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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 economic disasters in 182 countries since World War II. Our results suggest that extreme economic crises are associated with huge and remarkably persistent output loss. On average, output loss surges to above 26 percent in the first few years after the outbreak of an economic disaster and remains above 20 percent for as long as 20 years. It is only after more than 50 years that the loss is fully recovered.

Key words: economic disaster, output loss, economic recovery.

JEL: E32; N10.

Number of Words: 6,658

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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 percent. This study analyzes the recovery of output after economic disasters on a long historical timeline.

Since the most recent global economic 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 20^{th} century can account for excess returns on stocks relative to returns on government bonds - the well-known Mehra and Prescott (1985) equity premium puzzle. A number of ensuing studies suggest that rare-disasters models are suitable for modelling many other financial phenomena. Examples include the low risk-free rate (Gabaix 2012), predictability of excess equity returns (Watcher 2013), corporate bond spreads that are higher than expected credit losses (Gabaix 2012, Gourio 2013), excess volatility of exchange rates and the failure of uncovered interest rate parity (Farhi and Gabaix 2016), and option prices (Seo and Wachter 2019, Barro and Liao 2020). The economic disaster framework is also used to analyze business cycles (Gourio 2012, Isore and Szczerbowicz 2015), debt intolerance of emerging economies (Rebelo et al. 2019) and welfare effects of economic disasters (Barro 2009).

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 modelled 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 economic disasters, and hence, significantly affect the outcomes of rare-disasters models (see Gourio 2008, Nakamura et al. 2013 and 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-disasters 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 (see Christiano et al. 2018 and Kehoe et al. 2018 for reviews of modern business cycle models). 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 empirical approaches to distinguish between the competing hypotheses, but have not reached a conclusive answer. The short list of studies includes 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).

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 onset of SARS-CoV-2 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. The Bureau of Economic Analysis reported that the US economy shrank at an annual rate of 32.9 percent in the second quarter of 2020 - its worst quarterly plunge on record. Double-digit drops in quarterly growth rates have been recorded in a number of economies across the world. As the virus continues to spread, it is increasingly likely that the current economic crisis may reach the scale of economic disaster in many countries.

Our study systematically documents the dynamics of output following economic disasters. The study is based on Barro and Ursúa's (2010) output data for 38 OECD and non-OECD countries over the last two centuries, which includes 180 economic disasters. We also use Ćorić's recent (2020) 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. Our 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 long-run effects on output. In the second part of the analysis we employ a local projection estimator to explore the dynamics of output after economic disasters. Our results point to large, long-run output losses following economic disasters. The process of recovering from losses is 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 2 discusses related economic research. Section 3 presents our unit root analysis. Section 4 describes the model and methodology we use to estimate the dynamics of output after disasters and discusses the results. Section 5 concludes.

2. Related studies

Our research is related to few recent studies. This research can be regarded as a part of the broader debate in macroeconomics on whether output should be modelled 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 argue that output should instead be considered difference stationary. In 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. Our study concentrates on economic disasters, so we employ the results of unit root tests to specify an empirical model of output and estimate the average dynamic of output after economic disasters.

To estimate the output dynamic, we build on Carra 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 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 impulse-response functions (IRF) than the standard recursive calculation used by Carra 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).

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. Our research contributes to and substantially extends their findings.

Gourio (2008) enhances Barro's (2006) rare-disasters 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 20^{th} 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) arithmetic abstracts from 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) develop 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 about 27 percent, but approximately half of this loss is reversed in the long-run. Consequently, the implied long-run consumption loss is about 14 percent. 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-disasters 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's (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 dynamics after economic disasters in the post-WWII period are different from estimates based on older historical data.[1]

3. Unit root analysis

3.1. Methodology

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[1] Gourio's (2008) results are based on Barro's (2006) initial data on output disasters for 35 countries over the 20th century. This dataset is not only smaller in both dimensions compared to the dataset used in our study, but it is also problematic because it relies on Maddison's output data, which have important shortcomings in construction, especially at the times of disasters (see Barro and Ursúa 2008, for a detailed discussion of these measurement problems).

Our inference on the output dynamics following 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.[2]

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

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[2] 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).

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

Where *y* represents the logarithm of output. α denotes a constant, *t* represents the linear 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:

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

where $\tau \in (0,1)$ and $Q_\tau\left(y_t \middle| y_{t-1}, \; \dots, y_{t-q}\right)$ denotes τ-th quantile of y_t conditional on its recent history, $y_{t-1}, \; \dots, y_{t-q}$. By estimating equation 3 at different quantiles, we obtain a sequence of estimates on $\theta(\tau)$ for each country and then test for $H_0\colon \theta(\tau) = 1$ 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 US to 1911 for Korea and South Africa.

3.3. Results

The results of our unit root tests appear in Tables 1 and 2. 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).[3]

Table 1 provides point estimates on $\theta(\tau)$ for 20 OECD countries where $\tau \in (0.05, \ldots, 0.95)$.[4] 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 persistence parameters reported for these quantiles are close to one,

[3] In a few selected models, Galvao's (2009) test fails to provide critical values for all quantiles. In these cases, we increase the number of lags included in the model to obtain the critical values for all quantiles. The number of lags is increased from 1 to 2 in the model for Austria; from 2 to 4 for Germany; from 3 to 4 for Japan; from 1 to 2 for Spain and from 1 to 3 for Taiwan.

[4] 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.

and the quantile autoregression based unit root test fails to reject $H_0: \theta(\tau) = 1$ at the 5 percent level of significance in almost all cases. The only exceptions 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 percent level.[5] Overall, the results do not support trend stationarity of output, but instead suggest that large negative economic shocks are likely to have long-run effects on output in OECD countries.

The results on θ(τ) for other quantiles show that in three countries, Canada, Norway and the UK, the unit root hypothesis cannot be rejected at the 5 percent level over the whole conditional output distribution. In other countries the unit root is more often rejected for the quantiles on the upper 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 reported in Table 2 are similar. Again, the tests fail to reject the unit root at τ = 0.05 and τ = 0.10 in almost all cases. The only exception are estimates on θ (0.05) for Indonesia and Russia.[6] 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 percent level in all quantiles,

[5] For Canada, the test does not reject unit root at τ = 0.05 and τ = 0.10, but the size of the persistence parameters appears to be relatively small, at 0.877 and 0.861, respectively.

[6] In this group, the size of persistence parameters is relatively small in a few countries (Argentina, Chile, Colombia, Turkey and Uruguay).

suggesting that across non-OECD countries all types of economic shock often have long-run effects on output.

Taken together, the results for both groups of countries suggest that output does not rebound to its pre-crisis trend path following large negative shocks, and output losses are unlikely to be temporary. These findings are consistent with Barro’s (2006) assumption of permanent effects of economic disasters on output which is commonly employed in rare-disasters models. To explore this issue further, in the next section we use the local projection method to estimate the average dynamics of output after economic disasters.

Table 1 Results of quantile autoregression based unit root tests for OECD countries

	Australia	Austria	Belgium	Canada	Denmark	Finland	France	Germany	Iceland	Italy	Japan	Netherland	N.Zealand	Norway	Portugal	Spain	Sweden	Switzerland	UK	US
Quantil	$\alpha(\tau)$	$\alpha(\tau)$	$\alpha(\tau)$	$\alpha(\tau)$	$\alpha(\tau)$	$\alpha(\tau)$	$\alpha(\tau)$	$\alpha(\tau)$	$\alpha(\tau)$	$\alpha(\tau)$	$\alpha(\tau)$	$\alpha(\tau)$	$\alpha(\tau)$	$\alpha(\tau)$	$\alpha(\tau)$	$\alpha(\tau)$	$\alpha(\tau)$	$\alpha(\tau)$	$\alpha(\tau)$	$\alpha(\tau)$
0.05	0.992 *	1.123 *	1.128 *	0.877 *	1.132 *	0.934 *	1.118 *	1.030 *	1.089 *	1.076 *	1.036 *	1.025 *	1.015 *	1.062 *	1.060 *	0.981 *	1.010 *	0.867	1.106 *	1.046 *
0.10	0.994 *	1.073 *	1.137	0.861 *	1.032 *	0.985 *	1.068 *	1.044 *	1.034 *	1.005 *	1.000 *	1.017 *	0.984 *	1.007 *	1.025 *	1.003 *	0.949 *	0.948 *	1.016 *	1.041 *
0.15	0.954 *	1.019 *	1.094	0.923 *	0.983 *	1.006 *	1.045 *	1.020 *	1.042 *	1.004 *	0.969 *	1.014 *	0.968 *	0.973 *	1.011 *	1.011 *	0.958 *	0.974 *	1.008 *	1.039 *
0.20	0.965 *	0.976 *	1.067 *	0.940 *	0.972 *	1.012 *	1.023 *	1.005 *	1.007 *	0.984 *	0.956 *	1.014 *	0.953 *	0.983 *	1.003 *	1.001 *	0.962 *	0.988 *	1.004 *	1.017 *
0.25	0.949 *	0.966 *	1.006 *	0.957 *	0.970 *	1.013 *	1.005 *	0.954 *	1.008 *	0.983 *	0.964 *	1.004 *	0.945 *	0.977 *	0.976 *	0.997 *	0.967 *	0.980 *	1.005 *	1.012 *
0.30	0.945 *	0.963 *	0.990 *	0.947 *	0.964 *	0.984 *	0.995 *	0.947	1.003 *	0.975 *	0.959 *	0.997 *	0.937 *	0.973 *	0.979 *	0.999 *	0.966 *	0.962 *	0.990 *	0.999 *
0.35	0.935 *	0.965 *	0.987 *	0.962 *	0.963	0.996 *	0.983 *	0.928	0.971 *	0.970 *	0.959 *	0.989 *	0.926 *	0.982 *	0.964 *	0.993 *	0.957 *	0.942 *	0.985 *	0.994 *
0.40	0.928	0.945	0.980 *	0.956 *	0.964	0.979 *	0.986 *	0.924	0.961 *	0.965 *	0.958 *	0.984 *	0.894 *	0.985 *	0.966 *	0.993 *	0.954	0.934 *	0.978 *	0.991 *
0.45	0.942 *	0.944	0.962	0.950 *	0.965 *	0.973 *	0.982 *	0.922	0.957 *	0.966	0.952	0.988 *	0.899 *	0.973 *	0.957 *	0.995 *	0.947	0.900 *	0.971 *	0.979 *
0.50	0.940 *	0.948	0.963	0.938 *	0.974 *	0.962 *	0.973 *	0.923	0.929 *	0.969 *	0.941	0.983 *	0.894 *	0.970 *	0.961 *	0.980 *	0.963 *	0.897 *	0.973 *	0.986 *
0.55	0.948 *	0.943	0.964	0.922 *	0.963 *	0.952 *	0.965 *	0.920	0.931 *	0.962	0.946	0.975 *	0.870	0.969 *	0.977 *	0.967 *	0.965 *	0.889 *	0.978 *	0.983 *
0.60	0.940 *	0.933	0.956	0.955 *	0.966 *	0.943	0.960 *	0.914	0.906	0.959	0.938	0.967 *	0.852	0.974 *	0.980 *	0.961 *	0.965 *	0.907 *	0.966 *	0.970 *
0.65	0.939 *	0.907	0.957 *	0.942 *	0.966 *	0.937	0.962 *	0.903	0.909	0.970 *	0.944 *	0.959	0.841	0.975 *	0.981 *	0.959 *	0.964 *	0.896 *	0.970 *	0.954
0.70	0.951 *	0.903	0.961 *	0.912 *	0.965 *	0.931	0.937	0.900	0.914	0.965 *	0.942	0.959	0.827	0.975 *	0.980 *	0.956	0.958	0.906 *	0.970 *	0.948
0.75	0.903	0.907	0.955 *	0.919 *	0.933	0.917	0.937	0.899	0.901	0.964 *	0.951	0.963	0.819	0.974 *	0.960	0.961 *	0.970 *	0.901 *	0.971 *	0.927
0.80	0.905	0.888	0.926	0.936 *	0.933	0.915	0.911	0.891	0.885	0.963 *	0.951 *	0.940	0.787	0.973 *	0.955 *	0.960	0.956	0.908 *	0.968 *	0.928
0.85	0.905	0.881	0.855	0.949 *	0.925	0.915 *	0.894	0.886	0.885	0.958 *	0.938	0.931	0.814	0.978 *	0.949 *	0.961 *	0.955	0.906 *	0.964 *	0.917
0.90	0.894	0.881	0.809	0.956 *	0.908	0.935 *	0.855	0.885	0.902	0.944 *	0.939	0.929 *	0.800	0.949 *	0.937	0.961 *	0.948	0.899	0.936 *	0.887 *
0.95	0.927	0.853	0.765	0.966 *	0.897	0.926	0.815	0.821	0.850	0.909	0.953 *	0.918 *	0.825	0.932 *	0.896	0.973 *	0.909 *	0.859	0.903 *	0.887 *
Obs.	190	140	164	140	192	150	190	159	140	149	140	203	150	180	145	160	210	159	180	220
Lags	10	2	7	10	1	4	3	4	2	4	4	2	10	1	9	2	1	10	1	1

Note: * indicate a 5% level of significance.

Table 2 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
Quantil	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 *	0.972 *	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 *	0.943 *	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 *	0.955 *	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 *	0.963 *	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 *	0.967 *	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 *	0.972 *	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 *	0.971 *	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 *	0.975 *	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 *	0.977 *	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 *	0.975 *	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 *	0.972 *	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 *	0.962	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 *	0.961	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 *	0.952	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 *	0.955 *	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 *	0.943	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 *	0.948 *	0.819	0.842 *	0.892 *
Obs	135	160	150	120	105	116	138	130	99	115	114	150	99	140	109	135	140	127
Lags	9	1	2	1	10	10	9	5	6	2	10	7	10	10	3	2	10	10

Note: * indicate a 5% level of significance.

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 statistically insignificant.

The output 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. 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 output responses, while the respective standard errors can be used to construct confidence bands.

As we consider a very long forecast horizon (see below), 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 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.[7]

Even though Jordà's (2005) estimator appears to be robust to specification errors, Teulings and Zubanov (2014) show that the method can be subject to bias that occurs due to estimator failure to use information on the crises occurring within the forecast horizon. 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:

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

[7] For a more comprehensive discussion on this and other advantages of using the local projection estimator, see Auerbach and Gorodnichenko (2013) and Teulings and Zubanov (2014).

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 above. The data for 38 OECD and non-OECD countries are pooled together into a panel sample that comprises 5,643 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 5,453. As we estimate a separate regression for each forecast horizon up to $k=60$, the effective sample size decreases gradually from 5,453 (for $k=0$) to 3,173 (for $k=60$). Through the whole projection period, the number of countries in the sample remain constant.

4.3. Results

Table 3 reports the sequences of estimates on ϕ_0^k for $k=0,\ldots,60$ for the total sample and for separate subsamples of OECD and non-OECD countries. 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.

Table 3 Output losses after economic disasters

	Historical output data				Historical output dana: OECD				Historical output dana: 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
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
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	-	-	-	-

The coefficients on ϕ_0^k for the total sample are plotted in Figure 1, while the corresponding standard errors are used to construct the 95 percent confidence interval. The plotted results show the average dynamics of output 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 percent. 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 percent, and remains statistically significant at the 5 percent level for 53 years. The estimated size of ϕ_0^{53} points to output loss of 8.2 percent. 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.

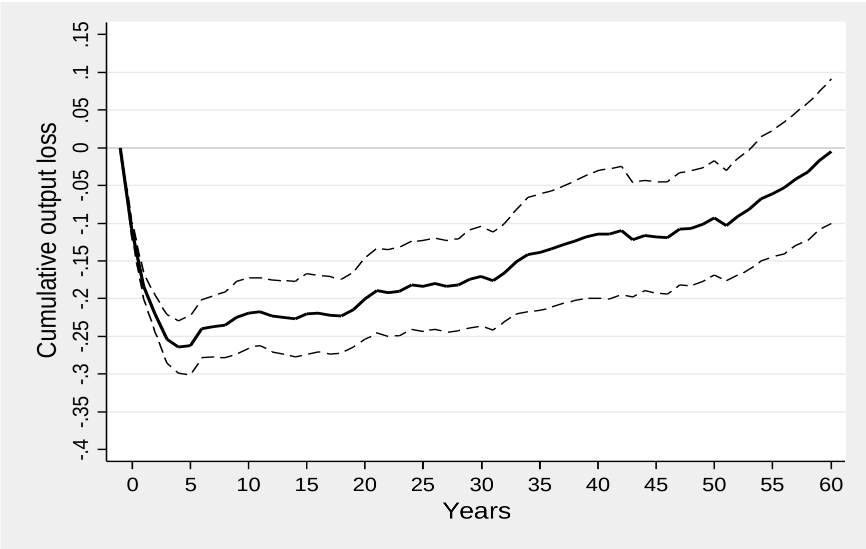

Figure 1 Output loss after economic disasters

The estimates on ϕ_0^k for OECD and non-OECD groups of countries are plotted in Figure 2, panels *a* and *b*, respectively. Figure 2 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 percent 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 percent at *k=13*. After 20 years, the loss in OECD countries reduces to 13.1 percent. 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 percent. Although the confidence bands are wider, estimates of 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 percent 60 years after an economic disaster.

(a) OECD countries

(b) non-OECD countries

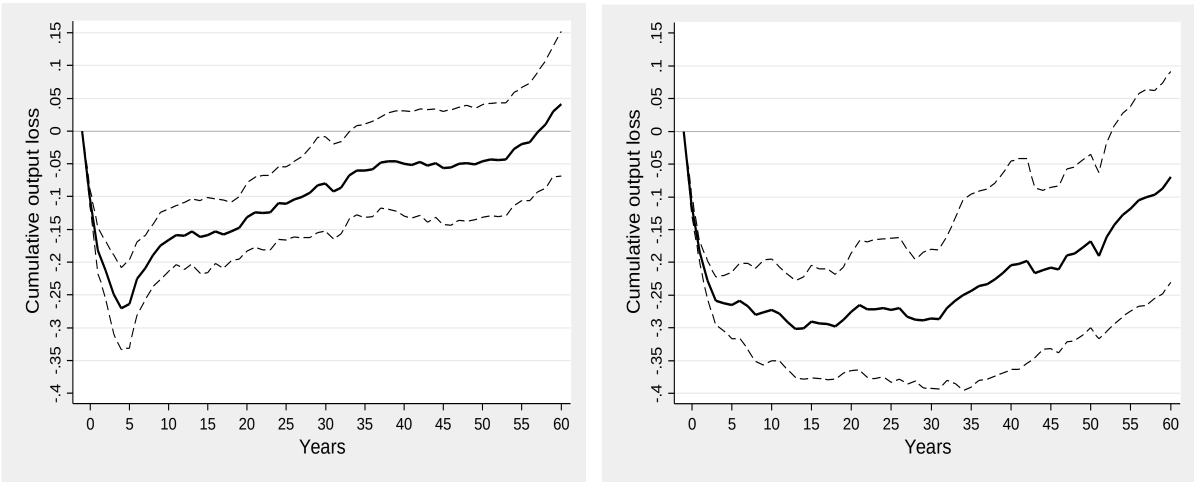

Figure 2 Output loss after economic disasters for OECD and non-OECD countries

The economic disasters 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 our 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 equation. The results reported in the Appendix (Figures A1 and A2) show that the estimates on output dynamics following economic disasters do not change substantially when the time effects are included in the model. The output loss appears to be even more persistent, but the coefficients on ϕ_0^k are less precisely estimated. Consequently, the confidence intervals are wider.

The estimates reported so far are based largely on disasters that took place before WWII.[8] Over the last seven decades, the structure of national economies and the conduct of economic policy have changed substantially. Thus, it is quite possible that the dynamics of output 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.

To explore this, we employ a new dataset on economic disasters in the post-WWII period by Ćorić (2020). The data are available for 211 countries from 1950 to 2017. As we are interested in dynamics of output over a very long horizon, we drop all countries for which the data start after 1970, i.e. we include only countries with at least 48 consecutive output observations. The data includes 182 countries and 204 economic disasters, and are pooled into a panel sample with 9,654 observations at $k=0$. As the forecast horizon increases the effective sample size reduces gradually to 2,374 at $k=40$, but the number of countries in the sample remains constant through the whole projection period.

[8] Out of 180 economic disasters in our main sample, 30 occurred after WWII (26 in non-OECD countries and only 4 in OECD countries).

The estimates on ϕ_0^k for the successive horizons (*k=0,…,40*) appear in Table 3 above. Figure 3 below plots the sequence of estimated coefficients together with the corresponding 95 percent 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.[9] Therefore, the proper results for comparison are the estimates for non-OECD countries plotted in Figure 2b.

Figure 3 shows very similar dynamics of output over the comparable forecast horizons (*k=0, …, 40*), as in Figure 2b. The output loss reach a maximum of 34.4 percent 11 years after an economic disaster (compared to 30.2 percent at *k=13* in Figure 2b). 20 years after an economic disaster, the output loss shrink to 27.1 percent (in Figure 2b the output loss at *k=20* is 27.6 percent). The estimate on ϕ_0^{40} indicates a loss of 23.3 percent (the corresponding loss in Figure 2b is 20.4 percent). The results suggest that output 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.

[9] The estimates for the subsample of non-OECD countries are almost identical (see Appendix, Figure A3).

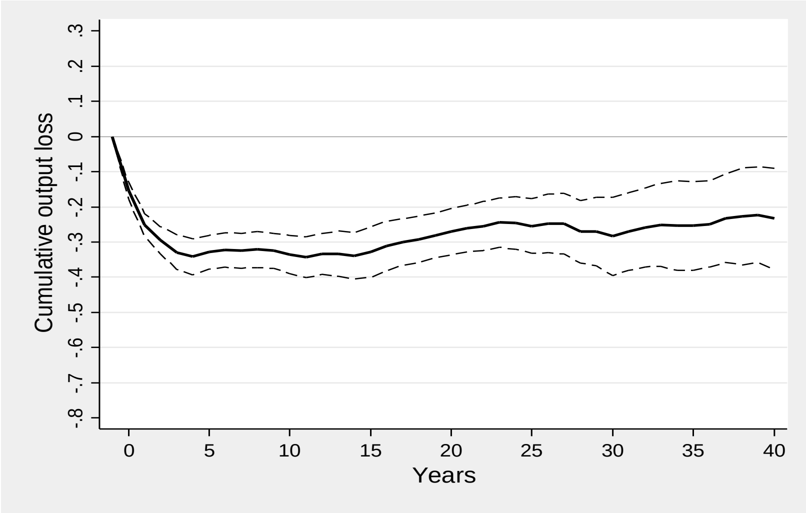

Figure 3 Output loss after economic disasters in the post-WWII period

The results presented in this section are truly staggering. However, we wish to highlight two points to avoid possible over-interpretation of these results. First, we do not argue that an occurrence of economic disaster is always exogenous with respect to output growth. Consequently, our estimates do not establish formal causality. They provide useful information on past experiences, but cannot be used as formal prediction tools.[10] Second, the results do not suggest that, following the onset of a typical economic disaster, a country will regain its pre-crisis level of output only after more than 50 years. Our results indicate output loss in respect to the long-run growth potential of the economy. To put this into perspective, assume, for example, that the average long-run output growth of an economy is 2 percent. The output in this economy would grow by 48.6 percent over 20 years and 185.6 percent over 53 years, absent any economic disaster. The reported output loss above of 20 percent at $k=20$ implies that 20 years after an economic disaster, cumulative output growth would be 20 percentage points

[10] For example, for prediction of the long-run effects of the economic disasters that may be induced by the COVID-19 pandemic.

lower than the economy's long-term growth potential prior to the event (28.6 instead of 48.6 percent). 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 potential (177.4 instead of 185.6 percent).

5. Conclusion

Our study provides an empirical analysis of output dynamics following economic disasters. The results show that economic disasters are associated with large and remarkably persistent output loss. Our estimates based on historical data suggest that, on average, in the first few years after the outbreak of an economic disaster, the output loss reach around 26 percent. Afterward, the loss gradually decline, but remain above 20 percent for 20 years. The output 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 loss in response to events occurring after WWII.

These findings 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. Our results pose a challenge for an explanation of the extreme persistence of output 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 in 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 economic 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 modelling their effects as permanent. Our results indicate that the use of more moderate assumptions of extremely persistent rather than permanent economic losses would be more appropriate. It would also be useful to investigate whether the results of current rare-disasters models are robust in respect to the modelling effects of economic disasters as being very persistent.

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Appendix

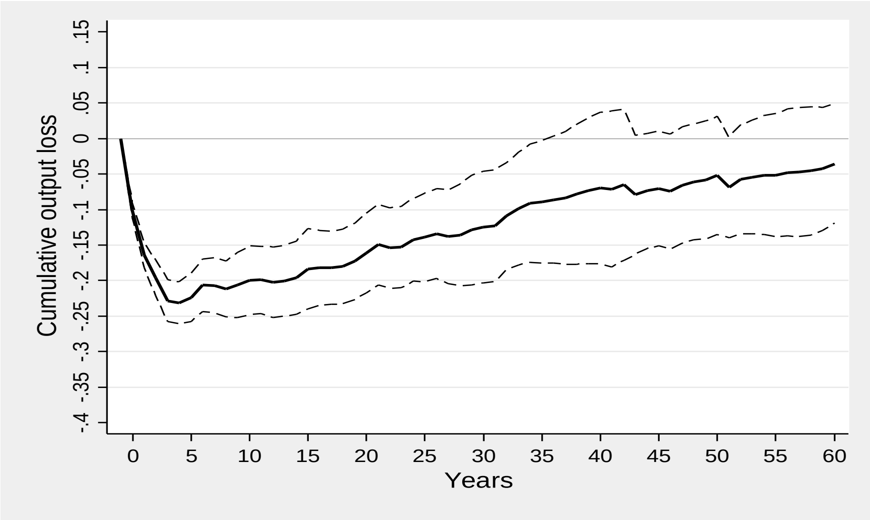

Figure A1 Output loss after economic disasters: forecast equation with country and time fixed effects

(a) OECD countries

(b) non-OECD countries

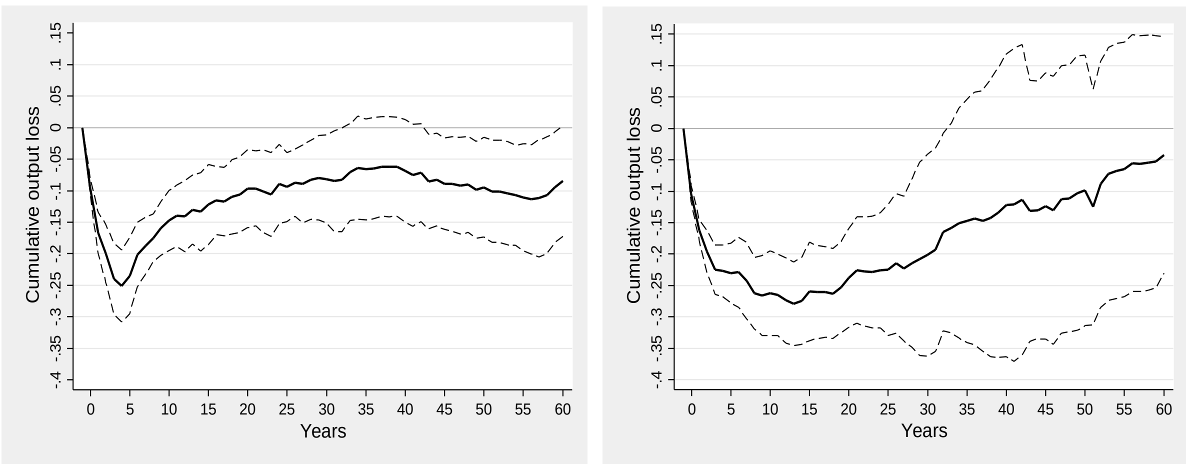

Figure A2 Output loss after economic disasters for OECD and non-OECD countries: forecast equation with country and time fixed effects

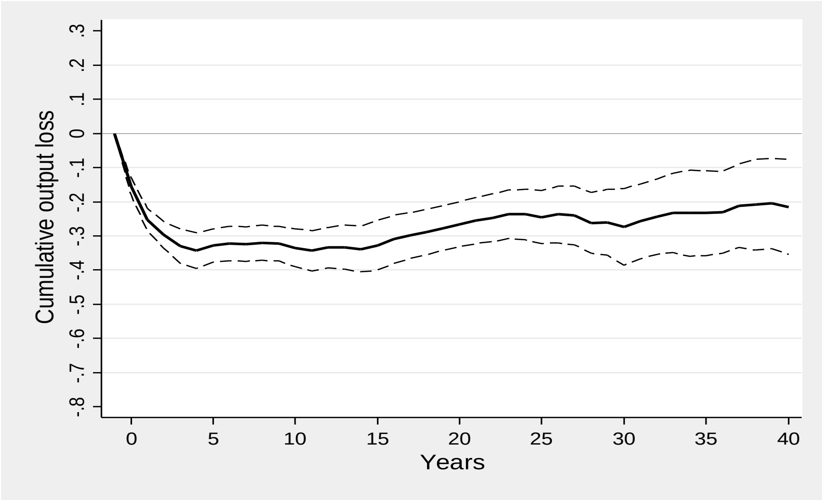

Figure A3 Output loss after economic disasters: post-WWII data for non-OECD countries

Abstrakt

Tato studie využívá dva velké datové soubory ke zkoumání dynamiky produkce po ekonomických katastrofách. První datový soubor zahrnuje 180 ekonomických katastrof z 38 různých zemí za období posledních 200 let. Druhý datový soubor zahrnuje 204 ekonomických katastrof ve 182 různých zemích od druhé světové války. Naše výsledky naznačují, že ekonomické krize jsou spojeny s vysokým a pozoruhodně persistentním poklesem produkce. Pokles produkce dosahuje v průměru více než 26 procent v prvních několika letech po vypuknutí ekonomické katastrofy a zůstává nad 20 procenty až po dobu 20 let. Až po více než 50 letech je obnovena původní produkce.

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