Financial Crises and Economic Recovery:

Cross-Country Heterogeneity and Cross-Sectional Dependence

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Abstract

This paper estimates the impulse responses of output to financial crises using a local projections panel estimator that accounts for cross-country heterogeneity and cross-sectional dependence. Using a long span of data (1870-2016) for a group of 17 advanced economies we show that once we control for unobserved common factors and parameter heterogeneity in the panel, there is strong evidence of economic recovery within the first 10 years after a financial crisis.

Keywords: *Financial Crisis, Recessions, Impulse Responses, Panel Data, Parameter Heterogeneity, Cross-Sectional Dependence*

JEL Classification: *C23, E32, E44, G01, N10, N20*

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1. Introduction

The study of the permanent effects of financial crises on macroeconomic outcomes has attracted considerable attention at the empirical level. Some recent applications include Bijapur (2012) and Papell and Prodan (2012), who found strong evidence supporting the view that the path of output tends to be substantially and persistently depressed after a financial crisis, with no rebound on average to the pre-crisis trend over the medium-run –although with substantial cross-country variation in the outcome, as shown by Papell and Prodan (2012). Other contributions have specifically focused on the effects derived from the most recent global financial crisis, such as Benati (2012) and Olivaud and Turner (2014), finding also sharp falls in fixed investment and output for OECD countries –while, again, the loss varies widely across countries as shown by Olivaud and Turner (2014).

The paper by Cerra and Saxena (2008) represents a seminal contribution to the study of economic recovery in the aftermath of banking crises. Using a dynamic model for output growth as a function of a dummy variable that captures the occurrence of a financial crisis, they found that the effect of a banking crisis on output is around 7.5% of GDP; and that less than 1% of the deepest output loss is regained by the end of 10 years following a banking crisis. However, Teulings and Zubanov (2014) demonstrated that their method is sensitive to misspecification, which can be important for the computation of the impulse-response functions (*IRFs*). They suggested the use of the local projections estimator developed by Jordá (2005); but they also pointed out that the latter suffers from a downward bias since it does not use the information on the crises occurring within the forecast horizon selected. They proposed a corrected local projection estimator which consists in augmenting the relevant regression with the dummy variables for the financial crises occurring within the forecast horizon. Their empirical results show that a banking crisis yields a GDP loss of just under 10% in 10 years, with little sign of recovery.

An important feature of all empirical studies that have aimed to quantify the persistent macroeconomic effects of financial crises is that they rely on several homogeneity assumptions that are unlikely to hold in worldwide macro panels: all economies are assumed to be characterized by a uniform transmission of financial shocks. As discussed above, several works have found evidence of substantial heterogeneity between countries (Papell and Prodan, 2012; Olivaud and Turner, 2014). In addition, macroeconomic and financial variables are interrelated across countries (Bailey *et al.*, 2016) and as a result the error terms of panel regressions can be cross-sectionally correlated.

In this paper, we fill a gap in the literature by studying the economic recovery that follows financial crises using a local projections panel estimator with heterogeneous coefficients and a general multifactor error structure that takes into account cross-country heterogeneity and cross-sectional dependence. This allows us to consider two characteristics of utmost importance. First, the possibility of various sources of heterogeneity, such as the cross-country variations in endowments, economic structures, and specific policies implemented after financial crises –all of which affect the transmission of global and regional shocks to countries. Second, the possible common effects associated with financial crises that impact simultaneously all countries, such as lower productivity levels, reductions in research and development expenditures and investment in physical capital, lower efficiency and intensity of resource utilization, and protracted liquidity traps –which are accounted for by introducing non-zero error covariances in the panel estimation.

To the best of our knowledge, this is the first empirical application that extends the local projections method to account for parameter heterogeneity and cross-sectional dependence. Our estimates suggest that, although a financial crisis leads to significant output losses in advanced economies, there are signs of economic recovery 10 years after the initiation of the crisis. Our results are in contrast with previous studies which suggest that the effects of crises are more persistent and long-lasting. Specifically, once we control for unobserved common factors and parameter heterogeneity in the panel, there is strong evidence of economic recovery after a financial crisis.

2. Data and Methodology

We use a long span of annual data over the period 1870 to 2016 for a sample of 17 OECD economies based on the Jordá-Schularick-Taylor *Macrohistory Database* (Jordá *et al.*, 2017). The variables used are the logarithm of the real GDP per capita ($y_{i,t}$) as a measure of output and the systemic financial crisis measure ($d_{i,t}$), which is a dummy variable equal to 1 if a banking crisis in country i starts in year t and 0 otherwise. In addition, we use a set of four factors that capture the underlying economic conditions of the OECD economies, namely, *credit*, *interest rates*, *stock market returns* and *public debt*. The data for all control variables are again taken from the Jordá-Schularick-Taylor *Macrohistory Database*.

We follow the approach proposed by Jordá (2005) and Teulings and Zubanov (2014) which consists in estimating *IRFs* directly from local projections. According to Teulings and Zubanov (2014), the *corrected* local projections estimator (CLPE) consists in augmenting Jordá's local projections estimation (LPE) equation with financial crises occurring within the forecast horizon, that is, between t and $t+k$. They show that, compared to the original LPE estimator, the CLPE produces *IRFs* estimates closer to the true *IRFs* and more robust to dynamic misspecifications. The CLPE equation for GDP in each future period k (where $k = 0,\ldots,10$ years in our case) is:

$$y_{i,t+k} = \delta_{0ik} + \delta_{0k}^{*} t + \sum_{r=1}^{R} \delta_{1rk} y_{i,t-r} + \sum_{l=0}^{L} \delta_{2lk} d_{i,t-l} + \sum_{l=0}^{k-1} \gamma_{2l} d_{i,t+k-l} + v_{i,t+k} \ , \ (1)$$

where $y_{i,t}$ is the measure of output and $d_{i,t}$ is the financial crisis dummy for country i in year t; δ_{0ik} and $\delta_{0k}^{*} t$ denote country fixed-effects and a common linear time trend, respectively; and $v_{i,t+k}$ is the error term. The CLPE shown in **Equation (1)** includes also the intermediate financial crises (between t and $t+k$) in order to generate unbiased estimates of the *IRFs*.[1]

One important aspect regarding the empirical estimates of the effects of financial crises on output using the local projections method is that such panel estimators have not considered the possibility of general multifactor error structures that take into account parameter heterogeneity and cross-sectional dependence. In brief, if the unobserved dependence between cross-sectional units is not accounted for, then the error term derived from these estimates will be autocorrelated, yielding biased regression results.

As discussed in Pesaran (2006), if **Equation (1)** is estimated without accounting for a multifactor error structure, both the unobserved common factors and the heterogeneous factor loadings will remain part of the error term. In this case, the error term will be correlated across units –that is, they will be cross-sectionally dependent– and the error term will not be *iid* anymore. Finally, if the observed explanatory variables and the unobserved common factors are correlated then an omitted variable bias problem occurs, yielding inconsistent results.

Here we incorporate the presence of general multifactor error structures by considering mean group (MG) estimations in dynamic panels with dependence between cross-sectional units, thus

[1] Following Cerra and Saxena (2008) and Teulings and Zubanov (2014) we include four lags of GDP and of the financial crisis dummy in our specification ($R = L = 4$).

estimating a common correlated effects (CCE) estimation procedure in a heterogeneous panel setting. The MG-type estimator estimates N-group specific OLS regressions and then averages the estimated coefficients across groups –that is $\hat{\pi}_{MG} = 1/N\sum_{i=1}^{N}\hat{\pi}_i$, where $\pi = (\delta_{1rk}, \delta_{2lk}, \gamma_{2l})'$; while, in order to control for cross-sectional dependence, the CCE estimation approach is employed, which consists in augmenting the panel regression with cross-sectional averages, and their lags, for both the dependent variable and the independent variables as well as for a set of additional covariates, as proposed by Pesaran (2006), extended in Chudik and Pesaran (2015), and implemented in Ditzen (2018).[2]

We thus consider the incorporation of the CCEMG estimation into the CLPE equation, allowing for heterogeneous coefficients and introducing linear combinations of the cross-sectional averages and their lags for the dependent variable ($y_{i,t}, y_{i,t+1}, ..., y_{i,t+k}$, for each period k, respectively), the lagged dependent variable ($y_{i,t-r}$), the financial crisis dummy ($d_{i,t}$), and a set of additional covariates ($g_{i,t}$) in **Equation (1)**. Hence, defining $\overline{y}_{t+k} = 1/N\sum_{i=1}^{N} y_{i,t+k}$ and $\overline{z}_t = 1/N\sum_{i=1}^{N} z_{i,t} = (\overline{y}_t, \overline{d}_t, \overline{g}_t, \overline{y}_{t-r})'$, and using an MG-type estimation method, we modify **Equation (1)** as follows:[3]

$$y_{i,t+k} = \delta_{0ik} + \delta_{0k}^{*} t + \sum_{r=1}^{R}\delta_{1rki} y_{i,t-r} + \sum_{l=0}^{L}\delta_{2lki} d_{i,t-l} + \sum_{l=0}^{k-1}\gamma_{2li} d_{i,t+k-l} + \zeta_{1i}\overline{y}_{t+k} + \sum_{r=0}^{R}\zeta_{2ri}\overline{z}_{t-r} + v_{0i,t+k} \ . \quad (2)$$

3. Empirical Results

Table 1 reports the estimates of the *IRFs* of output to a financial crisis from six alternative methods: fixed effects, MG and CCEMG estimation of both the Jordá (2005) LPE and Teulings and Zubanov (2014) CLPE methods.[4] We can observe that, ignoring heterogeneity and cross-

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[2] Pesaran (2006) and Chudik and Pesaran (2015) show that the asymptotic variance of the CCEMG estimator is computed nonparametrically using the formula $\hat{\Sigma}_{MG} = 1/(N-1)\sum_{i=1}^{N}(\hat{\pi}_i - \hat{\pi}_{MG})(\hat{\pi}_i - \hat{\pi}_{MG})'$.

[3] Following Chudik and Pesaran (2015), who suggest the use of additional covariates to deal with the effects of multiple unobserved common factors, we include four covariates (*credit*, *interest rates*, *stock market returns* and *public debt*) in the set of cross sectional averages. We thank an anonymous referee for drawing our attention to this point.

[4] Prior to the estimations we conducted the *Delta* test of Pesaran and Yamagata (2008) and the CD_p test of Pesaran (2004) to examine the properties of poolability and cross-sectional dependence in our panel. The results indicate strong presence of both heterogeneity and cross-section dependence. These results are available upon request.

sectional dependence (**Columns 1-2**), both the LPE and CLPE methods show strong evidence of GDP losses of approximately 8.4%-9.6% after 10 years. However, when we allow for heterogeneity (**Columns 3-4**) we note that the effect is significantly weaker (4.7%-6.1%); while in the case of the CCEMG CLPE estimation, where we allow for both heterogeneity and cross-sectional dependence (**Columns 5-6**), we can observe that the recession peaks after 5 years from a financial crisis (with a loss of approximately 3.1%-3.5%) and the effect is statistically non-significant and smaller after 10 years (around 1%). Therefore, there are strong signs of economic recovery 10 years after a financial crisis. The *IRFs* based on **Columns 2** and **6** are plotted in **Figure 1** together with their estimated confidence intervals. From **Figure 1** we can observe that the effect of a financial crisis is much weaker and in fact becomes statistically insignificant after 2 years of a financial crisis when using the CCEMG CLPE estimator, which accounts for heterogeneity and cross-sectional dependence. These results are in contrast with most previous studies which suggest that the effects of crises are more long-lasting (Cerra and Saxena, 2008; Papell and Prodan, 2012; Teulings and Zubanov, 2014); however, they are closer to the findings of Furceri and Mourougane (2012). Our findings show that, once we control for unobserved common factors and parameter heterogeneity in the panel, there is evidence of economic recovery after a financial crisis.

3.1 Robustness Checks

We perform three empirical exercises to check the robustness of our main findings, which are presented in the Online Appendix A. First, we use alternative sets of the factors (*credit*, *interest rates*, *stock market returns* and *public debt*) that we include as additional covariates in the set of cross-sectional averages in **Equation (2)**. We can observe from **Figure A.1** that using different sets and numbers of additional covariates in the estimation do not alter our main results. Further, we note that when we do not include any covariate in **Equation (2)** there is, in fact, stronger evidence of economic recovery. Second, we estimate the *IRFs* using the CCEMG CLPE estimator for three alternative sample periods. We can observe from **Figure A.2** that our main results are not affected when reducing the sample to the periods after 1900 and after the World War II. Third, we perform the CCEMG CLPE estimator, for the full sample, where we control in the regression equation (as well as adding them in the set of cross sectional averages) for the four factors that are associated with the underlying economic conditions of the OECD countries (*credit*, *interest rates*, *stock market returns* and *public debt*). From **Figure A.3**, we can observe again that our main findings do not change when we account for various control variables in **Equation (2)**.

4. Conclusions

In this paper, we estimate the responses of output to financial crises using a local projections estimator that accounts for parameter heterogeneity and cross-sectional dependence. Using a long span of data for 17 advanced economies, we explore the effects of financial crises on GDP allowing for a general multifactor error structure that takes into account heterogeneity and error dependence in the panel setting. Our estimates show that financial crises lead to significant output losses, but the empirical results are less strong relative to previous studies which have suggested that the effects of crises are long-lasting. We observe that, once we control for unobserved common factors and parameter heterogeneity in the panel, there is strong evidence of economic recovery within the first 10 years after a financial crisis. This paper provides the first application of the local projections method using a common correlated effects mean group estimation; however, further research is needed to examine the asymptotic properties of the proposed estimator.

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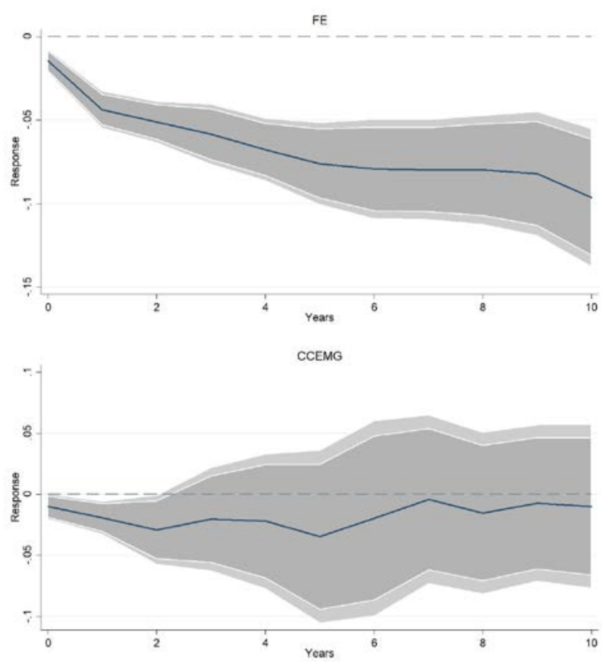
Tables and Figures

Table 1: Impulse Response Estimates for the Effect of a Financial Crisis on GDP

	Fixed Effects		*Mean Group*		*CCE Mean Group*	
Years after crisis (k)	*Jorda*	*Teulings & Zubanov*	*Jorda*	*Teulings & Zubanov*	*Jorda*	*Teulings & Zubanov*
0	-0.015***	-0.015***	-0.013***	-0.013***	-0.010*	-0.010*
1	-0.043***	-0.044***	-0.042***	-0.042***	-0.017***	-0.019***
2	-0.048***	-0.051***	-0.043***	-0.045***	-0.023*	-0.029**
3	-0.054***	-0.058***	-0.040***	-0.042***	-0.017	-0.020
4	-0.061***	-0.067***	-0.042***	-0.046***	-0.020	-0.022
5	-0.067***	-0.076***	-0.041**	-0.047***	-0.031	-0.035
6	-0.068***	-0.079***	-0.037**	-0.045**	-0.021	-0.019
7	-0.068***	-0.080***	-0.039***	-0.051***	0.006	-0.004
8	-0.067***	-0.080***	-0.037**	-0.049**	-0.001	-0.015
9	-0.070***	-0.082***	-0.037*	-0.047*	0.009	-0.007
10	-0.084***	-0.096***	-0.047**	-0.061**	0.013	-0.010
Financial Crisis Leads	*No*	*Yes*	*No*	*Yes*	*No*	*Yes*
Heterogeneous Coefficients	*No*	*No*	*Yes*	*Yes*	*Yes*	*Yes*
Cross Sectional Averages	*No*	*No*	*No*	*No*	*Yes*	*Yes*

Notes: *******, ****** and ***** denotes significance at the 1%, 5% and 10% significance levels, respectively.

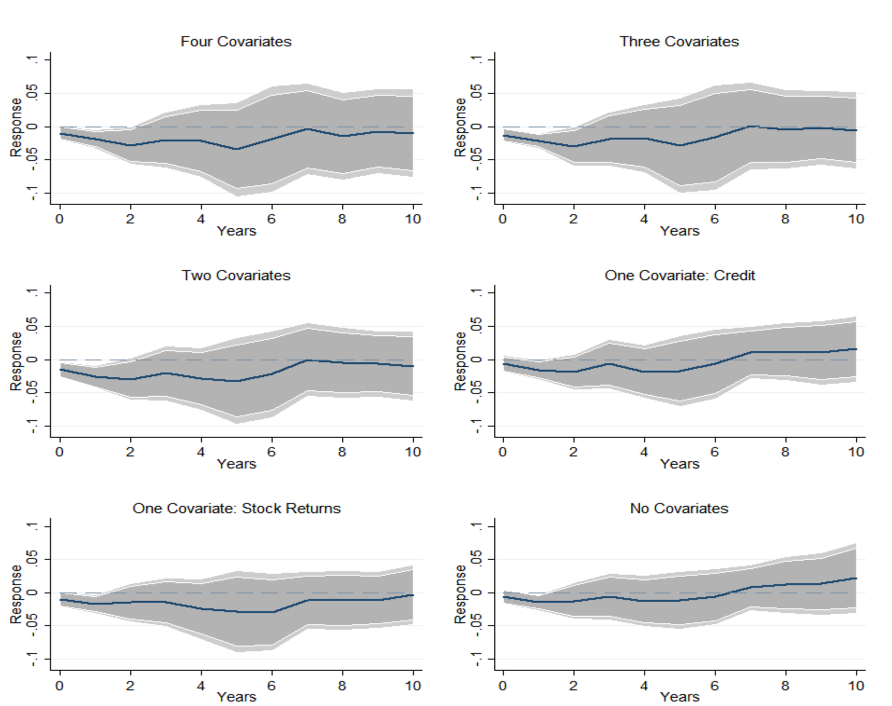
Figure 1: Predicted GDP Losses from a Financial Crisis using Local Projections Impulse Responses: FE *vs* CCEMG



Notes: Grey shaded areas are the 90% and 95% confidence intervals. Estimates are based on the corrected local projections FE and CCEMG estimators.

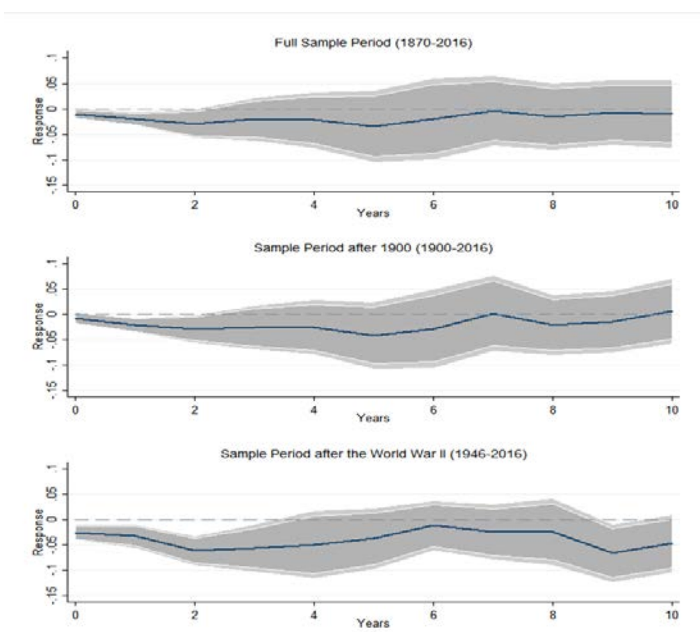
Online Appendix A. Robustness Checks

Figure A.1: Robustness over the Set of Covariates



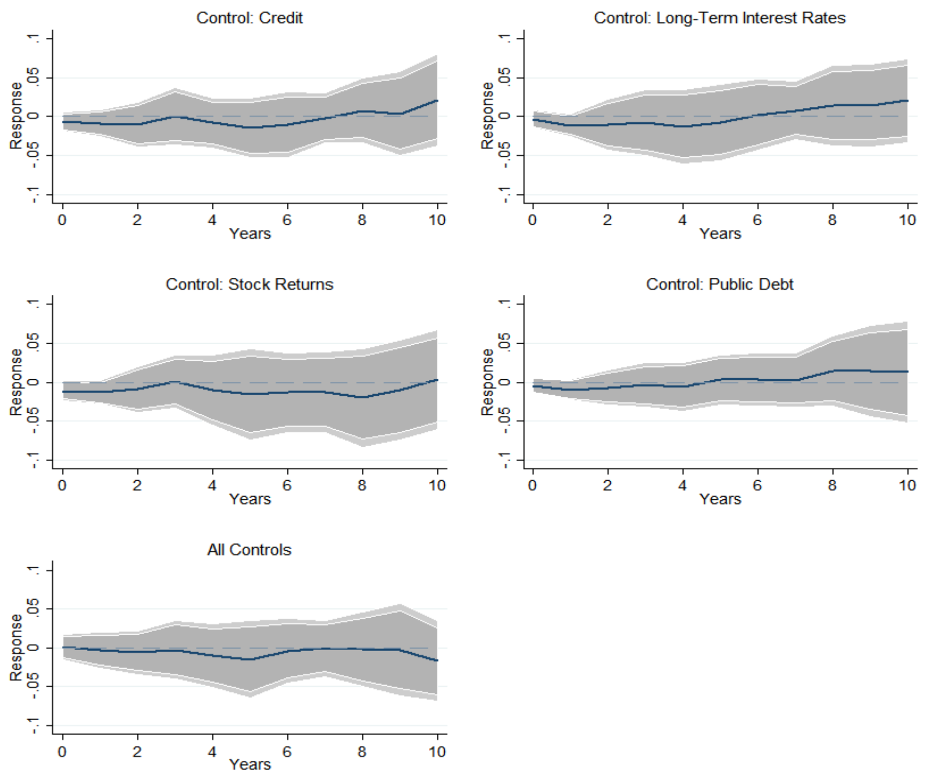
Notes: Grey shaded areas are the 90% and 95% confidence intervals. Estimates are based on the corrected local projections CCEMG estimator.

Figure A.2: Robustness over Alternative Samples



Notes: Grey shaded areas are the 90% and 95% confidence intervals. Estimates are based on the corrected local projections CCEMG estimator.

Figure A.3: Robustness over Controls



Notes: Grey shaded areas are the 90% and 95% confidence intervals. Estimates are based on the corrected local projections CCEMG estimator.