From Sovereign Debt Crisis to Economic Recovery: A High Dimensional Analysis of Macroeconomic Impacts

This dissertation investigates the impact of debt crises on output growth while addressing the high dimensionality problem that arises when a large number of control variables are included. I find that debt crises have significant effects on growth, which persist and hinder recovery. By comparing the results of a causal forest model and a dynamic panel data model, I find that the impacts vary over time (between 1980 and 2019) and depend on the pre-crisis economic conditions faced by countries. Therefore, the findings have policy implications for guiding sovereigns in mitigating the effects of default or debt restructuring.

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1 Introduction

A sovereign debt crisis is defined as a situation in which a country fails to meet its principal or interest payments on time or is forced to restructure its debt to fulfil its repayment obligations (Reinhart & Rogoff, 2009). Detragiache (2001) considers a crisis to occur when arrears on principal or interest exceed 5%. Nguyen et al. (2022) adopts a narrower definition, identifying crises as instances where the value of debt arrears or restructured debt equals at least 1% of GDP for three consecutive years or surpasses 7% of GDP in a single year.

The growth rate effects of standalone sovereign debt crises have received limited attention. In contrast, the impacts of banking and currency crises (Chang-Shaui et al. 2017, Turner et al. 2021), as well as the prediction of sovereign debt crises (Manasse & Roubini, 2003), are more widely studied. A few existing studies focus on the impact of debt crises on the level of GDP (Esteves et al., 2021) and the time taken for it to return to its pre-crisis value but I focus on the growth rate, examining whether shocks to it dissipate quickly or persist. Given fiscal pressures facing developed nations, **it is critical to estimate the potential growth rate impacts of impending sovereign debt crises as they influence the speed of recovery post crisis**. Understanding whether it is the accumulation of debt that reduces growth (Jalles & Medas, 2022), or if formal default and restructuring are equally important, is essential. The latter conclusion could give rise to strategic default, in which the benefits of fiscal expansion through debt accumulation outweigh the costs of the crisis.

It is crucial for policymakers to mitigate the impacts of debt crises by understanding whether debt crises have more severe effects on economic growth under specific pre-crisis conditions or certain post-crisis policy responses. It is equally important to assess whether debt crises trigger or are followed by other financial crises, compounding their impact, as they often disrupt private sector credit markets (IMF, 2024). Conditions that are conducive to crisis recovery guide monetary policy and influence whether exchange rate regimes that allow for flexible monetary policy are preferred. Ensuring that restructuring or refinancing can occur at a low cost helps limit the prolonged impacts of crises (Bech et al., 2012).

To identify the causal effect of debt crises on growth (the treatment effect), it is necessary to control for all factors that influence both the treatment and growth simultaneously. Including an adequate number of controls may lead to a high-dimensionality problem. High dimensionality is typically defined as the number of covariates in a model exceeding the available units for estimation. However, it can also refer to situations where the number of predictors is large, regardless of the sample size. As the number of predictors increases, models struggle to identify true patterns in the data and risk fitting noise instead (Leek et al., 2016).

This study aims to contribute to the literature on the impacts of sovereign debt crises on growth, over the estimation period of 1980-2019. Existing literature fails to explore whether the impacts of debt crises vary in relation to pre-crisis macroeconomic conditions across countries and over time and if occurring alongside other crises, a gap I intend to fill. As a baseline, I employ a dynamic panel data model, which assumes that the impacts of debt crises are constant across countries. I use Double LASSO (Belloni et al., 2014) to select the most relevant confounders, addressing the high-dimensionality problem. I compare the results to those estimated by a causal forest (Athey & Wager, 2019; Athey et al., 2019), a non-parametric model that aims to identify heterogeneity in the impacts of debt crises across countries without making assumptions about its functional form, while also dealing with the high-dimensionality issue. I use the variable importance scores from the causal forest to identify which pre-crisis conditions trigger heterogeneity in the impacts faced by countries.

I conclude that modelling the impacts of debt crises on growth as constant across countries and time is a misspecification. Results from the dynamic panel are weighted averages of true effects. Sovereign debt crises have heterogeneous effects on growth over time and between high- and low-income nations in certain years. Causal forest estimates suggest a negative shock of **between 1-5 percentage points within the first two years of the crisis**, with further persistence beyond. I also suggest that the joint propagation of both debt and other crises is not conclusively linked to more adverse effects on growth, although the pre-2000 period sees the frequent coincidence of many crises and more severe shocks to growth from them. In the years with the most severe impacts on growth, countries that are more resilient to crises are those less reliant on international credit markets.

Structure of the Paper: Section 2 elaborates on the high dimensionality problem and the existing literature linking sovereign debt crises to growth. Section 3 compares inference across different causal machine learning models. Section 4 discusses how I address issues related to data availability. Section 5 presents estimated impacts. Section 6 details tests for heterogeneity.

2 Literature Review

An external debt crisis occurs when a country faces challenges in servicing foreign-currency-denominated debt (Eaton and Gersovitz, 1981). Growth impacts of external debt crises are analysed in conjunction with "sudden stops". Calvo et al. (2008) define a sudden stop as a sudden reversal of foreign capital inflows of any kind. External debt crises often have more severe impacts on output and growth due to "sudden stops" in access to global capital markets, a phenomenon less common in domestic debt crises (Ozkan & Unzal, 2010). **A domestic debt crisis** occurs when a country faces difficulties in meeting its obligations on debt denominated in its own currency. Since domestic government debt is primarily held by the domestic financial sector, a domestic default is more likely to trigger a banking crisis (Panizza, Sturzenegger, & Zettelmeyer, 2007; 2009). A resulting credit crunch produces a decline in both short and long-term growth (De Marco, 2013). Reinhart & Rogoff (2009) argue that austerity measures are typically more aggressive and widespread following domestic debt crises, producing more severe growth impacts compared to external debt crises, refuting Ozkan & Unzal (2010).

There is growing empirical literature analysing short-term growth impacts of crises. Reinhart & Rogoff (2011) suggest that short-term growth costs are substantially higher for domestic than for external defaults (4% vs 1.2%). Others do not separate outcomes of external and domestic crises. Furceri & Zdzienicka (2012) find in a study of defaults between 1970-2008 that crises produce contractions in output growth by 6 percentage points soon after they hit using a dynamic panel data model. Borensztein & Panizza (2008) are more conservative in their estimates, arguing that sovereign defaults specifically are associated with a 1.4% point short-term decline in GDP growth. Few empirically analyse persistence in growth impacts post-crises. Forni et al. (2016) argue that debt crises have no conclusive long-term effects on GDP growth. They argue that debt restructurings fall into two categories: "final restructurings", where no further crises follow, leading to positive medium-term growth by avoiding "sudden stops" and investor panic; or alternatively, cases where default risks persist, resulting in a cumulative 5 percentage point decline over three years. Das et al. (2012) and Reinhart & Trebesch (2014, 2016) similarly argue that GDP growth may see 4-5 percentage point aggregate increases in the three years post-final restructurings.

When analysing twin crises, many focus on the "doom loop", where government intervention to rescue failing institutions following banking crises can trigger a sovereign debt crisis (Brunnermeier, 2016). Bank insolvencies, caused by losses on public debt, can lead investors to anticipate a sovereign debt default, prompting public bailouts to keep banks operational. This, in turn, exacerbates sovereign credit risk. As most debt crises involve debt held by external creditors, "doom loops" are rare. Few analyse the more common occurrence of a currency crisis that leads to a debt crisis. Herz et al. (2003) describe how a currency devaluation increases the value of foreign currency-denominated debt, which raises borrowing costs and pressure on debt servicing capacity. Minimal attention has also been given to the triple crisis, where sovereign default triggers a currency collapse from foreign investors selling bonds, leading to domestic financial institutions defaulting on external debt (Eijffinger & Karatas, 2023). Empirical analyses of the impacts of twin crises on output growth is limited, although Balteanu & Erce (2018) do so using a panel data model for crises between 1975 and 2008. Default by a sovereign triggering a banking crisis is estimated to have more than double the immediate impact on growth (-5 percentage points vs less than 2 percentage points) as standalone debt crises and require an additional three years for recovery from due to the disruption to the financial system (Balteanu & Erce, 2013).

Many studies examining the impact of crises on macroeconomic outcomes control for variables that influence both treatment and outcomes. However, the inclusion of an insufficient number of controls can lead to selection bias persisting. For instance, Borensztein & Panizza (2008) fail to include covariates related to financial sector vulnerability, which is crucial for mapping crisis incidence (Laeven, 2018). Navigating the trade-off between dimensionality issues and including sufficient controls is important. **High dimensionality** in cross sections concerns the number of variables exceeding the number of units $p \geq n$ (Tibshirani, 2001). The resulting OLS estimator for the treatment effect in the presence of a high-dimensional set of control variables can be imprecise with $Var(\hat{\tau})$ diverging and also inconsistent (Buhlmann & van de Geer, 2011). High dimensionality in panel data similarly distorts OLS estimation when the total number of observations, $n \times t$, is small relative to the number of predictors, p. The risk of overfitting however, whereby the model captures noise rather than meaningful relationships, remains significant even when the number of predictors alone is large, as p increasing implies the covariate space becomes increasingly sparse (Chernozhukov, 2016). Estimates become increasingly unstable as p increases. Similar issues pertain to machine learning models more generally (Johnstone and Titterington, 2009).

3 Methodology

I aim to uncover whether the impact of debt crises on growth is constant between countries at a given time, or varies due to differences in macroeconomic conditions. The set of conditions that lead to crises is also where I expect heterogeneity in their impacts to occur. I test heterogeneity in conditions by comparing the results of a dynamic panel data model, which assumes a constant effect from crises in all countries as a baseline, with a causal forest, which estimates heterogeneous impacts between countries. The causal forest is a non-parametric method, avoiding ex ante assumptions about the conditions which produce different impacts of crises across countries. When estimating both models, I resolve the issues that arise from high dimensionality with many controls. With the causal forest, I estimate the average impacts of debt crises among low-income and high-income countries to simplify analysis. Averaging country-level estimates yields more accurate group effects than fitting a constant-effect model by group. Given similarities within income groups, focusing on heterogeneity between them is informative. Classification criteria for the groups are obtained from the World Bank. Low-middle-income nations and high-middle-income nations, as per the World Bank's criteria, are added to the group of low and high-income nations respectively. [1]

I also use both models to test whether impacts of debt crises vary over time. With the dynamic panel, I compare the constant estimated impacts in two separate sub-periods: 1980–1999 and 2000–2019. This split is justified by the fact that the turn of the 21st century marks a significant change in the number of twin and triple crises. Since the causal forest doesn't directly handle panel data (due to its ignoring serial dependence from individual units over time), I estimate group-wise impacts separately for each year of the sample period (1980–2019). The same covariates are used in all models for consistency [2] Time-specific fixed effects are redundant in both models, given the substantial number of time-varying covariates.

I estimate the impacts of debt crises on GDP per capita growth in the year of the crisis t and up to five years after, via local projections with both models (Jordà, 2005). Impacts are on GDP per capita growth, to adjust for changes in population when estimating lagged shock responses. The impulse response is estimated by changing the response variable to GDP per capita growth at $t + h$.

[1] Classifications are only available from 1987; therefore, for the years 1980-1987, 1987 classifications are used. Where classifications are missing for some years, the next available classification will be used.

[2] The causal forest includes the lagged variables from the dynamic panel and models individual fixed effects with country specific dummies.

3.1 Baseline Model

The dynamic panel data model for projecting $y_{i,t+h}$ is specified as follows:

$$y_{i,t+h} = \delta_1 D_{it} + \sum_{j=1}^{4} \boldsymbol{\delta}'_{2j} \mathbf{D}_{i,t-j} + \sum_{j=1}^{4} \rho_j y_{i,t-j} + \boldsymbol{\beta}' \mathbf{X}_{it} + \boldsymbol{\theta}' \mathbf{M}_{it} + \epsilon_{i,t+h} + \mu_i \tag{1}$$

Let $y_{i,t+h}$ represent the GDP per capita growth rate for country i at time t, projected h periods ahead, where $h = 0, \ldots, 5$, $t = 1980, \ldots, 2019$. The sample comprises 206 countries, following Nguyen et al. (2022). The error term is denoted by $\epsilon_{i,t+h}$, and μ_i captures country-specific fixed effects. The model includes several key variables: $\mathbf{D}_{i,t-j}$, a vector of lagged crises dummies indicating whether country i experienced financial crises at time $t-j$, for $j = 1, \ldots, 4$; $\mathbf{M}_{it}$, a vector of contemporaneous crisis indicators [3]; $\mathbf{X}_{it}$, a vector of macroeconomic indicators and conditions; and $y_{i,t-j}$, the lagged values of GDP per capita growth for $j = 1, \ldots, 4$.

D_{it} is a dummy variable indicating a **standalone debt crisis**, and thus δ_1 captures its impact on the per capita GDP growth rate, expressed in **percentage points**. The coefficients on $\mathbf{M}_{it}$ represent the growth impacts of other types of crises.

The vector $\mathbf{X}_{it}$ includes indicators of domestic and external indebtedness, financial and political institutional quality[4], financial sector health, international financial flows, fiscal prudence, and basic macroeconomic conditions. The total number of covariates across $\mathbf{X}_{it}$ and $\mathbf{D}_{i,t-j}$ exceeds the number of countries.

The model is **dynamic** as I believe past values of GDP per capita growth and past debt crises are strong confounders for estimation at time t. I estimate an ARDL(4,4) specification. [5]

The fixed effects estimator in a dynamic panel data model is inconsistent for N (Nickell, 1981). As T increases however, the inconsistency in the coefficients tends to zero and does not distort inference [6] .

[3] Both vectors include twin, triple, banking, and currency crises but lagged vectors include past debt crises as well
[4] Often proxied due to limited availability of ICRG and CPIA measures
[5] The Bayesian Information Criterion (BIC) is minimized with four lags of each variable in all regressions.
[6] $T = 40$ is large enough in our case

3.1.1 Dealing with High Dimensionality

Estimating the model with OLS without addressing the issues arising from the high dimensionality of the covariate X_{it} and the lagged dummy vectors $D_{i,t-j}$ is problematic.

Therefore, I employ the Post-Double Selection procedure (Belloni et al., 2014)[7] to reduce dimensionality by selecting only the most relevant controls.

In the first stage, regressions of the treatment variable D_{it} and the outcome variable $y_{i,t+h}$ are performed on the covariate and lagged dummy vectors. The LASSO minimisation problems are:

$$\min_{\boldsymbol{\theta}} \left(\sum_{i=1}^{N} \sum_{t=1}^{T} \left(D_{it} - \sum_{j=1}^{4} \boldsymbol{\delta}_{2j}' \mathbf{D}_{i,t-j} - \boldsymbol{\beta}' \mathbf{X}_{it} \right)^2 + \lambda \sum_{j=1}^{p} |\theta_j| \right) \tag{2}$$

$$\min_{\boldsymbol{\phi}} \left(\sum_{i=1}^{N} \sum_{t=1}^{T} \left(y_{i,t+h} - \sum_{j=1}^{4} \boldsymbol{\delta}_{2j}' \mathbf{D}_{i,t-j} - \boldsymbol{\beta}' \mathbf{X}_{it} \right)^2 + \lambda \sum_{j=1}^{p} |\phi_j| \right) \tag{3}$$

$\boldsymbol{\theta}$ and $\boldsymbol{\phi}$ represent all coefficients, with p the total number of variables. The second term represents the regularisation penalty, which shrinks the coefficients of irrelevant predictors to zero. I use cross-validation to determine the optimal shrinkage parameter λ. Before LASSO, all regressors subject to double selection are standardised by their mean. Without standardisation, LASSO disproportionately penalises variables with larger scales, leading to inaccurate control selection (Tibshirani, 1996).

I gather the union of covariates whose coefficients are not shrunk to zero in either regression, selecting only those covariates that are relevant for inducing self-selection into treatment if omitted.

The model, after removing fixed effects, is specified as follows. All selected variables are in vector $\tilde{S}_{it}$. I then estimate using OLS Local Projections, with δ_1 as the coefficient of interest. [8]:

$$\tilde{y}_{i,t+h} = \delta_1 \tilde{D}_{it} + \sum_{j=1}^{4} \rho_j \tilde{y}_{i,t-j} + \beta' \tilde{S}_{it} + \boldsymbol{\theta}' \tilde{\mathbf{M}}_{it} + \tilde{\epsilon}_{it}. \tag{4}$$

[7] Double debiased machine learning (Chernozhukov et al., 2016) was also tested but produced nearly identical results.

[8] To address heteroskedasticity and serial correlation in the final stage of the Double LASSO procedure, I use HAC standard errors with Eicker-Huber-White corrections.

3.2 Heterogeneous Treatment Effect Estimation

I use the **causal forest** (Athey and Wager, 2019; Athey et al., 2019) to estimate the heterogeneous impacts of sovereign debt crises. The estimation is performed using the `CausalForestDML` class from the `EconML` library in Python. Being non-parametric, estimated treatment effects circumvent bias from model misspecification. After estimating the propensity scores and counterfactuals for untreated outcomes using separate non-parametric models, the final causal forest model is constructed to estimate the treatment effects. Propensity scores adjust treatment effect estimates for selection bias. Causal forests provide *doubly robust* estimates, meaning that even if one of the propensity or counterfactual models is misspecified, the overall treatment effect estimate remains consistent. Unlike traditional random forests, which aim to maximise sample purity in each child node (especially for classification tasks), trees in causal forests are built by determining splits based on covariates X_i that maximise heterogeneity in the treatment effects of the samples across child nodes, as well as treatment status heterogeneity within nodes (where the `criterion` argument is set to 'mse'). By using a subset of overall covariates to determine the optimal ones for splits, and aggregating predictions from many estimators, causal forests are powerful in dealing with high dimensionality.

I adopt an ensemble approach that averages predictions from separate causal forests, which use simple neural networks and random forests for propensity score and counterfactual estimation (nuisance parameters). This is particularly useful for increasing the precision of the estimate, given the small number of observations. Each propensity and counterfactual model uses random search (Bengio & Bergstra, 2012) to explore optimal hyperparameter configurations. Selecting the right hyperparameters for the causal forest itself is also important in avoiding overfitting with such few observations. Since I infer true treatment effects directly from the data, traditional cross-validation is not feasible. To improve precision, I adopt a configuration with **4,000 trees**, a number that far exceeds the number of observations. **All other hyperparameters are determined based on the package's `tune` method, which selects hyperparameters that maximise out-of-sample R-score performance (Machlanksi et al., 2023) relative to a set benchmark.**

The neural networks used for nuisance parameter estimation are limited to three hidden layers, due to the relatively small sample size.[9] I apply dropout (Srivastava, 2014) in each layer, with the rate determined through hyperparameter optimisation. Dropout randomly sets a fraction of neuron outputs

[9]Hyperparameter optimisation suggests using a large number of neurons per layer to capture non-linear patterns.

to zero during training, helping prevent overfitting. Each hidden layer uses **ReLU (rectified linear unit) activation functions**, which are effective in high-dimensional settings by deactivating nodes with negative values. Combined with dropout, this helps eliminate irrelevant variables. Random forests inherently perform dimensionality reduction when estimating nuisance parameters by selecting random subsets of variables for splitting at each tree node.

The estimated impact of a standalone debt crises on growth for a country with economic conditions x in a causal forest is:

$$\hat{\tau}(x) = \frac{\sum_{i=1}^{n} \alpha_i(x) \cdot (Y_i - \hat{y}(X_i)) \cdot (T_i - \hat{\pi}(X_i))}{\sum_{i=1}^{n} \alpha_i(x) \cdot (T_i - \hat{\pi}(X_i))^2} \tag{5}$$

$T_i = 1$ indicates a nation experienced a debt crisis and $T_i = 0$ otherwise. Y_i is the observed outcome for country i. $\hat{y}(X_i)$ is the predicted outcome given covariates under no treatment, and $\hat{\pi}(X_i)$ is the estimated propensity score, representing the probability of a debt crisis given covariates. The weights $\alpha_i(x)$ from the forest reflect how often country i shares a leaf node with a nation having covariates x, modelling non-parametric treatment effect heterogeneity in covariates.

$$\alpha_i(x) = \frac{1}{B} \sum_{b=1}^{B} \frac{\mathbf{1}(X_i \in L_b(x), i \in S_b)}{|\{i : X_i \in L_b(x), i \in S_b\}|},$$

where B is the total number of trees in the forest, S_b is the bootstrapped sample of observations used to partition the tree b, and $L_b(x)$ is the leaf node of tree b containing the query point x.

3.2.1 Estimating Variable Importance

I use the default variable importance attribute from the forest object to assess the conditions that contribute to heterogeneity in the impacts of debt crises, including whether other financial crises occurring concurrently (twin/triple crises) worsen the impacts. It measures the importance of each covariate in increasing the variance of treatment effect estimates between child nodes across the tree, where the tree is partitioned based on that covariate.

$$\text{Importance}(j) = \sum_{t \in \text{trees}} \sum_{n \in \text{nodes}} w(n) \cdot \frac{n_l \cdot n_r}{(n_l + n_r)^2} \cdot \sum_k (\hat{\tau}_l^k - \hat{\tau}_r^k)^2 \tag{6}$$

j is the covariate being evaluated. $w(n)$ is the weight of the node, typically $w(n) = \frac{1}{(1+\text{depth})^2}$. n_l and n_r are the number of samples in the left and right child nodes. $\hat{\tau}_l^k$ and $\hat{\tau}_r^k$ are the estimated treatment effects for the k-th observation in the left and right child nodes.

3.3 Identification Assumptions

To identify a consistent treatment effect in both models, I rely on the unconfoundedness assumption (Neyman, 1923; Rubin, 1974):

$$\{Y_i(0), Y_i(1)\} \perp\!\!\!\perp T_i \mid X_i.$$

This states that treatment assignment T_i is independent of the potential outcomes $Y_i(0)$ and $Y_i(1)$, conditional on the observed covariates X_i.

To guarantee that $\hat{\tau}(X_i) \xrightarrow{p} \tau(X_i)$ as $n \to \infty$ from a causal forest, the functions π, y, and τ, tree splits must ensure that at least a fraction $\gamma > 0$ of the parent node observations are placed in each child node.

While the stable unit treatment value assumption (SUTVA) is partially violated due to sovereign debt crises in one country impacting output elsewhere, the impact of this is minimal and does not invalidate inference. I estimate using an **honest approach** (Wager and Athey, 2019), where the observations used to estimate effects differ from those used to partition the tree. Even with such few observations, I find this significantly increases precision and eliminates bias.

Table 1: Crises data

Crisis type	**1980–1999**	**2000–2019**	**High-Income**	**Low-Income**
Twin Crisis (Currency)	212	29	138	105
Twin Crisis (Banking)	171	22	109	86
Standalone Debt Crisis	1061	801	1217	659
Triple Crisis	44	5	15	34

4 Data

I use the crises database from Nguyen et al. (2022), which includes data for 206 countries. To analyse the difference in impacts between types of twin crises, I separate them into two categories, **sovereign debt-banking crises** and **sovereign debt-currency crises**. Nguyen et al. (2022) define a twin crisis as the simultaneous occurrence of two crises within the interval $[t-1, t+1]$, where t denotes the year of a sovereign debt crisis. I refine this measure to require both crises to occur jointly in a given year, as when both crises occur in the same year, a feedback loop between them is more likely. The triple crisis variable is adjusted likewise. See Table 1 for a summary. Since GDP per capita growth data is available only until 2023, observations from 2019 are omitted when estimating five-year-ahead shock impacts. Data for covariates and real GDP per capita growth come from the World Bank Financial Development, International Development, and Debt Statistics databases[10] Variables reported at higher frequencies (daily, monthly, quarterly) are adjusted for annual terms.

The World Bank database provides extensive data from 1980 to 2019, but many variables have substantial missing values in specific years. Rather than omitting all of them, it is preferable to non-naively estimate their values. I test imputation using k-nearest neighbours (KNN) (Fix & Hodges, 1951)[11] and iterative imputation [12] with a random forest regressor using 100 estimators on sampled missing data at different frequencies. Among these methods, KNN produced the most accurate results for predicted covariate values, able to accurately estimate large proportions of missing data (Zhang, 2021). Where GDP per capita growth data is missing, I also use k-nearest neighbours to estimate values, although there are minimal missing values for GDP per capita growth. KNN imputation is performed for each year individually with inverse distance weights and 7 neighbours, which is appropriate for smaller datasets. Standardisation is crucial in KNN imputation and for the calculation of accurate nearest neighbours for each observation. Covariate availability varies over time and thus affects imputation accuracy, but I assume that limited bias is introduced by KNN and therefore minimal concerns arise when comparing treatment effects across years.

[10] Availability of control data is what limits investigation from an earlier time period, as Nguyen's database starts from 1950.

[11] Imputes missing values based on the weighted average of the k nearest neighbours, identified using distance metrics (Euclidean is used here).

[12] Iteratively imputes missing values by modelling each variable as a function of the others using another model, filling in the missing values one variable at a time.

5 Results

I uncover significant heterogeneity in effects across covariates and time, resulting in a discrepancy between the estimated effects of debt crises from each model. Formal testing in Section 6 suggests misspecification of the baseline model (1).

Under misspecification, the baseline estimator of impacts from standalone and twin/triple crises is necessarily inconsistent. The coefficient estimate is a weighted average of true heterogeneous treatment effects, where the weights are non-convex functions of covariates (Chaisemartin & Haultfoeuille, 2019).

5.1 Baseline Model Results

Results from the model are shown in Table 2. The instantaneous shock of debt crises (column (1)) on GDP per capita growth at time t is negative but statistically and economically insignificant, with a small predicted effect of -0.12 percentage points post-crisis over the full period. However, the shock is substantially larger in the first period (1980-1999) than in the second period (2000-2019), with an estimated effect of -0.716 percentage points. Neither treatment effect is statistically significant at the 5% level; thus, the evidence for asymmetrical impacts over time is inconclusive.

Shocks across all periods are substantially smaller than those predicted by Furceri & Zdzienicka (2012) and Sturzenegger (2004), who use similar models, although I include more controls. The absence of a significant causal channel may be attributable to the effects of pre-crisis debt accumulation, which often hampers growth by increasing risk premia and limiting fiscal space (Schumacher and Żochowski , 2017). The negative and statistically significant coefficients on external debt stocks and claims on government for the full period, reported in columns (5) and (6), support this interpretation. They suggest that, when controlling for debt accumulation, debt crises themselves are not important in affecting growth. However, a true “sudden stop” occurs only during a default or restructuring (Mendoza, 2010), which undermines this argument in the context of an external debt crisis. Coefficients on debt accumulation are also not significant within each individual period.

For longer horizons, estimates of the growth impacts from the baseline model are close to zero, suggesting minimal effects on recovery speeds. The insignificance of debt crises at time t on GDP per capita growth beyond t across all periods, and consequently on post-crisis recovery, is consistent with Forni et al. (2016), albeit under final restructurings only.

5.1.1 Twin and Triple Crises Impacts

Each crisis dummy at time t represents the mean difference in GDP per capita growth associated with that crisis occurring, compared to no other crises occurring.

There is no additional negative shock in growth rates from a doom loop or other twin crises. Columns (2) and (3) show that the effects of twin crises are positive instantaneously, albeit statistically insignificant and small in magnitude. Column (4) shows that the impacts of triple crises are minimally negative and insignificant. Although these coefficients are insignificant, it is not rational for a stand-alone crisis and triple crises to produce negative effects, while both twin crises generate positive effects. The positive direction of twin crises coefficients is also spurious economically and contradicts other literature, such as Balteanu & Erce (2013, 2018), even when considering the differences in controls used.

Additional crisis dummies for separate and whole periods are jointly insignificant instantaneously. A null hypothesis of equal instantaneous impacts of twin crises, triple crises, and stand-alone debt crises is also not rejected, failing to support the Noy and Hutchinson (2005) argument that twin crises produce effects that equal the compounded effects of individual crises. The model's lack of difference in the impacts of banking and currency twin crises contradicts ideas that twin currency-debt crises and triple crises have more adverse effects, as they are closely tied to external debt crises that produce "sudden stops" (Ozkan & Unzal, 2010).

The speed of recovery of GDP per capita is generally not affected by triple and twin crises, with growth rates quickly reverting to their mean post-shock in the 1st and 2nd periods. Analysing the entire period, only after triple and stand-alone debt crises does growth revert to its mean. The persistent effects of twin crises on growth, however, are minimal but seemingly spurious.

Table 2: Double LASSO estimation results

	Crisis types				Main debt variables only		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Time	Debt	Twin Banking	Twin Currency	Triple	Claims on Govt	Ext. Debt	R^2
Whole Period (1980-2019)							
t	-0.120	0.570	0.665	-0.176	-0.403*	-0.288*	0.212
	(0.234)	(0.626)	(0.519)	(0.965)	(0.202)	(0.146)	
t+1	0.000	0.291***	0.246***	-0.066	-0.001	0.003	0.631
	(0.001)	(0.037)	(0.030)	(0.064)	(0.002)	(0.006)	
t+2	0.001*	0.290***	0.247***	-0.065	-0.001	0.003	0.631
	(0.000)	(0.037)	(0.031)	(0.066)	(0.002)	(0.006)	
t+3	0.000	0.291***	0.246***	-0.068	-0.002	0.003	0.631
	(0.000)	(0.037)	(0.031)	(0.065)	(0.002)	(0.006)	
t+4	0.000	0.292***	0.246***	-0.070	0.006	0.003	0.631
	(0.000)	(0.036)	(0.030)	(0.065)	(0.003)	(0.006)	
t+5	0.000	0.290***	0.248***	-0.067	-0.002	0.004	0.631
	(0.000)	(0.036)	(0.031)	(0.064)	(0.002)	(0.006)	
1st Period (1980-1999)							
t	-0.716	0.856	0.715	-0.061	-0.497	-0.385	0.247
	(0.450)	(0.994)	(0.641)	(1.024)	(0.380)	(0.218)	
t+1	0.000***	0.058***	0.060	-0.006	0.002	0.014	0.573
	(0.000)	(0.007)	(0.008)	(0.006)	(0.003)	(0.008)	
t+2	0.002	0.059***	0.060***	-0.005	0.001	0.016	0.572
	(0.000)	(0.007)	(0.008)	(0.007)	(0.003)	(0.007)	
t+3	0.001	0.059***	0.060***	-0.006	0.000	0.016	0.569
	(0.000)	(0.007)	(0.008)	(0.006)	(0.003)	(0.007)	
t+4	0.000	0.058***	0.060***	-0.005	0.000	0.016	0.566
	(0.001)	(0.007)	(0.008)	(0.007)	(0.003)	(0.008)	
t+5	0.000	0.059***	0.060***	-0.005	0.000	0.016	0.574
	(0.000)	(0.007)	(0.008)	(0.007)	(0.003)	(0.007)	
2nd Period (2000-2019)							
t	-0.216	0.957	0.923	-0.621	-0.080	-0.256	0.244
	(0.326)	(0.783)	(0.731)	(1.341)	(0.278)	(0.192)	
t+1	-0.001	0.039	0.008	0.000	0.001	-0.003	0.573
	(0.001)	(0.005)	(0.003)	(0.002)	(0.002)	(0.007)	
t+2	0.000	0.038	0.008***	0.000	0.001	0.001	0.571
	(0.001)	(0.005)	(0.002)	(0.002)	(0.002)	(0.006)	
t+3	0.001**	0.039	0.007***	0.001	0.000	0.001	0.570
	(0.000)	(0.005)	(0.002)	(0.002)	(0.002)	(0.006)	
t+4	0.001	0.039	0.008***	0.000	0.004	0.000	0.569
	(0.000)	(0.005)	(0.002)	(0.002)	(0.005)	(0.006)	
t+5	0.001	0.039	0.008***	0.001	0.004	0.002	0.572
	(0.001)	(0.005)	(0.002)	(0.002)	(0.002)	(0.006)	

Notes: **Dependent variable is GDP per capita growth**. HAC standard errors are in parentheses. Claims on government are measured as the annual growth rate in % of broad money. External debt is measured as % of GNI. Significance levels: * 5%, ** 2.5%, *** 1%

5.2 Results From Investigating Heterogeneity

Estimates from the causal forest suggest clear heterogeneity in the impacts of crises on growth when grouping countries by income, as well as over time in how all countries are affected. [13] According to my estimations, deeper recessions are not necessarily those in which recovery is suppressed. Point estimates of impacts are shown in Figure 2. Pooled confidence intervals are calculated for each group effect using individual bootstrapped standard errors for each country and plotted separately for clarity in Figure 3.

5.2.1 Variation In The Instantaneous Response of Sovereign Debt Crises

Controlling for the accumulation of debt, debt crises are estimated to negatively affect GDP per capita growth within the year they are propagated for both high and low-income countries (statistically significant in many years, but not all, as shown in Panels 3b and 3a highlighting variability in impacts over time). Effects are more severe in low-income nations in many, but not all, years. Over the period studied, the immediate cost of debt crises to GDP growth is estimated at between -1% and -4% points in most years, substantially more than estimates in Section 5.1. There is no clear trend of increasing severity of impacts over time; however, the most severe impacts occurred between 1986 and 2000 (within the first period), with lower-income groups generally experiencing more severe shocks.

This can be explained by many countries prior to 2000 being on managed or fixed exchange rate regimes, which limited monetary easing post-crises. This meant that sudden international capital stops to the private sector were not offset by domestic credit, particularly in cases where the domestic financial system was stable post-crisis, as discussed by Calvo & Reinhart (2000) and Sachs & Radelet (1998) in the context of the Asian Financial Crisis. This is evidenced by the lower average domestic private sector credit as a percentage of GDP during the first period. The pre-2000 period also saw far more currency and banking crises coinciding with debt crises. Arteta & Hale (2006) argue that "sudden stops" during the period were worse when currency crises accompanied debt crises as the value of collateral denominated in domestic currency fell. Monetary tightening to control the currency value arguably restricted private sector capital access further, producing more adverse impacts on growth than debt crises by themselves. My estimates do not suggest a similar idea. **In no year before 2000**

[13] Factors influencing heterogeneity are determined based on their variable importance, calculated via the method in Section 3.2.1

is the presence of a currency crisis and banking crises around or in the years before a debt crisis an instantaneous source of heterogeneity in growth impacts as per the variable importance measure. Restrictions on private sector credit from managing the exchange rate outside of currency crises may have already been adverse.

Panel 1a shows that the instantaneous impacts of sovereign debt crises are estimated to have been particularly adverse in the years 1986, 1989, 1991, and 2000, with worse impacts for low-income nations.[14]

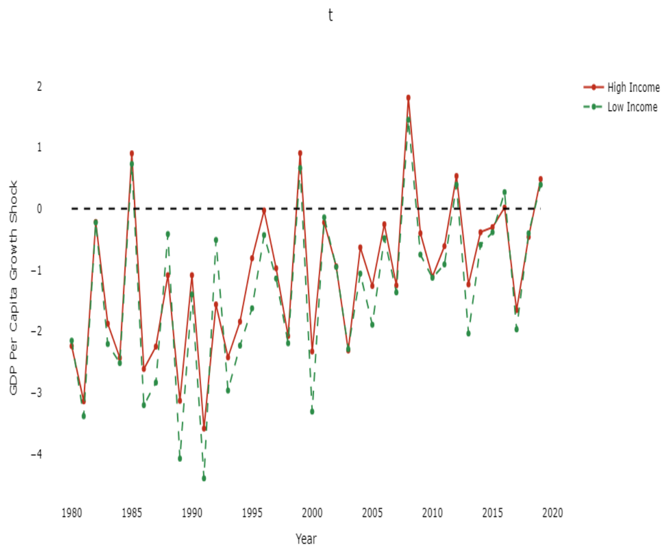
Significant heterogeneity in the instant shock is observed in **Foreign direct investment (FDI)** inflows in these years. In these years, low-income countries had substantially lower levels of FDI inflows and outflows compared to high-income countries. The direct impacts of FDI from a debt crisis are typically delayed, typically delayed, implying that FDI at time t serves as a covariate influencing the treatment effect, rather than being a source of reverse causality. Countries shut off from credit markets or unable to borrow due to a high-risk premium, likely found alternative sources of instantaneous finance for domestic industries in FDI. Domestic industries receiving FDI are typically more resilient to fiscal shocks and austerity measures, being less reliant on public sector subsidies, which are reduced or eliminated during a crisis (Loungani & Razin, 2001).

Gross Domestic Savings (existing savings) are also a source of heterogeneity for the instant shock in these years and are lower on average amongst low income nations in these years. This can be explained by domestic savings and credit helping private entities stay afloat post capital flight and "sudden stops" in these years. More generally, they allow sovereigns to restructure on better terms than with foreign creditors swiftly, eliminating fiscal constraints (Higgins and Klitgaard, 2011).

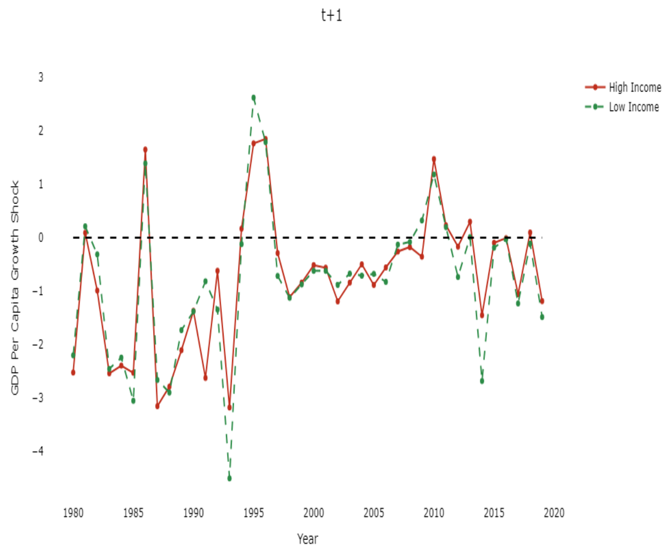
Growth in GDP per capita a year before crises additionally produces variation in the initial shock on growth post crises in these years. Among low-income countries in these years, the average GDP per capita growth in the year prior is negative (-0.3% compared to 1.62% for high income nations). Heterogeneity can be explained by low prior growth harming fiscal reserves and external buffers to manage the shock, producing more severe austerity.

Positive instantaneous responses are also observed in a few years, notably 1985, 1999, and 2008. These are not statistically significant. Responses are followed by significant negative impacts at $t+1$, indicating a delayed response to the shock across countries, instead of the absence of any.

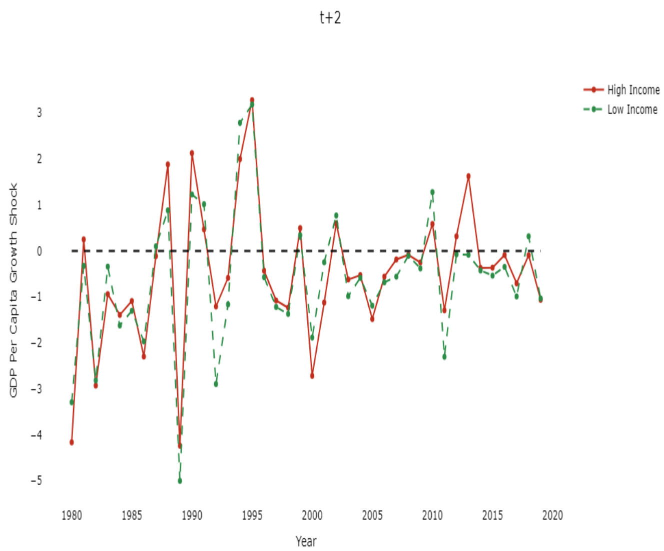
[14]Estimates in these years are statistically significant and statistically significantly different between low and high-income nations.



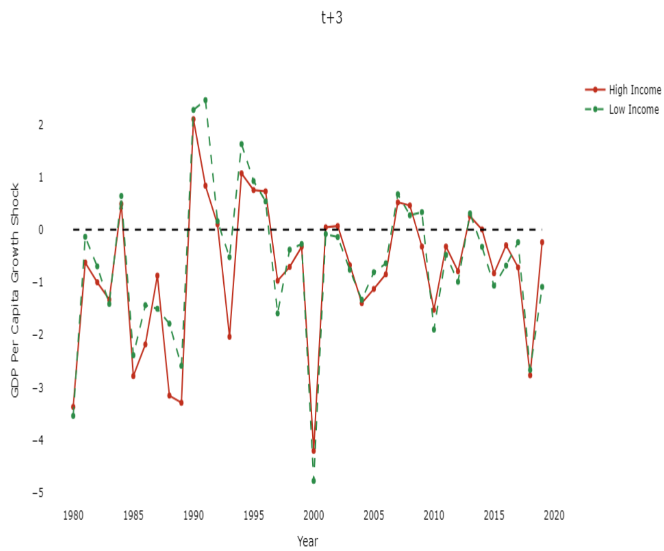
(a) t



(b) t+1

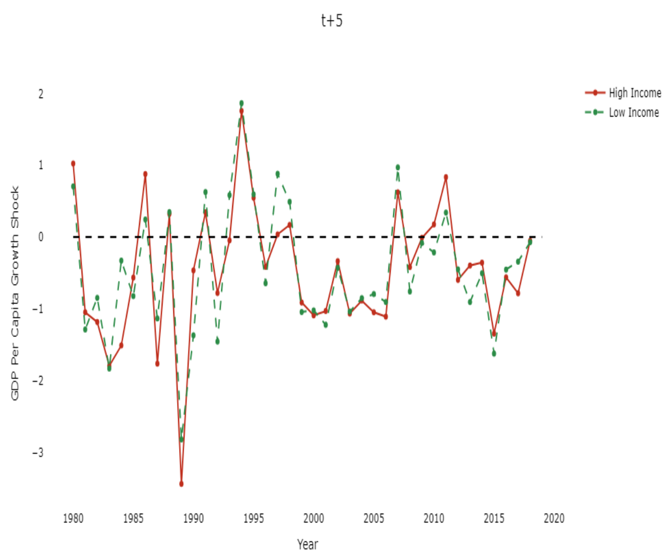


(c) t+2



(d) t+3

(e) t+4



(f) t+5

Figure 2: Impulse response plot for impact of debt crises on GDP per capita growth at time t to $t+5$ (causal forest) via local projections

5.2.2 Variation In The Long Term Response Of Sovereign Debt Crises

There is clear evidence of persistent impacts of debt crises on the speed of recovery, beyond what is suggested by equation (1) suggests. The existence and nature of this persistence vary by country, but it is apparent that shocks from sovereign debt crises are felt earlier in some cases than in others. Estimated impacts one to five years after the shock, most notably in the first two years, are statistically different from zero as shown in Figure 3, and are substantially negative in many years. The period from 2003 to 2006 in particular shows significant persistence, with an average predicted -1% shock to growth even five years after the crises. This period experienced a substantial number of delayed restructurings (Benjamin and Wright, 2009), as creditors waited for default risk to subside, potentially suppressing fiscal activity long after the crises itself. Similar shocks were observed across both income groups. The variable importance measure reveals heterogeneity in persistence based on GDP per capita growth before the crises, but this appears similar for both low- and high income nations during the period.

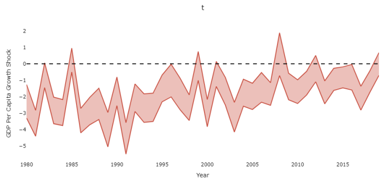
In many years, there is no consistent pattern in how treatment effects evolve from period t to $t+h$, with effects not consistently reaching a significant depth after h periods post-crisis, followed by a recovery. The recovery path of the shock does distinctly differ between income groups in many years. In a few years post-recovery, I find that nations experiencing debt crises may see improvements in GDP per capita growth compared to those that do not, as Reinhart & Tresbesch (2014, 2016) and Das (2012) suggest for restructurings, particularly in 1995-1996 at period $t+1$ and in other years over longer horizons.

The recovery of output growth between 1994-1996 and 2010-2013 is found to be faster compared to most other years. Arguably, post the 2008 financial crisis, zero interest rate policies and lax monetary measures mitigated the long-term impact of sovereign debt crises, particularly by preventing widespread loss of credit access and limiting the impacts of debt restructuring on fiscal austerity during these years, reconciling with Bloise & Vailakis (2022). However, the Eurozone debt crises during this period were extremely slow to recover from in some cases. Examining estimates for Greece in 2010 highlights substantial persistence in post-crisis growth impacts, as Alogoskoufis (2012), among others, suggests. Low- and high-income nations recovered equally quickly between 2010-2013[15].

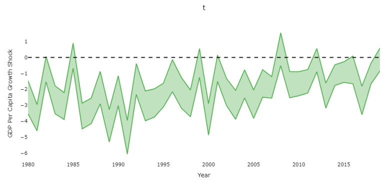
[15] Estimated impacts at time $t+1$ for both groups in these years are not significantly different from zero and small in magnitude

Figure 3: Confidence intervals for causal forest estimates

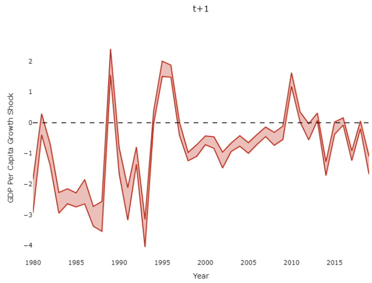
(a) (t) High Income



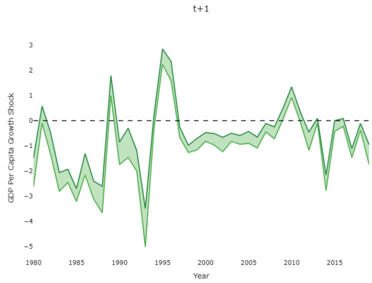
(b) (t) Low Income



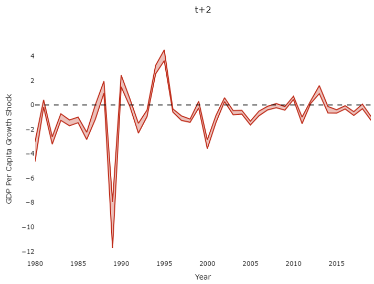
(c) (t+1) High Income



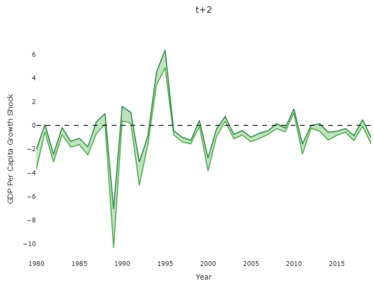
(d) (t+1) Low Income



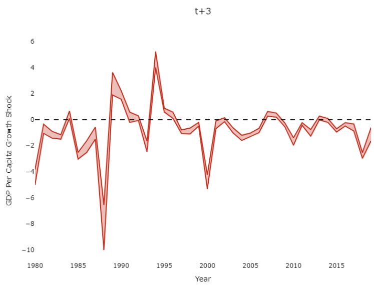
(e) (t+2) High Income



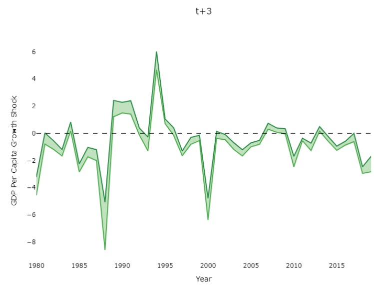
(f) (t+2) Low Income



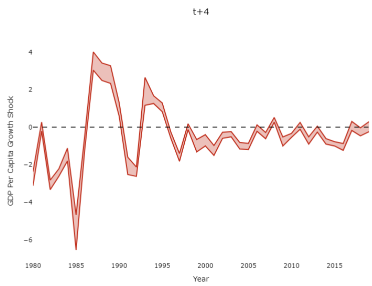
(g) (t+3) High Income



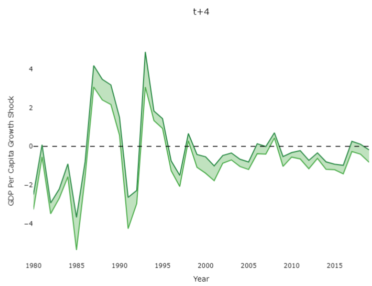
(h) (t+3) Low Income



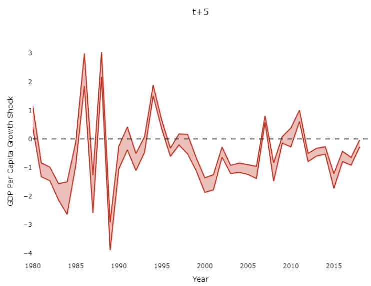
(i) (t+4) High Income



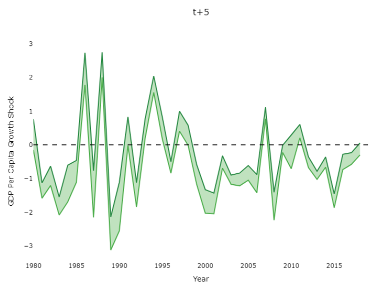
(j) (t+4) Low Income



(k) (t+5) High Income



(l) (t+5) Low Income



Between 1994-1996, institutional fiscal tightening restored foreign investor confidence and reduced debt servicing costs quickly, arguably a product of the formal emerging debt markets created post-"Brady plan". Swift bailouts from international financiers also likely played a key role in quickly rebuilding investor confidence post-crises. "Sudden stops" and crippling austerity post-crises were thus limited. Heterogeneity between low and high-income nations recovery speed is observed only in 1994[16] Heterogeneity is observed in the net financial account prior to crises, with low-income nations having substantially smaller deficits. This reflects the difference in investor confidence when holding assets from low versus high-income nations, a key 'pull' factor behind the longer exclusion of low-income nations from international financial markets after crises (Boresztein & Panizza, 2009). This may have led to more adverse post crises fiscal consequences on recovery speeds in low income nations as a result.

In all periods, no clear difference in recovery speeds is observed where there are substantially more twin and triple crises compared to standalone crises. Experiencing a currency or banking crisis alongside a debt crisis is not an important splitting covariate for long-term post-crises impacts in all years.

6 Robustness Checks

Beyond observing heterogeneity, I formally test for it using a causal forest model with a permutation method.[17] For simplicity, I use only the causal forest with counterfactuals and propensity scores estimated by neural networks.

The test is conducted for a single year (1989) to assess the treatment effect at time t, as detecting significant heterogeneity in covariates influencing treatment effects within one year is sufficient to reject the notion that the baseline model is misspecified. The year 1989 is among those with the most severe estimated impacts of crises.

Most covariates produce statistically significant heterogeneity in impacts of crises. Selected covariates with particularly high variable importance, some of which are discussed in Section 5.2 are reported in Table 3.

While the causal forest reveals significant heterogeneity in certain macroeconomic conditions, being non-

[16]Minimal but statistically significant negative impacts are experienced at time $t+1$ for low-income nations (see panel 3d), but not for high-income nations (see panel 3c).

[17]Permutation tests (Eden and Yates, 1933) randomise treatment assignment multiple times (500 in my case), re-estimating the model and its variable importance scores. P-values are determined by the proportion of iterations in which the variable importance scores exceed those observed under the true assignment.

Table 3: Permutation Test Results for 1989: (Selected Variables)

Variable	P-Value
Foreign direct investment, net outflows (% of GDP)	0.000
Foreign direct investment, net inflows (% of GDP)	0.000
General government final consumption expenditure (constant 2015 US$)	0.002
Short-term debt (% of total external debt)	0.004
Foreign direct investment, net (BoP, current US$)	0.006
Lagged GDP per capita growth (1st Lag)	0.016
Claims on central government (annual growth as % of broad money)	0.022
Net financial flows, bilateral (current US$)	0.030
Gross domestic savings (% of GDP)	0.042
Trade (% of GDP)	0.048

parametric, it does not provide a precise functional form for this heterogeneity. I therefore investigate whether the observed ex-post heterogeneity can be confirmed with the baseline model, further suggesting its misspecification. Data for the entire period are used in this analysis.

I use equation (1) to interact the treatment variable with key covariates that exhibit high variable importance across multiple years, particularly those analysed in Section 5. These covariates include **foreign direct investment inflows, gross domestic savings, first lag of GDP per capita growth, lending rate, and broad money (M1 + M2 + M3)**. The Double LASSO method is retained to address issues of dimensionality.

$$y_{i,t+h} = \delta_1 D_{it} + \boldsymbol{\gamma}_3' \mathbf{Z}_{it} \cdot D_{it} + \sum_{j=0}^{4} \boldsymbol{\delta}_{2j}' \mathbf{D}_{i,t-j} + \sum_{j=1}^{4} \rho_j y_{i,t-j} + \boldsymbol{\beta}' \mathbf{X}_{it} + \boldsymbol{\theta}' \mathbf{M}_{it} + \epsilon_{i,t+h} + \mu_i \tag{7}$$

Here, $\mathbf{Z}_{it}$ denotes the vector of these covariates.

The interaction terms are directionally consistent with earlier findings discussed in Section 5.2.1. However, only a subset are statistically significant, suggesting that the heterogeneity exists, but in certain covariates may take a more complex, non-linear form.

Time	(1) Broad × Debt	(2) Lend × Debt	(3) Growth × Debt	(4) Savings × Debt	(5) FDI × Debt	R^2
t	-0.238 (0.674)	-0.3949* (0.2188)	-0.0198 (0.0892)	-0.2377 (0.1985)	-0.7576 (0.8991)	0.1929
t+1	0.008 (0.011)	0.0795*** (0.121)	0.0058*** (0.0017)	-0.0576 (0.0492)	-0.0452 (0.0472)	0.6390
t+2	0.007 (0.010)	0.0797*** (0.0121)	0.0058*** (0.0017)	-0.0586 (0.0493)	-0.0424 (0.0471)	0.6390
t+3	0.008 (0.010)	0.0796*** (0.0121)	0.0058*** (0.0017)	-0.0582 (0.0493)	-0.0448 (0.0469)	0.6402
t+4	0.008 (0.010)	0.0796*** (0.0121)	0.0058*** (0.0017)	-0.0583 (0.0493)	-0.0450 (0.0469)	0.6402
t+5	0.008 (0.010)	0.0796*** (0.0121)	0.0058*** (0.0017)	-0.0582 (0.0493)	-0.0448 (0.0469)	0.6402

Notes: **Dependent Variable: GDP per capita growth**. HAC standard errors are in parentheses. Significance levels: * 5%, ** 2.5%, *** 1%.

Table 4: Regression results with interactions of debt crises

7 Conclusion

Results from Section 6, along with the discrepancy between causal forest and panel data estimates for the period 1980-2019, clearly show that the immediate adverse impacts of debt crises on growth cannot be explained solely by the accumulation of debt, and that these effects vary across countries and over time. Demonstrating that the impacts of debt crises on growth are not constant suggests that the panel data model is misspecified, and that inference on its estimated impacts from stand-alone and twin/triple crises is spurious.

While there is no explicit form for this, in most years, low-income nations with weaker domestic credit markets, lower savings rates, and limited foreign direct investment prior to crises tend to be more severely affected than high-income nations in the short term, particularly in years when the adverse impacts are more pronounced. In general, the negative shocks from debt crises do not dissipate quickly, and there is substantial cross-country variation in the speed of recovery, although this variation is not strictly along income-group lines. In certain years, even where the immediate impacts are adverse, debt crises may have positive long-term effects on growth, consistent with findings in the existing literature. Findings that crises occurring during periods of monetary easing and that are resolved quickly tend to have less negative consequences for growth are also well supported. Estimates that debt crises coinciding with currency or banking crises do not consistently produce more adverse growth outcomes across both models are less well supported.

The policy implications are consistent with existing literature. To avoid disruption to growth from debt crises, the private sector and governments must be able to borrow from alternate sources if international investors withdraw. Higher risk premiums before a crisis can make it more difficult to secure financing afterward; therefore, policy should aim to prevent risk premiums from rising excessively before a crisis. Ensuring swift restructuring and keeping the costs of refinancing or restructuring low after a default helps limit the persistence of crisis effects.

Insufficient data on arrears and the timing of crises do not allow for a sophisticated comparison of external versus domestic debt crises, which further research should seek to explore, alongside modelling the economic conditions that produce heterogeneity in each. Many papers (e.g., Forni, 2016) focus on restructurings specifically, but a comparison of growth impacts between restructurings and outright defaults, and the heterogeneity in restructuring partners is also important.

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