Macroeconomic Dynamics (2024), **28**, pp. 1023–1048
doi:10.1017/S1365100523000366

ARTICLE

Recovery from economic disasters

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Abstract
This study uses two large datasets to explore the output dynamics following economic disasters, one including 180 economic disasters across 38 countries over the last two centuries and the other including 204 disasters in 182 countries since World War II. Our results suggest that extreme economic crises are associated with huge and remarkably persistent loss. On average, output loss surges to above 26% in the first few years after the outbreak of a disaster and remains above 20% for as long as 20 years. It is only after more than 50 years that the loss is fully recovered.

Keywords: Economic disaster; economic recovery; output loss

1. Introduction

Economic disasters are rare but extremely large economic crises, defined in Barro and Ursúa (2008) as a cumulative decline in output and/or consumption over one or more years of at least 10%. This study analyzes the recovery of output after economic disasters on a long historical timeline.

Since the global crisis in 2008–2009, researchers have become increasingly interested in models of asset pricing and macroeconomic dynamics that include a low probability of large economic disasters. In his seminal contribution, Barro (2006) shows that the frequency of economic disasters observed throughout the 20th century can account for excess returns on stocks relative to returns on government bonds. A number of ensuing studies suggest that rare disaster models are suitable for modeling many other financial phenomena (see e.g. Gabaix (2012), Gourio (2013), Wachter (2013), Farhi and Gabaix (2016), Seo and Wachter (2018) and Barro and Liao (2020)). The rare disaster models are also used to analyze welfare effects of economic disasters (Barro (2009)), business cycles (Gourio (2012), Isoré and Szczerbowicz (2017)), and debt intolerance of emerging economies (Rebelo et al. (2022)).

Compared to the growing literature that focuses on the relationship between the frequency of economic disasters and various financial and economic issues, much less attention has been paid to the behavior of output after economic disasters. Following Barro (2006), in almost all studies on economic disasters, output/consumption is modeled as a random walk with drift process that includes disasters identified as large and permanent drops in output/consumption. The assumption that losses are permanent can overstate the riskiness of disasters and hence significantly affect the outcomes of rare disaster models (see Gourio (2008), Nakamura et al. (2013), Tsai and Wachter (2015)). Consequently, better understanding of output dynamics following economic disasters is important to evaluate the results of this literature and for further development of rare disaster models.

More insights into the dynamics of recovery are important from a broader macroeconomic perspective as well. Business cycles and economic growth are commonly treated as separate issues in macroeconomics. Cycles are regarded as short-run variations around a smooth growth path of output, caused by economic shocks that have temporary effects on output. However, the literature on output hysteresis provides an alternative perspective (see Cerra et al. (2023), for the comprehensive literature review). Nelson and Plosser (1982) contest the common perception of short-term effects of economic shocks on output. They provide empirical evidence that output does not show a strong tendency to return to previous trend after a shock, suggesting that the effects of economic shocks may be permanent. Their influential research led to the extensive debate on trend stationarity versus unit root. Succeeding studies have used different unit root tests and empirical models, but have not reached a conclusive answer (see for example Hamilton (1989), Rudebusch (1993), Diebold and Senhadji (1996), Murray and Nelson (2000), Darné (2009), Shelley and Wallace (2011), Aslanidis and Fountas (2014) and Cushman (2016)). Recently, several studies have considered an alternative empirical approach to the issue of output hysteresis. Cerra and Saxena (2008) estimate a dynamic model of output growth for a large sample of countries and calculate output responses to financial and political shocks. The estimated impulse response functions (IRFs) suggest that the output loss associated with financial crises is permanent. Ensuing studies corroborate similar results for different types of financial crises (see e.g. Furceri and Muorougane (2012), Furceri and Zdzienicka (2012), Teulings and Zubanov (2014), da Rocha and Solomou (2015) and Tola and Waelti (2018)).

Given the large size of economic disasters, the persistence of output losses associated with them is an important macroeconomic and policy issue. To understand how economies work and how best to inform economic policy, it is essential to know whether massive output losses brought about by economic disasters are temporary and quickly rectified, or whether they are permanent. Current economic circumstances add interest to this issue. The 2020 outbreak of COVID-19 pandemic has struck a devastating blow to global health. The rapid spread of the virus has forced national governments to mandate social distancing, travel restrictions, quarantines, lockdowns, and school and business closures. These restrictions have led to record-breaking falls in output across the world.

Our study systematically documents the recovery of output after economic disasters. The study is based on Barro and Ursúa (2010) output data for 38 OECD and non-OECD countries over the last two centuries, which includes 180 economic disasters. We also use Ćorić (2021) recent data covering 182 countries, which include 204 economic disasters occurring since World War II (WWII). The analysis involves two parts. We first employ a quantile autoregression-based unit root test to check for the unit root in the lower tail of conditional output distributions. The results suggest that output does not rebound to its pre-crisis trend path in the short run after large recessionary shocks, but that large negative shocks are likely to have permanent effect on output. Nevertheless, unit root tests can suffer from serious size distortions and have very low power. The autoregressive coefficients close to one imply a highly persistent, rather than permanent, effect of shocks on output. Hence, in the second part of the analysis we employ a local projection estimator to explore further the dynamics of output growth after economic disasters. The results of our analysis point to large, long-run output losses following economic disasters. The process of recovering from losses appears to be gradual and very slow; it encompasses decades rather than years. Our results show that, on average, output losses remain significant as long as fifty years after the onset of an economic disaster.

The paper is organized as follows. Section 1 discusses related economic research. Section 2 presents our unit root analysis. Section 3 describes the model and methodology we use to estimate the dynamics of output after disasters. Section 4 presents our main empirical results. Section 5 concludes.

https://doi.org/10.1017/S1365100523000366 Published online by Cambridge University Press

2. Related studies

Our research can be regarded as a part of the broader debate in macroeconomics on whether output should be modeled as being trend or difference stationary. As noted above, Nelson and Plosser (1982) challenged the hypothesis that output returns to a deterministic log-linear time trend shortly after a shock and argued that output should instead be considered difference stationary. With respect to the large succeeding literature, our analysis is closest to research conducted by Hosseinkouchack and Wolters (2013). To check whether large recessions have temporary or permanent effects on output, Hosseinkouchack and Wolters (2013) apply a quantile autoregression-based unit root test to post-WWII US output data. Our study also considers the issue of the unit root in the lower tail of output distribution, but in a much broader context. We apply the same testing procedure to historical output data for 38 OECD and non-OECD countries. Besides, quantile unit root testing is the first step of our empirical analysis. In the succeeding step, we specify an empirical output growth model to estimate the average dynamic of output growth after an economic disaster by using a local projection method.

To estimate the output growth dynamic, we build on Cerra and Saxena's (2008) study of economic recoveries after financial crises. They estimate a dynamic model of output growth and use the regression results for a recursive calculation of output responses to occurrences of financial crisis. We use the same empirical concept. However, to obtain estimates on average output growth dynamics after economic disasters, we employ a recent extension of a local projection method suggested by Teulings and Zubanov (2014). As discussed below, this estimator provides a more robust method for calculating IRF than the standard recursive calculation used by Cerra and Saxena (2008); it is also more robust than the original Jordà (2005) local projection method employed by recent empirical studies on recoveries from financial crises (da Rocha and Solomou (2015), Romer and Romer (2017) and Tola and Waelti (2018)). Compared to this strand of the literature on output hysteresis, our study also differs regarding the topic of research. This literature concentrates mostly on the aftermath of financial crises in the post-WWII period. Instead, we focused on economic disasters and historical data. The long series of historical data enable us to consider the dynamics of output recovery over a much longer time horizon compared to these studies.

Our focus on recovery after economic disasters relates our research to Gourio (2008) and Nakamura et al. (2013). At present, the only empirical evidence on recovery after economic disasters is comprised of the results reported in these two studies.[1] Our research contributes to and substantially extends their findings.

Gourio (2008) enhances Barro's (2006) rare disaster model to control for the possible effect of economic recovery. To support the introduction of recovery into the model, he provides preliminary evidence on output recovery after 57 economic disasters that occurred in the 20th century. Specifically, he computes the average cumulative growth of output over the first five years after the end of economic disasters and calculates how much of the average cumulative output decline during disasters is regained in each year.

Gourio's (2008) calculation does not include the formal empirical modeling of output. The use of an empirical model to estimate the dynamics of recovery is important because output typically grows in the long run. Hence, the simple arithmetical calculation, which suggests that output reaches the pre-disaster level after a certain number of years, does not imply that the output losses induced by the economic disaster are regained. Our study augments Gourio (2008) in this respect. As discussed below, we use an autoregressive model of output growth that includes a dummy for the occurrence of economic disasters and a local projection method to estimate the average dynamic of output recovery after economic disasters.

Nakamura et al. (2013) developed a model of consumption disasters that allows disasters to be systematically followed by recoveries. Their empirical estimates suggest that the average length of consumption disasters is about six years. During this period, consumption decreases by about

27%, but approximately half of this loss is reversed in the long run. Consequently, the implied permanent long-run consumption loss is about 14%. Nakamura et al. (2013) concentrate on consumption disasters because the underlying asset pricing theory in the rare disaster models relates to consumption. In contrast to their study, we focus on output disasters. Barro and Ursúa (2008) show that it makes little difference for the results of rare disaster models whether consumption or output data are used, because economic disasters occur similarly in consumption and output. The empirical advantage of output data is that they are available for a much wider set of countries and time spans.

Employing output data enables us to provide more comprehensive evidence on recovery from economic disasters, especially for the post-WWII period. Nakamura et al.'s (2013) estimates are based on historical consumption data for 24 countries. Our empirical results derive from the historical output data, which are longer and are available for 38 countries. Furthermore, we provide evidence on output recovery from 204 economic disasters observed after WWII. This additional evidence is important because, in Barro and Ursúa (2010) historical data, used by both studies, most economic disasters occurred before WWII, more than 70 years ago. The structure of economies and the conduct of economic policy has evolved substantially since then. These changes can have considerable effects on the dynamics of economic recovery. Hence, it is important to check whether estimates on output recovery after economic disasters in the post-WWII period are different from estimates based on older historical data.

3. Unit root analysis

3.1. Methodology

Our inference on the output recovery after economic disasters starts with a unit root analysis of output data. If output follows a trend stationary process, it will rebound after an economic disaster to its pre-crisis trend path. Consequently, output losses will be recovered relatively quickly.

As our analysis concentrates on the aftermath of economic disasters, we employ a quantile autoregression-based unit root test that enables us to check the unit root hypothesis not only in the conditional mean of output but also in the tails of distribution. We use Galvao's (2009) extension of the original quantile autoregression-based unit root test developed by Koenker and Xiao (2004). Compared to the original test, Galvao's (2009) test allows for a linear time trend that is essential for unit root tests of ascending time series-like output.

The quantile autoregression-based test has the ability to uncover potentially different behaviors of outputs over various quantiles. It allows for the possibility that shocks of different signs and magnitude may have different impacts on output. In our case, this is crucial because we are interested in output dynamics following economic disasters that correspond to the estimates in the lower tail of conditional output distribution. Further, Galvao's (2009) test has higher power than conventional unit root tests when innovations are non-Gaussian heavy-tailed. This is an important advantage in our case, because economic disasters are typical examples of economic events that cause heavy-tails in conditional output distribution. The standard testing procedure rejects the normal distribution of residuals in output models for the vast majority of countries in our sample (available on request). Since the number of observations per country in our sample ranges from 99 for Korea to 220 for the USA (see Table 1 below), this may raise concerns with respect to the robustness of our results. However, Galvao (2009) uses bootstrapping and resampling method to calculate the critical values and solve small sample properties of the test. He shows that the test has better finite sample properties than the standard unit root test. In particular, the results of Galvao's (2009) Monte Carlo simulations show that when distribution of residuals is non-normal heavy-tailed the test has higher power than standard augmented Dickey-Fuller tests for $n = 100$ and $n = 200$.

Table 1. Data sample

OECD countries	Time period	Non-OECD countries	Time period
Australia	1820–2009	Argentina	1875–2009
Austria	1870–2009	Brazil	1850–2009
Belgium	1846–2009	Chile	1860–2009
Canada	1870–2009	China	1890–2009
Denmark	1818–2009	Colombia	1905–2009
Finland	1860–2009	Egypt	1894–2009
France	1820–2009	India	1872–2009
Germany	1851–2009	Indonesia	1880–2009
Iceland	1870–2009	Korea	1911–2009
Italy	1861–2009	Mexico	1895–2009
Japan	1870–2009	Peru	1896–2009
Netherlands	1807–2009	Russia	1860–2009
New Zealand	1860–2009	S. Africa	1911–2009
Norway	1830–2009	Sri Lanka	1870–2009
Portugal	1865–2009	Taiwan	1901–2009
Spain	1850–2009	Turkey	1875–2009
Sweden	1800–2009	Uruguay	1870–2009
Switzerland	1851–2009	Venezuela	1883–2009
United Kingdom	1830–2009		
United States	1790–2009		

Note: the countries are classified in OECD groups based on the original Barro and Ursúa (2008, 2012) classification, which does not include Turkey and recent new OECD members.

To test for the unit root, we model output as an *AR(q)* process with a linear time trend.

$$y_t = \alpha + \beta t + \sum_{i=1}^{q} \gamma_i y_{t-i} + \varepsilon_t, \quad t = q+1, q+2, \ldots, n \tag{1}$$

where y represents the logarithm of output. α denotes a constant, β represents the slope of time trend, and ε_t is the error term.

Rearranging equation (1) and writing the sum of autoregressive coefficients as $\theta = \sum_{i=1}^{q} \gamma_i$ leads to the output specification,

$$y_t = \theta y_{t-1} + \alpha + \beta t + \sum_{i=1}^{q-1} \psi_i \Delta y_{t-i} + \varepsilon_t \tag{2}$$

that can be used to test the standard unit root null hypothesis, H_0: $\theta = 1$. If $\theta = 1$, output can be considered a difference stationary process with permanent effects of economic shocks on output. If, instead, $|\theta| < 1$ output is trend stationary, it returns to its deterministic trend after the shock, and consequently, economic shocks have only a temporary effect on output.

This *AR(q)* process at quantile τ can be written as:

$$Q_\tau \left(y_t | y_{t-1}, \ldots, y_{t-q} \right) = \theta \left(\tau \right) y_{t-1} + \alpha \left(\tau \right) + \beta \left(\tau \right) t + \sum_{i=1}^{q-1} \psi_i \left(\tau \right) \Delta y_{t-i} \tag{3}$$

where $\tau \in (0, 1)$and $Q_\tau(y_t|y_{t-1}, \ldots, y_{t-q})$ denotes τ-th quantile of y_t conditional on its recent history, $y_{t-1}, \ldots, y_{t-q}$. By estimating equation (3) at different quantiles, we obtain a sequence of

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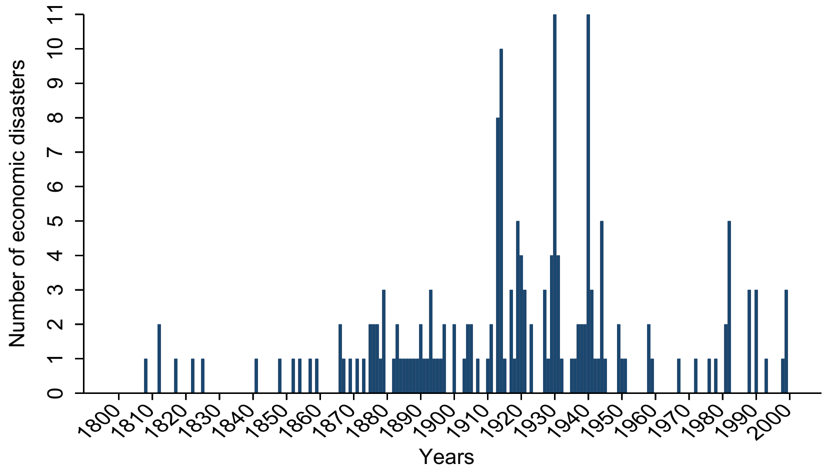

Figure 1. Dispersion of economic disasters by years.

estimates on $\theta(\tau)$ for each country and then test for $H_0: \theta(\tau) = 1$ using Galvao's (2009) quantile autoregression-based unit root test.

3.2. Data

We employ Barro and Ursúa's (2010) long series of historical data. Economic disasters are relatively rare and thus may be absent in short time series for individual countries. Barro and Ursúa (2010) upgrade and improve upon Angus Maddison's historical data and provide the real GDP per capita for 42 OECD and non-OECD countries. We employ data for 20 OECD and 18 non-OECD countries for which continuous output series are available. The annual output data are available up to 2009, while country starting dates vary, ranging from 1790 for the USA to 1911 for Korea and South Africa. Table 1 provides the time span for each country in the data sample, while Fig. 1 illustrates the dispersion of economic disasters by years.

3.3. Results of the unit root analysis

The number of lags included in the model is selected separately for each country using the modified Akaike information criterion suggested by Ng and Perron (2001). The maximum number of lags is set at 10. The results are robust to using a different lag length selected using Schwert's criteria (available upon request).

As economic disasters correspond to the observations at the very end of the lower tail of conditional output distribution, we focus on the results for the lowest quantiles, $\tau = 0.05$ and $\tau = 0.10$. The complete set of results for each country is provided in Appendices A and B. The persistence parameters reported for these quantiles are close to one, and the quantile autoregression-based unit root test fails to reject $H_0: \theta(\tau) = 1$ at the 5% level of significance in almost all cases. The only exceptions for OECD countries are estimates on θ (0.10) for Belgium and θ (0.05) for Switzerland. In these two cases, the unit root is rejected at the 5% level. Overall, the results do not support trend stationarity of output, but instead suggest that large negative economic shocks are likely to have permanent effect on output in OECD countries.

The results on $\theta(\tau)$ for other quantiles show that in three countries, Canada, Norway, and the UK, the unit root hypothesis cannot be rejected at the 5% level over the whole conditional output distribution. In other countries, the unit root is more often rejected for the quantiles on the upper

https://doi.org/10.1017/S1365100523000366 Published online by Cambridge University Press

side of the conditional output distribution. Overall results point to asymmetric effects of economic shocks across OECD countries. Our findings indicate that, in comparison to negative economic shocks, positive shocks are less likely to have permanent effects on output.

The results for non-OECD countries (Appendix B) are similar. Again, the tests fail to reject the unit root at $\tau = 0.05$ and $\tau = 0.10$ in almost all cases. The only exception are estimates on θ (0.05) for Indonesia and Russia. For estimates at other quantiles, asymmetry in the effects of economic shocks on output is less pronounced than those for OECD countries. For 10 of 18 countries, the test fails to reject the unit root at the 5% level in all quantiles, suggesting that across non-OECD countries all types of economic shock often have permanent effect on output.

Taken together, the results for the lowest quantiles suggest that output does not rebound to its pre-crisis trend path following large negative shocks, and output losses are unlikely to be temporary. As economic disasters correspond to the observations in the lower tail of conditional output distribution, these results are *consistent* with the hypothesis that output losses associated with economic disasters are permanent. However, even though Galvao's (2009) test has higher power than conventional unit root tests when innovations are non-Gaussian heavy-tailed, the power of the test still remains an issue that casts doubt on the robustness of our results. Hence, in next section we concentrate particularly on economic disasters and use the local projection method to estimate directly the average dynamics of output after economic disasters.[2]

4. Output dynamic after economic disasters

4.1. Methodology

The unit root tests reject trend stationarity of output. Thus, to estimate the average dynamic of output following economic disasters, we use the model of output in log differences. We employ a panel autoregressive model that includes current and lagged variables for economic disasters,

$$y_{i,t} - y_{i,t-1} = \alpha_i + \sum_{j=1}^{4} \psi_j \Delta y_{i,t-j} + \sum_{l=0}^{4} \phi_l ED_{i,t-l} + u_{i,t} \tag{4}$$

where y represents the logarithm of output. i and t superscripts index countries and time, respectively. ED is the variable for economic disasters. It is constructed as a dummy variable equal to 1 if an economic disaster in country i starts in year t and 0 otherwise. We also include country-specific fixed effects, α_i, to capture the possibility that the average rate of output growth can differ across countries. $u_{i,t}$ is the error term. The number of lags is set to four as we find the coefficients beyond the fourth lag to be mainly statistically insignificant.

The output growth dynamic after disasters is estimated using Jordà's (2005) local projection method. This method estimates the IRF directly from the forecast equation for output k periods ahead,

$$y_{i,t+k} - y_{i,t-1} = \alpha_i^k + \sum_{j=1}^{J} \psi_j^k \Delta y_{i,t-j} + \sum_{l=0}^{L} \phi_l^k ED_{i,t-l} + u_{i,t+k} \tag{5}$$

where the k superscript denotes the time horizon being considered, while the difference $y_{i,t+k} - y_{i,t-1}$ denotes the cumulative change in the logarithm of output from time *t-1* to $t+k$. The method estimates separate regressions for the increasing horizons between time t and time $t+k$. The sequence of estimates on a dummy variable capturing the onset of economic disaster, ϕ_0^k, provides the cumulative output growth responses, while the respective standard errors can be used to construct confidence bands.

As we consider a very long forecast horizon (see Section 5.1), in our case the local projection method has an important advantage over the standard recursive calculation of IRF, in which IRF is calculated for each period ahead by expressing the conditional expectation of the variable of

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interest as a function of the model's estimated parameters (equation (4) in our case). Teulings and Zubanov (2014) show that, as a model includes more lags of the explanatory variables and as a length of the forecast horizon k increases, IRF becomes a complex expression that is increasingly sensitive to even slight specification errors. In contrast, the local projection method appears to be robust to a variety of misspecification in the underlying model, because instead of using the same set of coefficients for all forecast horizons a separate set of coefficients is estimated for each k. For a more comprehensive discussion on this and other advantages of using the local projection estimator, see Gorodnichenko and Auerbach (2013) and Teulings and Zubanov (2014).

Even though Jordà's (2005) estimator appears to be robust to specification errors, the method can be subject to bias that occurs due to estimator's failure to use information on the crises occurring within the forecast horizon (Teulings and Zubanov (2014)). Therefore, we apply the extension of the local projection method proposed by Teulings and Zubanov (2014). We augment forecast equation (5) with the variables for economic disasters occurring within the forecast horizon, that is, between t and $t+k$, and estimate the following empirical specification:[3]

$$y_{i,t+k} - y_{i,t-1} = \alpha_i^k + \sum_{j=1}^{4} \psi_j^k \Delta y_{i,t-j} + \sum_{l=0}^{4} \phi_l^k ED_{i,t-l} + \sum_{l=0}^{k-1} \delta_l^k ED_{i,t+k-l} + u_{i,t+k} \tag{6}$$

4.2. Data

To run the sequential estimates of equation (6), we employ the Barro and Ursúa (2010) data on output and economic disasters described in Section 3.2. The data for 38 OECD and non-OECD countries are pooled together into a panel sample that comprises 5643 annual output observations and 180 economic disasters. The model includes the four lags of variables for economic disasters and first differences of output. These lags reduce the number of observations available for estimation to 5453. As we estimate a separate regression for each forecast horizon up to $k = 60$, the effective sample size decreases gradually from 5453 (for $k = 0$) to 3173 (for $k = 60$). Through the whole projection period, the number of countries in the sample remains constant.

5. Results

5.1. Baseline results

Table 2 reports the sequences of estimates on ϕ_0^k for $k = 0, \ldots, 60$ for the total sample of historical output data. The coefficients are estimated using a fixed effects estimator with serially correlation robust standard errors. Introduction of country fixed effects in the context of dynamic panel data creates bias in the estimated coefficients on the lagged dependent variable. However, in our sample the order of bias, T^{-1} (Nickell (1981)), is very small as our average $T = 148.5$.

The coefficients on ϕ_0^k for the total sample are plotted in Fig. 2, while the corresponding standard errors are used to construct the 95% confidence interval. The plotted results show the average dynamics of cumulative output growth after the onset of an economic disaster across 38 OECD and non-OECD countries over the last two centuries. On average, the output loss in first 4 years following an economic disaster amounts to 26.4%. Recovery typically begins 5 years after the onset of disaster. However, the losses are recouped extremely slowly. Even after 20 years, the output loss is as high as 20% and remains statistically significant at the 5% level for 53 years. The estimated size of ϕ_0^{53} points to output loss of 8.2%. The coefficients on ϕ_0^k remain negative for the rest of the forecast horizon, barely reaching zero at $k = 60$. Thus, our results suggest that after a typical economic disaster, an economy requires, on average, more than half a century to recoup losses.

To put this into perspective, consider that the average output growth in our historical sample is near 2% per year. Thus, the average economy would grow by 48.6% over 20 years and 185.6%

https://doi.org/10.1017/S1365100523000366 Published online by Cambridge University Press

Table 2. Output losses after economic disasters

	Historical output data				Historical output data: OECD				Historical output data: non-OECD				Post-WWII output data			
k	ϕ_0	p-value	count.	obs.	ϕ_0	p-value	count.	obs.	ϕ_0	p-value	count.	obs.	ϕ_0	p-value	count.	obs.
0	−0.107	0.000	38	5453	−0.101	0.000	20	3261	−0.112	0.000	18	2192	−0.154	0.000	182	9654
1	−0.183	0.000	38	5415	−0.182	0.000	20	3241	−0.185	0.000	18	2174	−0.251	0.000	182	9472
2	−0.220	0.000	38	5377	−0.212	0.000	20	3221	−0.228	0.000	18	2156	−0.295	0.000	182	9290
3	−0.254	0.000	38	5339	−0.249	0.000	20	3201	−0.259	0.000	18	2138	−0.329	0.000	182	9108
4	−0.264	0.000	38	5301	−0.271	0.000	20	3181	−0.262	0.000	18	2120	−0.342	0.000	182	8926
5	−0.262	0.000	38	5263	−0.264	0.000	20	3161	−0.265	0.000	18	2102	−0.329	0.000	182	8744
6	−0.240	0.000	38	5225	−0.225	0.000	20	3141	−0.259	0.000	18	2084	−0.323	0.000	182	8562
7	−0.237	0.000	38	5187	−0.209	0.000	20	3121	−0.267	0.000	18	2066	−0.325	0.000	182	8380
8	−0.235	0.000	38	5149	−0.190	0.000	20	3101	−0.280	0.000	18	2048	−0.322	0.000	182	8198
9	−0.225	0.000	38	5111	−0.175	0.000	20	3081	−0.276	0.000	18	2030	−0.325	0.000	182	8016
10	−0.219	0.000	38	5073	−0.166	0.000	20	3061	−0.272	0.000	18	2012	−0.335	0.000	182	7834
11	−0.217	0.000	38	5035	−0.159	0.000	20	3041	−0.278	0.000	18	1994	−0.343	0.000	182	7652
12	−0.223	0.000	38	4997	−0.160	0.000	20	3021	−0.291	0.000	18	1976	−0.334	0.000	182	7470
13	−0.225	0.000	38	4959	−0.153	0.000	20	3001	−0.302	0.000	18	1958	−0.333	0.000	182	7288
14	−0.227	0.000	38	4921	−0.162	0.000	20	2981	−0.300	0.000	18	1940	−0.339	0.000	182	7106
15	−0.221	0.000	38	4483	−0.158	0.000	20	2961	−0.290	0.000	18	1922	−0.328	0.000	182	6924
16	−0.220	0.000	38	4845	−0.153	0.000	20	2941	−0.294	0.000	18	1904	−0.311	0.000	182	6742

Table 2. Continued

	Historical output data				Historical output data: OECD				Historical output data: non-OECD				Post-WWII output data			
k	ϕ_0	*p*-value	count.	obs.	ϕ_0	*p*-value	count.	obs.	ϕ_0	p-value	count.	obs.	ϕ_0	*p*-value	count.	obs.
17	−0.222	0.000	38	4807	−0.157	0.000	20	2921	−0.294	0.000	18	1886	−0.300	0.000	182	6560
18	−0.223	0.000	38	4769	−0.153	0.000	20	2901	−0.298	0.000	18	1868	−0.292	0.000	182	6378
19	−0.215	0.000	38	4731	−0.147	0.000	20	2881	−0.288	0.000	18	1850	−0.281	0.000	182	6196
20	−0.200	0.000	38	4693	−0.131	0.000	20	2861	−0.276	0.000	18	1832	−0.271	0.000	182	6014
21	−0.190	0.000	38	4655	−0.124	0.000	20	2841	−0.265	0.000	18	1814	−0.262	0.000	182	5832
22	−0.193	0.000	38	4617	−0.125	0.000	20	2821	−0.272	0.000	18	1796	−0.254	0.000	182	5650
23	−0.190	0.000	38	4579	−0.124	0.000	20	2801	−0.271	0.000	18	1778	−0.245	0.000	182	5468
24	−0.182	0.000	38	4541	−0.110	0.001	20	2781	−0.269	0.000	18	1760	−0.246	0.000	182	5286
25	−0.183	0.000	38	4503	−0.110	0.001	20	2761	−0.273	0.000	18	1742	−0.254	0.000	182	5104
26	−0.180	0.000	38	4465	−0.104	0.001	20	2741	−0.270	0.000	18	1724	−0.247	0.000	182	4922
27	−0.184	0.000	38	4427	−0.101	0.003	20	2721	−0.283	0.000	18	1706	−0.248	0.000	182	4740
28	−0.182	0.000	38	4389	−0.094	0.010	20	2701	−0.288	0.000	18	1688	−0.271	0.000	182	4558
29	−0.174	0.000	38	4351	−0.082	0.029	20	2681	−0.288	0.000	18	1670	−0.270	0.000	182	4376
30	−0.170	0.000	38	4313	−0.080	0.031	20	2661	−0.286	0.000	18	1652	−0.284	0.000	182	4194
31	−0.177	0.000	38	4275	−0.092	0.015	20	2641	−0.287	0.000	18	1634	−0.270	0.000	182	4012
32	−0.166	0.000	38	4237	−0.086	0.018	20	2621	−0.270	0.000	18	1616	−0.259	0.000	182	3830
33	−0.151	0.000	38	4199	−0.068	0.047	20	2601	−0.259	0.000	18	1598	−0.251	0.000	182	3648
34	−0.142	0.001	38	4161	−0.060	0.080	20	2581	−0.250	0.002	18	1580	−0.254	0.000	182	3466
35	−0.139	0.001	38	4123	−0.060	0.092	20	2561	−0.243	0.003	18	1562	−0.254	0.000	182	3284
36	−0.134	0.001	38	4085	−0.058	0.114	20	2541	−0.236	0.003	18	1544	−0.249	0.000	182	3102
37	−0.129	0.002	38	4047	−0.048	0.162	20	2521	−0.234	0.003	18	1562	−0.232	0.000	182	2920
38	−0.123	0.003	38	4009	−0.046	0.208	20	2501	−0.226	0.005	18	1508	−0.228	0.001	182	2738

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Table 2. Continued

	Historical output data				Historical output data: OECD				Historical output data: non-OECD				Post-WWII output data			
k	ϕ_0	p-value	count.	obs.	ϕ_0	p-value	count.	obs.	ϕ_0	p-value	count.	obs.	ϕ_0	p-value	count.	obs.
39	−0.119	0.006	38	3971	−0.046	0.227	20	2481	−0.217	0.008	18	1490	−0.223	0.001	182	2556
40	−0.115	0.009	38	3933	−0.049	0.214	20	2461	−0.204	0.015	18	1472	−0.233	0.002	182	2374
41	−0.114	0.011	38	3895	−0.051	0.201	20	2441	−0.202	0.017	18	1454	–	–	–	–
42	−0.110	0.013	38	3857	−0.047	0.236	20	2421	−0.198	0.016	18	1436	–	–	–	–
43	−0.122	0.002	38	3819	−0.053	0.215	20	2401	−0.216	0.003	18	1418	–	–	–	–
44	−0.116	0.003	38	3781	−0.049	0.232	20	2381	−0.212	0.002	18	1400	–	–	–	–
45	−0.119	0.002	38	3743	−0.056	0.190	20	2361	−0.208	0.002	18	1382	–	–	–	–
46	−0.120	0.003	38	3705	−0.056	0.202	20	2341	−0.211	0.003	18	1364	–	–	–	–
47	−0.108	0.006	38	3667	−0.050	0.241	20	2321	−0.189	0.008	18	1346	–	–	–	–
48	−0.107	0.007	38	3629	−0.049	0.258	20	2301	−0.187	0.009	18	1328	–	–	–	–
49	−0.102	0.009	38	3591	−0.050	0.231	20	2281	−0.177	0.012	18	1310	–	–	–	–
50	−0.093	0.018	38	3553	−0.046	0.281	20	2261	−0.168	0.016	18	1292	–	–	–	–
51	−0.103	0.007	38	3515	−0.043	0.304	20	2241	−0.190	0.006	18	1274	–	–	–	–
52	−0.091	0.022	38	3477	−0.044	0.302	20	2221	−0.161	0.031	18	1256	–	–	–	–
53	−0.082	0.043	38	3439	−0.043	0.309	20	2201	−0.142	0.064	18	1238	–	–	–	–
54	−0.068	0.102	38	3401	−0.027	0.514	20	2181	−0.128	0.102	18	1220	–	–	–	–
55	−0.061	0.148	38	3363	−0.020	0.635	20	2161	−0.118	0.129	18	1202	–	–	–	–
56	−0.053	0.226	38	3325	−0.016	0.705	20	2141	−0.105	0.191	18	1184	–	–	–	–
57	−0.041	0.348	38	3287	−0.002	0.970	20	2121	−0.101	0.214	18	1166	–	–	–	–
58	−0.032	0.483	38	3249	0.010	0.831	20	2101	−0.097	0.216	18	1148	–	–	–	–
59	−0.017	0.705	38	3211	0.030	0.539	20	2081	−0.087	0.268	18	1130	–	–	–	–
60	−0.005	0.921	38	3173	0.041	0.442	20	2061	−0.069	0.377	18	1112	–	–	–	–

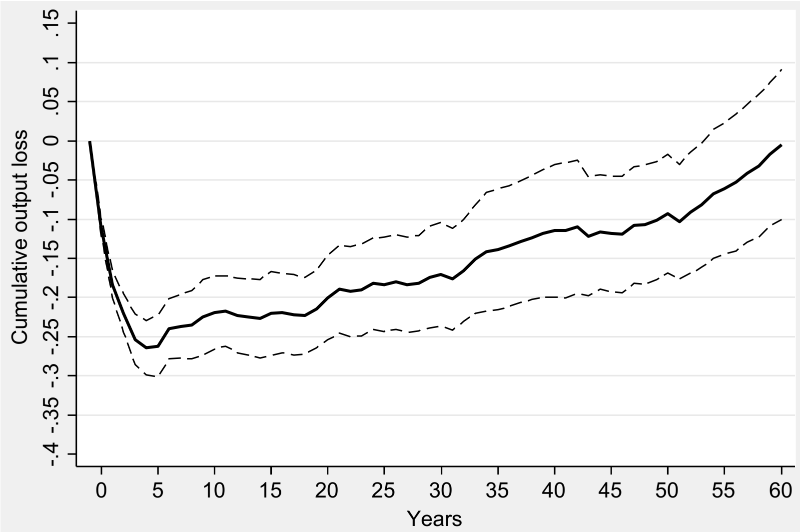

Figure 2. Output loss after economic disasters.

over 53 years. The reported output loss of 20% at $k = 20$ implies that 20 years after an economic disaster, cumulative output growth of the average economy would be 20 percentage points lower (28.6 instead of 48.6%). The estimated loss at $k = 53$ suggests that 53 years after an economic disaster, cumulative output growth would still be 8.2 percentage points lower than the average economy's long-run growth potential (177.4 instead of 185.6%).

5.2. Endogeneity and robustness tests

Our baseline estimates rely on the assumption that economic disasters are independent of all realizations of the error term. Even though macroeconomic models, including rare disaster models, standardly treat realizations of economic shocks as exogenous disturbances, we cannot dismiss the possibility that economic disasters are endogenous. This section provides the results of the alternative estimators and model specifications to address endogeneity issues and the robustness of our baseline estimates.

To address the possible endogeneity of economic disasters, we use the system GMM by Blundell and Bond (1998) and the estimator by Lewbel (2012). Specifically, we first employ a widely used system GMM estimator. We use a one-step system GMM estimator robust to heteroscedasticity. The second lags of economic disasters are used as instruments for economic disasters. Following Roodman (2009b), the instruments are collapsed to restrict their number. The complete set of results is available upon request. Fig. 3 depicts the sequence of coefficients on ϕ_0^k for $k = 0,\ldots,60$ along with the corresponding 95% confidence bands. The system GMM estimates of output growth dynamics after economic disasters appear to be consistent with our baseline results.

The crucial assumption for the validity of the system GMM estimator is that the employed internal instruments are exogenous. The IRF in Fig. 3 illustrates the results of 60 consecutive regressions. The results of the Hansen and Arellano-Bond tests support the validity of the instruments in almost all regressions.[4] However, the instrument proliferation in system GMM can weaken the power of the Hansen test (Roodman (2009b)). Hence, Roodman (2009a) recommends keeping the number of instruments lower than the number of groups in the sample. Despite collapsing the instruments, in our case, the number of instruments exceeded the number of groups/countries for $k > 27$. The system GMM estimates can also be biased owing to the weak

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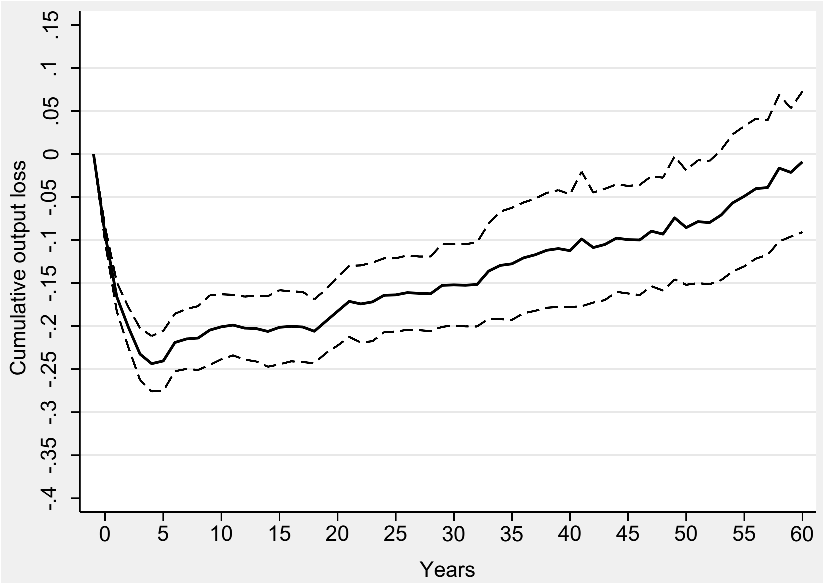

Figure 3. Output loss after economic disasters: system GMM estimates.

instruments problem (Bazzi and Clemens (2013)). Therefore, we employ an estimation method developed by Lewbel (2012) for an additional check of our results.

The estimator by Lewbel (2012) allows the identification of the structural parameters in regression models with endogenous regressors by using internal instruments that are created as a function of the model's data. The method comprises constructing valid instruments by exploiting the information contained in heteroscedastic standard errors. The method is implemented by using the *ivregh2* STATA module that allows application of the estimator by Lewbel (2012) in panel data regressions (Baum and Lewbel (2019)). The diagnostic tests suggest that under-identification and weak identification are not a problem in 60 and 59 regressions, respectively; while the validity of instruments is supported in 52 regressions (the results are available on request). The estimates (Appendix C) appear to be in line with our baseline and system GMM results.

Lewbel (2012) underlines the usefulness of using heteroscedasticity-based instruments to deal with the endogeneity caused by omitted variables. This is particularly relevant in the present case. The occurrence of economic disasters and long-run output growth may be determined by common factors. To address additionally the concern that our baseline estimates can overestimate the output loss due to joint determinacy, we include control variables in our model. Please note that our set of control variables is inevitably constrained by limited data availability.

We introduce the level of output per capita, the level of inflation, the quality of institutions, and population growth into the model. The variable for the level of output is calculated as the logarithm of the real GDP per capita. The relevant data are obtained from Barro and Ursúa (2010) and the World Bank's data for the GDP per capita in PPP-adjusted 2005 dollars. The annual data on inflation are obtained from Reinhart and Rogoff's (2011) dataset. For the quality of institutions, we use the indicator *xconst* from the Polity IV Project database. The population data are from Maddison (2010). All data are available on request. Furthermore, the economic disasters in our sample are clustered around a few prominent historical events, including the Spanish influenza and WWI, the Great Depression, and WWII. As they share periods of economic instability, many countries in the sample also shared the era of fast economic growth between WWII and the oil shocks of the 1970s. To control for common economic developments and to address the potential issue of cross-sectional dependence, we include time-specific fixed effects into the forecast

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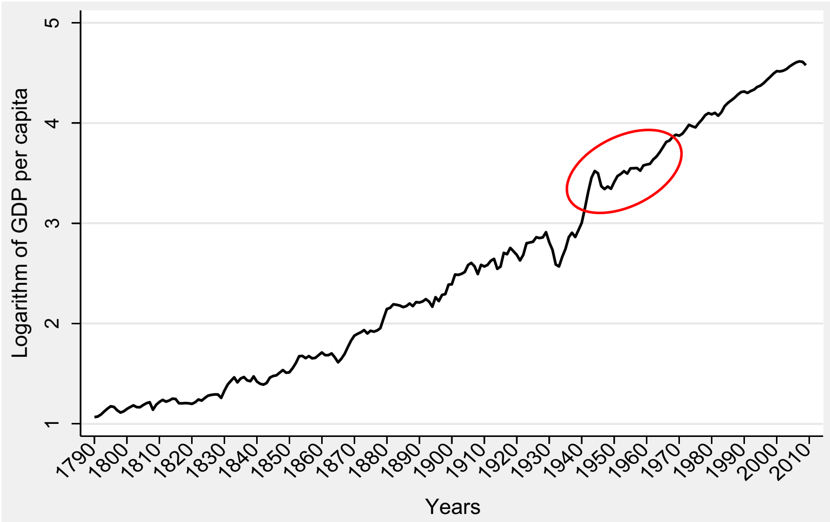

Figure 4. US GDP per capita.

equation. The results reported in Appendix D show that the estimates on output growth dynamics following economic disasters do not change substantially when the control variables and time effects are included in the model. The output loss remains very persistent, but the coefficients on ϕ_0^k are less precisely estimated. Consequently, the confidence intervals are wider. The results also remain consistent when we estimate the more parsimonious model; that is, the model in which the variable for the economic disasters enters just contemporaneously, without lags, and which does not include the control variables and time dummies (Appendix E).

Our baseline results can also overestimate the true output loss to the extent that economic disasters "correct" for the excessive output build-up during the booming periods preceding disasters. For example, Barro and Ursúa (2010) classify economic crises in the USA between 1945 and 1947 as disasters because cumulative drop in output was larger than 10%. In line with our empirical results, Fig. 4 reveals an apparent lack of fast output recovery after this crisis. However, an alternative explanation is more plausible in this case. Fig. 4 also illustrates that this output drop can outline the return of the US economy toward its steady-state growth path, probably related to the cessation of military production and demobilization at the end of WWII.

To control for the possible correction effect, for every country in the sample, we calculate the average rate of output growth. Then, for each economic disaster in the sample, we calculate the average rate of output growth over the 10 years before the onset of the economic disaster. We compare each 10-year average with the average output growth in the corresponding country and eliminate all economic disasters for which the average growth in the 10-year time span was over one percentage point larger than the average growth in the corresponding country. This procedure reduces the number of economic disasters in our sample from 180 to 111. The results in Fig. 5 show that the size and persistence of the output loss remain in line with our baseline estimates when these economic disasters are excluded from the sample. The results also remain robust when 5-, 15-, and 20-year time spans are used (Appendix F).

5.3. Variation in the aftermath of economic disasters

Not all economic disasters are similar. It is plausible that the response of the economy and policymakers to economic disasters differ across countries. The relatively wide confidence intervals in the above figures suggest that variations in the output loss can be considerable. A better

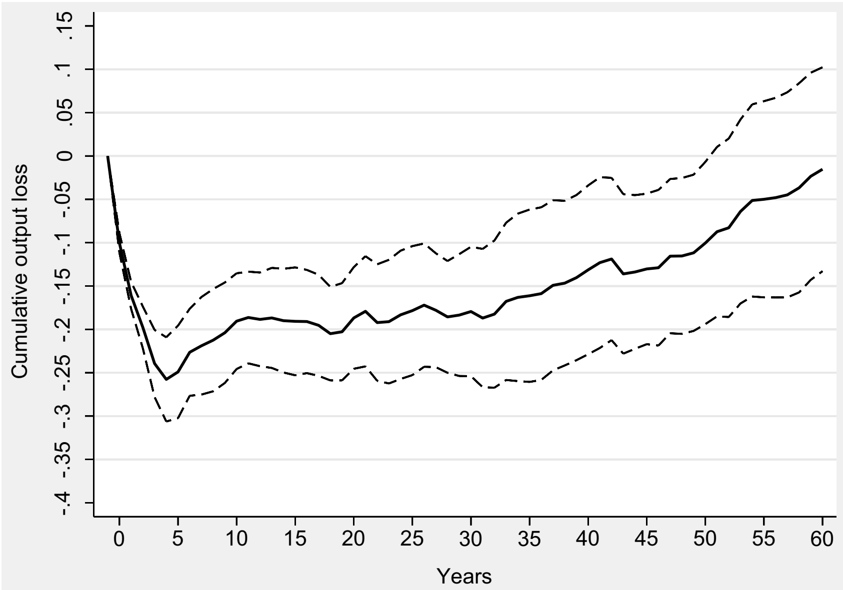

Figure 5. Output loss after economic disasters: controlling for the correction effect.

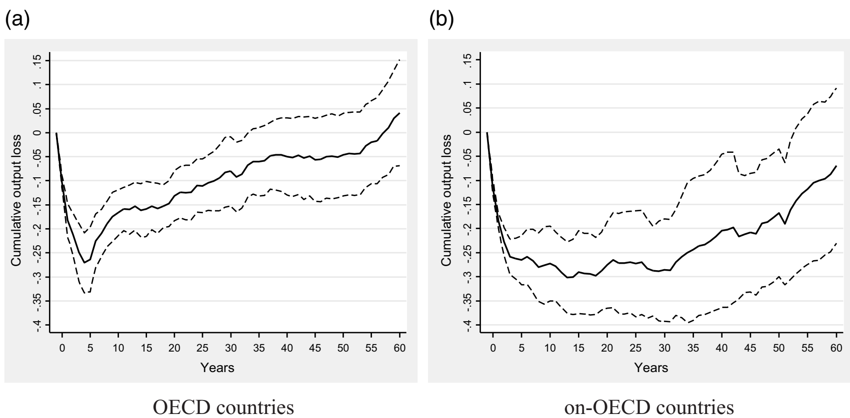

Figure 6. Output loss after economic disasters for OECD and non-OECD countries.

understanding of these variations is an important issue that deserves further investigation. This section provides initial empirical estimates.

We first split our data sample into OECD and non-OECD countries. Table 2 reports the sequences of estimates on ϕ_0^k for $k = 0, \ldots, 60$ for the separate subsamples. The results for OECD and non-OECD groups of countries are plotted in Fig. 6, panels *a* and *b*, respectively. Fig. 6 reveals a larger output loss and slower recovery in non-OECD countries compared to OECD countries. The loss in the first 4 years after an economic disaster amounts to about 27% in both groups. While in the OECD countries the recovery begins after this point, in non-OECD countries, the output loss continues to increase over the next 9 years, reaching a maximum of 30.2% at $k = 13$. After 20 years, the loss in OECD countries reduces to 13.1%. The estimates on ϕ_0^k remain negative up to $k = 57$ and are statistically significant for 33 years. In contrast, the output loss at $k = 20$ in the non-OECD group of countries is 27.6%. Although the confidence bands are wider, estimates of

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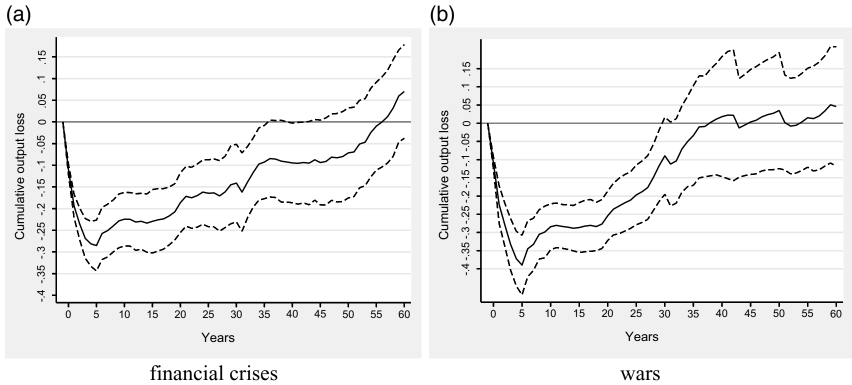

Figure 7. Output loss after economic disasters associated with financial crises and wars.

ϕ_0^k remain significant up to $k = 52$. The coefficients are consistently negative over the entire forecast horizon, pointing to losses of 6.9% 60 years after an economic disaster.

Cerra and Saxena (2008) find a difference in the persistence of output loss after wars and financial crises. To distinguish between economic disasters that are associated with financial crises and wars, we employ data by Reinhart and Rogoff (2011) on financial crises between 1800 and 2010, and list of all wars by Sarkees and Wayman (2010) from 1816 to 2007. We use a simple rule to classify economic disasters. We categorize economic disasters as associated with financial crises if the financial crisis took place one year before or in the year of the onset of an economic disaster. The same rule applies to wars. Altogether, we identified 99 economic disasters associated with financial crises and 50 disasters associated with wars.[5] Fig. 7 (panels *a* and *b*) illustrates the results for each economic disaster category. The estimates suggest that economic disasters associated with wars are, on average, deeper than disasters associated with financial crises. However, consistent with Cerra and Saxena (2008), output loss is typically more persistent after disasters associated with financial crises.

Reinhart and Rogoff (2011) also provide data on different types of financial crises. To estimate the aftermath of economic disasters associated with different types of financial crises, we employ their data on banking crises, currency crashes, sovereign debt crises, inflation crises, and stock market crashes. Appendix G provides the estimates for each category. Somewhat surprisingly, the results reveal that the output loss is less persistent after an economic disaster associated with banking crises compared to the economic disaster associated with other types of financial crises. However, the number of economic disasters in each category is relatively small, the confidence intervals are wide, and different types of financial crises often overlap. Therefore, the results should be interpreted with caution.

5.3. Economic disasters in the post-WWII period

The estimates reported so far are based largely on disasters that took place before WWII. Out of 180 economic disasters in our main sample, 30 occurred after WWII (26 in non-OECD countries and only 4 in OECD countries). Over the last seven decades, the structure of national economies and the conduct of economic policy have changed substantially. These changes can have considerable effects on the dynamics of economic recovery. Thus, it is quite possible that the dynamics of output growth may be different in the current economic context than the dynamics suggested by historical data. The output loss after contemporary economic disasters might be smaller and/or less persistent, and hence, less important for policymakers, financial markets, and economics in general.

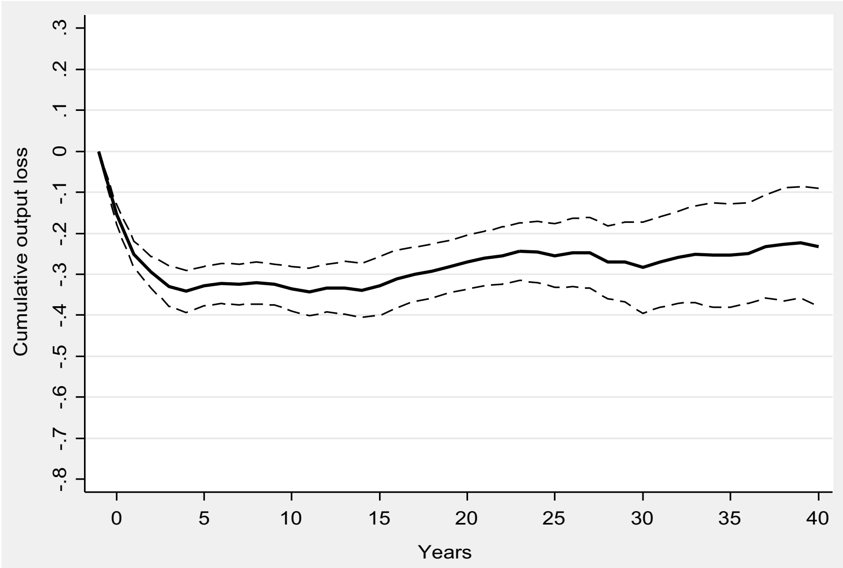

Figure 8. Output loss after economic disasters in the post-WWII period.

To explore this, we employ a new dataset on economic disasters in the post-WWII period by Ćorić (2021). The data are available for 211 countries from 1950 to 2017. As we are interested in dynamics of output growth over a very long horizon, we drop all countries for which the data start after 1970, that is we include only countries with at least 48 consecutive output observations. The data include 182 countries and 204 economic disasters and are pooled into a panel sample with 9654 observations at $k = 0$. As the forecast horizon increases, the effective sample size reduces gradually to 2374 at $k = 40$, but the number of countries in the sample remains constant throughout the whole projection period.

The estimates on ϕ_0^k for the successive horizons ($k = 0, \ldots, 40$) appear in Table 2 above. Fig. 8 below plots the sequence of estimated coefficients together with the corresponding 95% confidence bands. As the number of economic disasters after WWII in OECD countries is very small, the estimates are almost entirely based on events in non-OECD countries.[6] Therefore, the proper results for comparison are the estimates for non-OECD countries plotted in Fig. 6b.

Fig. 8 shows very similar dynamics of output growth over the comparable forecast horizons ($k = 0, \ldots, 40$), as in Fig. 6b. The output loss reaches a maximum of 34.4% 11 years after an economic disaster (compared to 30.2% at $k = 13$ in Fig. 6b). 20 years after an economic disaster, the output loss shrink to 27.1% (in Fig. 6b the output loss at $k = 20$ is 27.6%). The estimate on ϕ_0^{40} indicates a loss of 23.3% (the corresponding loss in Fig. 6b is 20.4%). The results suggest that output growth dynamics following economic disasters in non-OECD countries after WWII are very similar to the dynamics suggested by the historical data. In other words, our results do not suggest declines in the size and/or persistence of output loss after economic disasters across non-OECD countries in the post-WWII period.

6. Conclusion

Extreme economic events often challenge existing views and expose shortcomings in the knowledge of economists (Yellen (2016)). This study provides an empirical analysis of output dynamics

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following economic disasters. Our main results show that economic disasters are associated with large and extraordinarily persistent output growth loss. The estimates based on historical data suggest that, on average, in the first few years after the outbreak of an economic disaster, the output growth loss reaches around 26%. Afterward, the loss gradually declines, but remains above 20% for 20 years. The output growth loss is completely recouped only after more than 50 years. Our analysis of post-WWII data on economic disasters does not reveal changes in the scale and/or persistence of output growth loss in response to events occurring after WWII.

Our study contributes to the literature on output hysteresis in two important respects. First, compared to the current studies, we focus on economic disasters and provide evidence of the huge output growth loss associated with them. Second, the usage of historical data allows us to consider a much longer forecast horizon compared to the current literature. This is important because, based on the forecast horizon of 5–10 years, current studies often argue that the output growth loss is permanent. Our study shows that concerning economic disasters, the output growth loss is not permanent, but rather extremely persistent.

Our results have important macroeconomic implications. They run contrary to the standard dichotomy between business cycles and growth literature, according to which the effects of economic shocks are considered to be temporary. The documented size of output growth loss and its extreme persistence make the issue of economic disasters very important from a long-run economic perspective. We provide an assessment that may inform policymakers to answer the question: How long, on average, would it take for a country to recover output growth losses after an economic disaster? This is an important question, especially, in times of high uncertainty, pandemics, wars, large social, and political conflicts. Our results pose a challenge for an explanation of the extreme persistence of output growth loss we observe. The size of estimated loss suggests that it would also be very useful to better understand variations in the frequency of economic disasters. This issue is especially interesting with respect to the intriguing dispersion of economic disasters observed in contemporary data. The data indicate that developed countries have mostly succeeded in "avoiding" disasters in the post-WWII period, while the number of economic disasters in developing countries over the same period has been substantial. This discrepancy may be attributed simply to good luck. Developed countries may have just been lucky in comparison to developing countries in avoiding large exogenous shocks, such as the current pandemic of COVID-19, over the last 70 years. However, it is also possible that the lack of economic disasters can be partially related to sound policy. For example, it is plausible that the efficient conduct of short-run economic policy can prevent the evolution of "ordinary" recessions into an economic disaster. The lack of economic disasters might also point to the importance of long-run policies aimed towards building institutions that contribute to social, political, and economical stability at national and international levels.

In the context of the literature on economic disasters, our results suggest that current models of asset pricing and macroeconomic dynamics overstate to some extent the riskiness of economic disasters by modeling their effects as permanent. Our results indicate that the use of more moderate assumptions of extremely persistent rather than permanent economic effects would be more appropriate. It would also be useful to investigate whether the results of current rare disaster models are robust with respect to the modeling effects of economic disasters as being very persistent.

Acknowledgement. We thank Mehdi Hosseinkouchack for the help with the implementation of the Matlab code for quantile autoregression unit root test. We also thank Coen Teulings and Nikolay Zubanov for their help with implementing the local projection method. All remaining errors are ours.

Funding. This work was supported by the Croatian Science Foundation under Grant IP-2020-02-9710.

Notes

1 The issue of recovery after economic disasters is addressed by Jordà et al. (2022), as well, but they focus on the response of the natural rate of interest to pandemics.

2 Economic disasters can be understood as structural breaks (large, but rare shocks with permanent effects on output). It is known that the order of integration analysis of time series is affected by unattended structural breaks. If economic disasters correspond to structural breaks, then it can be expected that after these structural breaks are taken into account, the economic shocks of "normal" size are likely to have just temporary effects on output. Therefore, we employ (Carrion-i-Silvestre et al. (2009)) GLS-based unit root tests with multiple structural breaks. The results appear to be in line with this expectation (available upon request). In particular, after we allow for the structural breaks, the results of unit root tests suggest much more often that economic shocks have only temporary effects on output, compared to our results in Appendices A and B. Nevertheless, the structural breaks estimated by Carrion-i-Silvestre et al. (2009) method rarely correspond to Barro and Ursúa's (2010) estimates of economic disasters. The estimated structural breaks match the economic disasters in only 22% of the cases (We take that the structural break matches the economic disaster if it is detected within the period of 2 years before and after the corresponding economic disaster. When we consider only breaks and disasters estimated in the same year, the match decreases to 1.6%). Consequently, our results suggest that economic disasters cannot be considered as equivalent to structural breaks.

3 Please note that for $k = 0$ and $l = 0$, it might appear that the last two terms in equation (6) are identical. However, by definition lower limit of sigma operator ($l = 0$ in our case) has to be smaller or equal to upper limit (k-1 in our case). Hence, for $k = 0$ and $l = 0$ the sum of the last term becomes the empty sum that is equal to zero by definition. Hence, this term disappears from the specification of model for $k = 0$ and $l = 0$.

4 The Hansen test supports the validity of the instruments in 59 out of 60 regressions, while the Arrelano-Bond test supports validity in 56 out of 60 cases.

5 Please note that because of the data limitation, we cannot identify direct causality. That is, we do not argue that the selected disasters are caused by financial crises or wars, but that they are just associated with them. Furthermore, we could not avoid the overlaps between wars and financial crises. Hence, our results should be interpreted with caution.

6 The estimates for the subsample of non-OECD countries are almost identical (see Appendix H).

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https://doi.org/10.1017/S1365100523000366 Published online by Cambridge University Press

Appendix

Appendix A. Results of quantile autoregression-based unit root tests for OECD countries

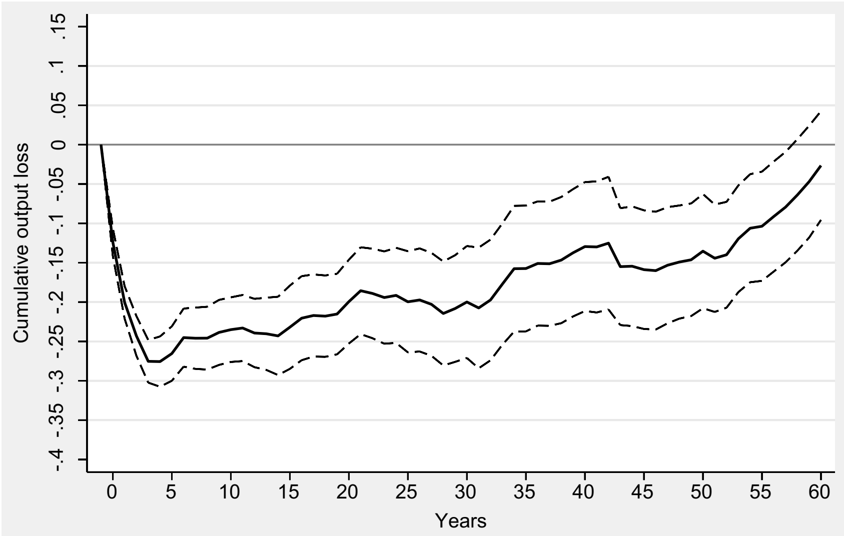
	Australia	Austria	Belgium	Canada	Denmark	Finland	France	Germany	Iceland	Italy	Japan	Netherlands	New Zealand	Norway	Portugal	Spain	Sweden	Switzerland	UK	US
Quantile	α(τ)	α(τ)	α(τ)	α(τ)	α(τ)	α(τ)	α(τ)	α(τ)	α(τ)	α(τ)	α(τ)	α(τ)	α(τ)	α(τ)	α(τ)	α(τ)	α(τ)	α(τ)	α(τ)	α(τ)
0.05	0.992*	1.170*	1.128*	0.877*	1.132*	0.934*	1.118*	1.021*	1.089*	1.076*	1.098*	1.025*	1.015*	1.062*	1.066*	1.072*	1.010*	0.867	1.106*	1.046*
0.10	0.994*	1.107*	1.137	0.861*	1.032*	0.985*	1.068*	1.024*	1.034*	1.005*	1.014*	1.017*	0.984*	1.007*	1.044*	0.996*	0.949*	0.948*	1.016*	1.041*
0.15	0.954*	1.049*	1.094	0.923*	0.983*	1.006*	1.045*	1.002*	1.042*	1.004*	0.985*	1.014*	0.968*	0.973*	1.001*	0.997*	0.958*	0.974*	1.008*	1.039*
0.20	0.965*	0.984*	1.067*	0.940*	0.972*	1.012*	1.023*	1.005*	1.007*	0.984*	0.962*	1.014*	0.953*	0.983*	0.992*	1.003*	0.962*	0.988*	1.004*	1.017*
0.25	0.949*	0.962*	1.006*	0.957*	0.970*	1.013*	1.005*	0.945	1.008*	0.983*	0.957*	1.004*	0.945*	0.977*	0.995*	1.005*	0.967*	0.980*	1.005*	1.012*
0.30	0.945*	0.968*	0.990*	0.947*	0.964*	0.984*	0.995*	0.939	1.003*	0.975*	0.959*	0.997*	0.937*	0.973*	0.981*	1.002*	0.966*	0.962*	0.990*	0.999*
0.35	0.935*	0.954*	0.987*	0.962*	0.963	0.996*	0.983*	0.930	0.971*	0.970*	0.959*	0.989*	0.926*	0.982*	0.976*	0.995*	0.957*	0.942*	0.985*	0.994*
0.40	0.928	0.944	0.980*	0.956*	0.964	0.979*	0.986*	0.926	0.961*	0.965*	0.951*	0.984*	0.894*	0.985*	0.971*	0.992*	0.954	0.934*	0.978*	0.991*
0.45	0.942*	0.934	0.962	0.950*	0.965*	0.973*	0.982*	0.925	0.957*	0.966	0.951	0.988*	0.899*	0.973*	0.965*	0.986*	0.947	0.900*	0.971*	0.979*
0.50	0.940*	0.935	0.963	0.938*	0.974*	0.962*	0.973*	0.930	0.929*	0.969*	0.958*	0.983*	0.894*	0.970*	0.976*	0.978*	0.963*	0.897*	0.973*	0.986*
0.55	0.948*	0.938	0.964	0.922*	0.963*	0.952*	0.965*	0.917	0.931*	0.962	0.938	0.975*	0.870	0.969*	0.971*	0.979*	0.965*	0.889*	0.978*	0.983*
0.60	0.940*	0.936	0.956	0.955*	0.966*	0.943	0.960*	0.905	0.906	0.959	0.936	0.967*	0.852	0.974*	0.977*	0.962*	0.965*	0.907*	0.966*	0.970*
0.65	0.939*	0.937	0.957*	0.942*	0.966*	0.937	0.962*	0.903	0.909	0.970*	0.939	0.959	0.841	0.975*	0.979*	0.963*	0.964*	0.896*	0.970*	0.954
0.70	0.951*	0.919	0.961*	0.912*	0.965*	0.931	0.937	0.904	0.914	0.965*	0.936	0.959	0.827	0.975*	0.978*	0.959*	0.958	0.906*	0.970*	0.948
0.75	0.903	0.899	0.955*	0.919*	0.933	0.917	0.937	0.901	0.901	0.964*	0.936	0.963	0.819	0.974*	0.968*	0.952	0.970*	0.901*	0.971*	0.927
0.80	0.905	0.895	0.926	0.936*	0.933	0.915	0.911	0.886	0.885	0.963*	0.946*	0.940	0.787	0.973*	0.955*	0.958*	0.956	0.908*	0.968*	0.928
0.85	0.905	0.881	0.855	0.949*	0.925	0.915*	0.894	0.881	0.885	0.958*	0.935	0.931	0.814	0.978*	0.950*	0.959*	0.955	0.906*	0.964*	0.917
0.90	0.894	0.863	0.809	0.956*	0.908	0.935*	0.855	0.872	0.902	0.944*	0.931	0.929*	0.800	0.949*	0.942	0.967*	0.948	0.899	0.936*	0.887*
0.95	0.927	0.837	0.765	0.966*	0.897	0.926	0.815	0.809	0.850	0.909	0.928*	0.918*	0.825	0.932*	0.906	0.948*	0.909*	0.859	0.903*	0.887*
No. of obs.	190	140	164	140	192	150	190	159	140	149	140	203	150	180	145	160	210	159	180	220
No. of lags	10	1	7	10	1	4	3	2	2	4	3	2	10	1	10	1	1	10	1	1

Note: *indicate a 5% level of significance.

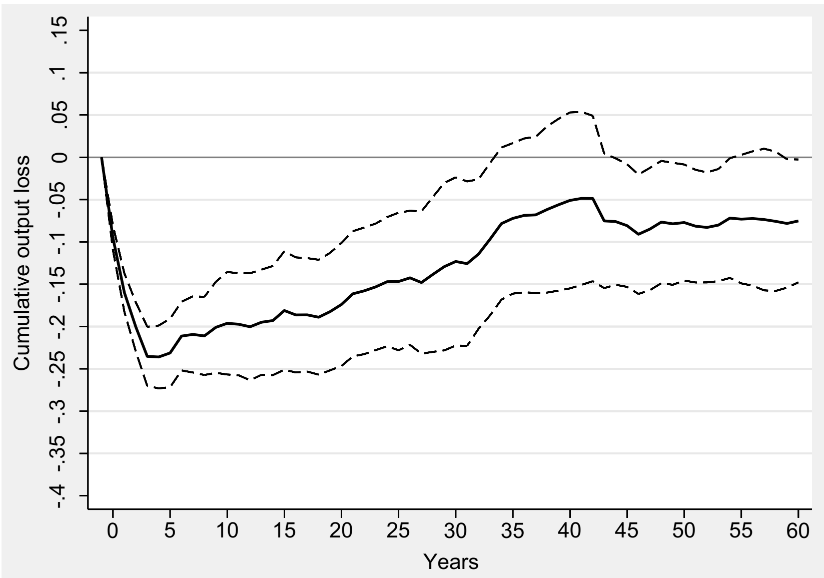
Appendix B. Results of quantile autoregression-based unit roots test for non-OECD countries

	Argentina	Brazil	Chile	China	Colombia	Egypt	India	Indonesia	Korea	Mexico	Peru	Russia	S. Africa	Sri Lanka	Taiwan	Turkey	Uruguay	Venezuela
Quantile	α(τ)	α(τ)	α(τ)	α(τ)	α(τ)	α(τ)	α(τ)	α(τ)	α(τ)	α(τ)	α(τ)	α(τ)	α(τ)	α(τ)	α(τ)	α(τ)	α(τ)	α(τ)
0.05	0.789*	0.976*	0.681*	1.061*	0.889*	0.995*	1.071*	0.903	0.975*	1.007*	0.902*	1.119	0.972*	1.068*	0.974*	0.870*	0.808*	1.077*
0.10	0.862*	0.993*	0.838*	1.052*	0.905*	0.987*	1.099*	1.020*	0.957*	0.911*	1.013*	1.014*	0.974*	1.010*	0.946*	0.930*	0.836*	1.058*
0.15	0.953*	0.980*	0.866*	1.052*	0.871*	0.976*	1.049*	1.044*	0.969*	0.904*	0.998*	0.992*	0.985*	0.998*	0.964*	0.912*	0.818*	1.046*
0.20	0.899*	0.979*	0.908*	1.035*	0.855	0.976*	1.034*	1.011*	0.969*	0.910*	0.981*	0.964*	0.990*	1.015*	0.972*	0.918*	0.795*	1.004*
0.25	0.827*	0.986*	0.887*	1.032*	0.846	0.980*	1.017*	1.012*	0.977*	0.933*	0.983*	0.964*	0.963*	1.027*	0.972*	0.954*	0.754*	1.008*
0.30	0.817*	0.992*	0.877*	1.029*	0.846	0.974*	1.005*	1.018*	0.977*	0.956*	1.003*	0.956*	0.962*	1.030*	0.973*	0.920*	0.781*	0.991*
0.35	0.836*	1.001*	0.871*	1.020*	0.840*	0.984*	1.009*	1.014*	0.971*	0.930*	0.964*	0.956*	0.994*	1.044*	0.974*	0.927*	0.793*	0.999*
0.40	0.828*	0.995*	0.921*	1.010*	0.859*	0.981*	1.012*	1.010*	0.968*	0.939*	0.961*	0.961*	1.008*	1.050*	0.979*	0.825	0.789*	0.987*
0.45	0.803*	0.989*	0.919*	1.006*	0.895*	0.976*	1.009*	0.974*	0.965*	0.944*	0.964*	0.960*	1.010*	1.045*	0.984*	0.838	0.819*	0.991*
0.50	0.777*	0.990*	0.942*	1.004*	0.912*	0.983*	1.030*	0.974*	0.963*	0.934*	0.965*	0.957*	1.004*	1.044*	0.975*	0.848	0.807*	0.994*
0.55	0.743*	0.988*	0.946*	1.005*	0.908*	0.962*	1.045*	0.972*	0.961*	0.950*	0.985*	0.954*	1.003*	1.046*	0.978*	0.812	0.789*	0.976*
0.60	0.749	0.968*	0.945*	1.001*	0.928*	0.966*	1.034*	0.972*	0.960*	0.955*	0.971*	0.951*	0.991*	1.046*	0.968*	0.811	0.816*	0.974*
0.65	0.764	0.963*	0.935*	0.993*	0.939*	0.969*	1.027*	0.970*	0.967*	0.953*	0.979*	0.928*	0.989*	1.035*	0.965*	0.817	0.769*	0.977*
0.70	0.743	0.971*	0.931*	0.991*	0.942*	0.969*	1.030*	0.963	0.974*	0.959*	0.975*	0.923*	0.977*	1.041*	0.963*	0.845	0.824*	0.947*
0.75	0.780	0.973*	0.937*	0.984*	0.968*	0.964*	1.044*	0.944	0.967*	0.959*	0.973*	0.905	0.964*	1.036*	0.952*	0.839	0.809*	0.959*
0.80	0.810	0.979*	0.935*	0.976*	1.008*	0.979*	1.050*	0.939	0.968*	0.969*	0.975*	0.898	0.954*	1.027*	0.957*	0.845	0.835*	0.958*
0.85	0.815	0.983*	0.917*	0.976*	1.012*	0.978*	1.062*	0.937	0.962*	0.986*	0.982*	0.902	0.944*	1.030*	0.938	0.807	0.800*	0.954*
0.90	0.793	0.963*	0.857	0.976*	1.021*	0.962*	1.068*	0.925	0.951*	1.008*	0.993*	0.893	0.967*	1.012*	0.932	0.735	0.730	0.946*
0.95	0.823*	0.975*	0.842	0.978*	0.871*	0.972*	1.095*	0.932*	0.939*	1.030*	0.925*	0.907	0.919*	1.024*	0.926	0.819	0.842*	0.892*
No. of obs.	135	160	150	120	105	116	138	130	99	115	114	150	99	140	109	135	140	127
No. of lags	9	1	2	1	10	10	9	5	6	2	10	7	10	10	1	2	10	10

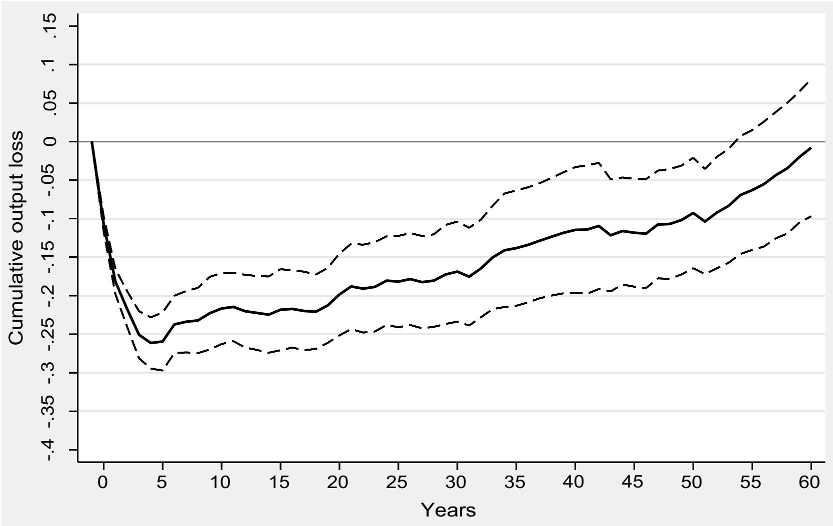
Note: *indicate a 5% level of significance.



Appendix C. Output loss after economic disasters: Lewbel estimator

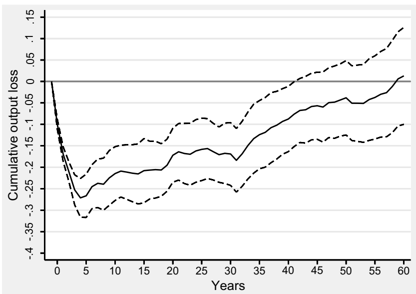


Appendix D. Output loss after economic disasters: forecast equation with control variables and time fixed effects



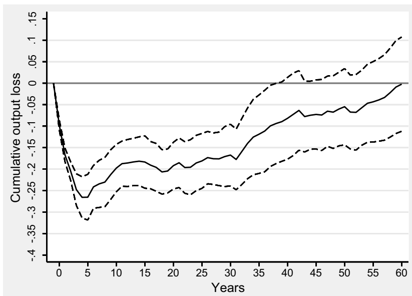
Appendix E. Output loss after economic disasters: forecast equation without lagged variables for economic disasters

(a)



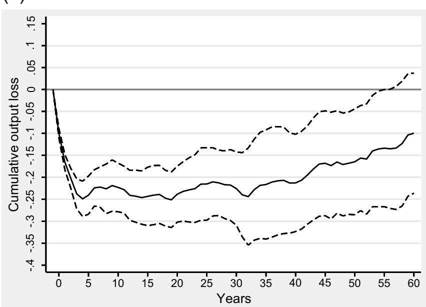
20 years time-span

(b)



15 years time-span

(c)



5 years time-span

Appendix F. Output loss after economic disasters: controlling for correction effect

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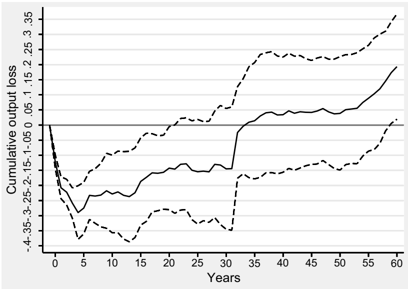
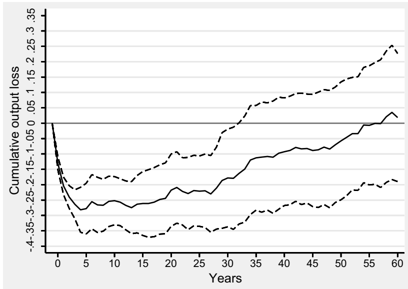
(a)



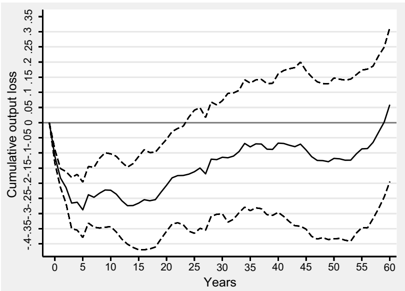
Banking crises

(b)



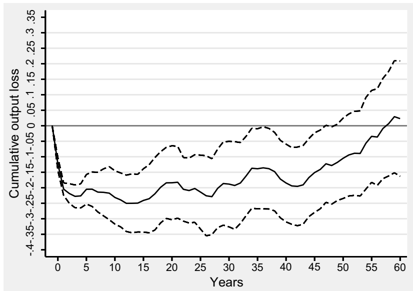
Currency crises

(c)



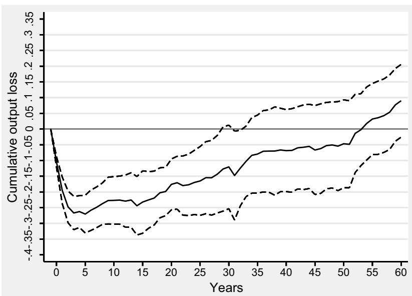
Debt crises

(d)



Inflation crises

(e)



Stock market crashes

Appendix G. Output loss after economic disasters associated with banking, currency, debt, inflation and stock market crises

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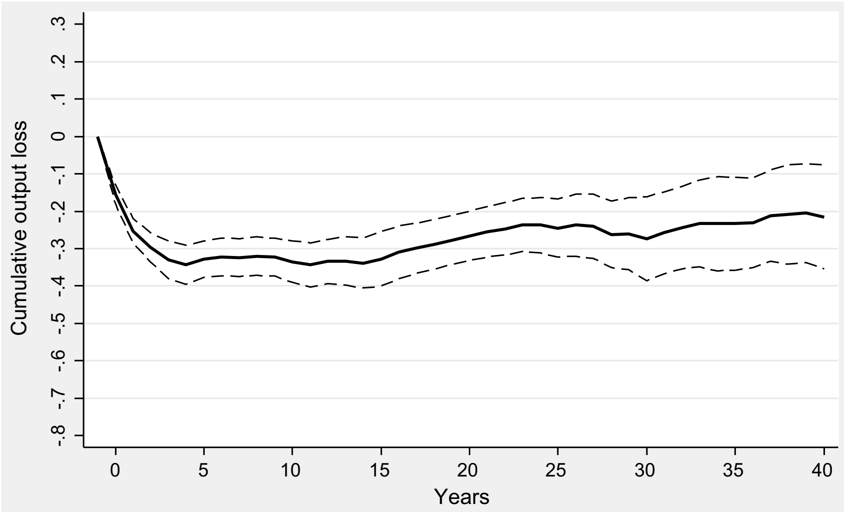

Appendix H. Output loss after economic disasters: post-WWII data for non-OECD countries

Cite this article: Ćorić B and Škrabić Perić B (2024). "Recovery from economic disasters." *Macroeconomic Dynamics* **28**, 1023–1048. https://doi.org/10.1017/S1365100523000366