to the development of financial institutions rather than markets in the country.

4.4.2 Clustering CPIA and FI components (4 variables)

Given that the market-related components of FD are missing for many countries, thus resulting in substantial attrition, we consider a similar analysis in this section as in Section 4.4.1, but now using only the 3 FI components and discarding the 3 FM components. Figures 14, 15, 16, and 18 present the analysis above using only the three FI related components out of the six financial development indicators. These are available for more countries in
Figure 13: Cluster means over time in the 7-variate model
The figure contains the values of 5 cluster validation criteria as well as the MSE for the bivariate clustering location-scale model without regressors and without cluster switching using CPIA and the three financial institutions constituents (FIA, FID, FIE). Better clustering performance is indicated by higher Calinski Harabasz, Hartigan, Krzanowski-Lai, and Silhouette indices, and by lower Davies-Bouldin index values. The in-sample mean squared error (MSE) always decreases in the number of clusters and is therefore not suitable for selecting the number of clusters.

Figure 14 confirms our earlier finding of 2 clusters. Only the Davies-Bouldin index appears to have a second minimum as 4 clusters, though still slightly higher than its minimum value at 2 clusters. Comparing the cluster assignments between Figure 15 for FI and Figure 4 for FD, the results are highly similar, with some incidental countries switching clusters, such as Albania, Armenia, Georgia, Kazakhstan, North Macedonia, Romania, Tunisia, and Uzbekistan.

Comparing the cluster averages of CPIA and the FI constituents in Figure 16 with those for the FD analysis in Figure 5, we again see strong similarities. It appears that the lower FD scores in Figure 5 for cluster 2 are mainly driven by lower scores on access (FIA) and depth (FID). In terms of efficiency, the bands largely overlap, though cluster 2 still shows a substantial
Figure 15: Group membership for CPIA plus three FI constituents

Figure 17 presents the (unclustered) panel regression using the three FI components (compare with Figure 2). Figure 18 presents the clustered panel data regression results. Comparing with Figure 6, the components of FI provide mixed contributions to CPIA, and the fixed effects appear flatter.

4.4.3 Robustness: FSI instead of CPIA

In our final robustness analysis, we replace the CPIA score with the Fragile States Index (FSI), to investigate whether the cluster compositions and the negative association between FD and state fragility persist. The FSI is also available for many developed countries. However, we do not add these to the sample in order to retain comparability with the earlier results. First note that the CPIA score measures resilience, whereas the FSI measures fragility. All signs in the regressions thus have to be flipped when comparing the results to those of the previous sections.

Figures 19 and 20 present the linear panel regressions using FD and the three components of FI, respectively. The results are remarkably similar to each other. Compare with Figures 2 and 17. The country fixed-effects are a
Figure 16: Population-weighted time-varying cluster means the three FI constituents

The figure shows the population-weighted time-varying cluster means. The clusters are obtained by clustering the 4T-dimensional observations \((CPIA_{i,1}, \ldots, CPIA_{i,T}, FIA_{i,1}, \ldots, FIE_{i,T})\), with static cluster membership. The figure also shows the 90%-quantile bands based on the estimated coefficients, again population weighted.

Mirror image of the results using the CPIA score, as expected. The coefficient estimates also follow the same general pattern. In both cases the coefficient for military expenditure becomes statistically significant. The time fixed-
effects have a wholly distinct pattern, although their magnitudes are small in both cases.

Figures 21 and 22 present the clustering without regressors and cluster switching as a baseline. They should be compared to Figures 4 and 15. All four groupings only differ by a few countries.

Figures 23 and 24 present the panel regressions using FSI, the controls, and FD and the FI constituents of FD, respectively. The results are remarkably similar between Figures 6 and 23. The coefficient estimates preserve the same relative magnitude, with the only notable difference being that here, both clusters have a statistically significant coefficient for military expenditure. The concavity in the clustered fixed effects is attenuated, which can be explained by the shorter timeframe considered. The clustering is also highly consistent across the two estimations. A few countries deviate, and mostly in Africa.

Figure 24, compared to Figure 18, shows, again, an unbalanced grouping outcome, but with different assignments in some regions. The time fixed-effects are strongly concave, as in most other estimates, but contrary to Figure 18. It also differs by showing all coefficients regarding the components of FI to have the same sign and ordering across clusters.
Figure 18: Panel-data regression results with cluster-specific coefficients for CPIA plus three FI constituents.

(a) Cluster-specific slope coefficients

(b) Cluster-specific time-effects $\alpha_{k,t}$

(c) Cluster membership

5 Conclusions

In this paper, we explored the relationship between state fragility and financial development. We measured state fragility by the CPIA score, and financial development by the IMF FD index. Given the substantial endogeneity problems with investigating this relationship, we cannot make any statements on causal relationships. However, we accounted in different ways
for observed and unobserved heterogeneity in the model using both regression and clustering techniques to mitigate any omitted variable biases. In all cases, a robust finding was a positive association between CPIA scores (higher scores meaning lower fragility) and the FD index. A tentative, further disaggregate analysis was suggestive of the association being mainly associated with the development of a country’s financial institutions rather than its financial markets.

As a novel contribution, we also investigated the effect of allowing for cluster membership switches over time in a clustering setting to account
for unobserved heterogeneity. Interestingly, the methodology endogenously suggested structural break type of changes rather than incidental, scattered time partitions. Allowing for either one or two switches, we found that the
switch periods were located in the first half of the sample, even at 25% of the sample for the case of only one switch. The number of countries that switched cluster membership from one time partition to the next was quite limited, in line with the nature of the variables under scrutiny: fast incidental changes and reversals are less likely in settings where variables relate to structures woven into the very fabric of economies and cultures. Still, the changes shed additional light on the dynamic evolution of countries
Figure 24: Panel-data regression results with cluster-specific coefficients using FSI as the dependent variable and the components of FI as covariates.

(a) Cluster-specific slope coefficients
(b) Cluster-specific time-effects $\alpha_{k,t}$
(c) Cluster membership

in terms of their CPIA score and its relationship with financial development and other controls, something that could not be obtained by a static analysis only.

The results were also robust to a number of design changes. In particular, the negative association between financial development and state fragility remained if we used alternative proxies for fragility, such as the FSI index, or if we disaggregated the FD index into its market- and institution-related
components.

Directions for future research include an extension of the multivariate model with grouped heterogeneity, with or without cluster switching, towards the inclusion of control variables and/or lags of the dependent variables. Furthermore, as mentioned above, our current methodology detects associations in the data, but does not permit a causal interpretation of the coefficients due to the endogeneity among country fragility, financial development, and, potentially, other country characteristics. An investigation of the causal relationships between these variables could, for instance, be conducted using a structural model. Even then, however, we would still face the challenge of either finding suitable instrumental variables, or developing an alternative identification strategy. From a methodological point of view, combining structural simultaneous equations modeling for panel data with unobserved, grouped heterogeneity could be a promising avenue for future research.

References


A Additional results

Figure A.1: Time-varying cluster assignments, 3 clusters and 2 partitions.
Figure A.2: Time-varying cluster assignments, 2 clusters and 3 partitions.
Figure A.3: Time-varying cluster assignments, 3 clusters and 3 partitions.
The cluster averages of each cluster in all six variables used are plotted, with two different partitions being plotted as different, unconnected lines. CPIA and FD are strongly separated throughout the sample period. Cluster 2 presents radically different mean of Inflation on the first partition, and this difference shrinks in the second partition. The ordering of cluster 1 and 2 for the averages of GDP growth, Military spending, and Natural resource rents is much less consistent over time.
Figure A.5: Cluster averages, 2 clusters and 3 partitions.

The cluster averages of each cluster in all six variables used are plotted, with three partitions being plotted as different, unconnected lines. CPIA and FD are strongly separated throughout the sample period. Cluster 2 presents radically different mean of Inflation on the first partition, and a consistent, but much smaller difference in the second and third partitions. The ordering of cluster 1 and 2 for the averages of GDP growth, Military spending, and Natural resource rents is much less consistent over time.
Table A.1: Transitions from partition 1 (rows) to 2 (columns), 2 clusters, 3 partition total, 4 controls

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Table A.2: Transitions from partition 2 (rows) to 3 (columns), 2 clusters, 3 partition total, 4 controls

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Table A.3: Transitions from partition 1 (rows) to 2 (columns), 3 clusters, 2 partition total, 4 controls
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<td>Bulgaria, Mexico, North</td>
<td>Arab rep., Guinea-Bissau,</td>
<td>Cambodia, Lao PDR, Chad,</td>
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<td>Thailand, Türkiye</td>
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<td>3</td>
<td>Romania</td>
<td>Ecuador, Paraguay, Ukraine</td>
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Table A.4: Transitions from partition 1 (rows) to 2 (columns), 3 clusters, 3 partition total, 4 controls
Table A.5: Transitions from partition 2 (rows) to 3 (columns), 3 clusters, 3 partition total, 4 controls

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