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## Worldwide Economic Recoveries from Financial Crises Through the Decades

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Third revised version, March 2020

### Abstract

The profiles of economic recoveries after a financial crisis are identified through a self-organizing map, covering 104 countries during 1973-2017. First and surprisingly, only 55% of the 276 events belong to the usual V-U-L classification. New S-shaped bounce-back recoveries, D(oomed) ones, and double-dip M occur in 23%, 18%, and 4% of the cases, respectively. Second, the frequencies of profiles vary with the crisis type, countries' development and location, and over time. Third, unlike government spending, supporting domestic credit, liquidity, foreign trade or else the exchange rate after the crisis may help activity bounce back.

**JEL classification numbers: E44, F32, G01.**

**Keywords: Economic Recovery; Early Warning Signals; Financial Crises; Output Gap; Self-Organizing Map; Multinomial Logit Model**

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**Declaration of interest: none**

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## 1. INTRODUCTION

The economic aftermath of the great financial crisis (GFC) in 2008 is still an issue for both researchers and policy makers. As time passes, uneven recoveries raise further concerns. The business cycles in OECD countries were almost fully synchronized right after the 2008 crisis, though the strength of their recovery tended to diverge in subsequent years (Reinhart and Rogoff, 2009, 2014; Romer and Romer, 2017, 2018). Some studies have questioned the strength of the subsequent economic rebound after a financial crisis (Calvo *et al.*, 2006; Tsangarides, 2012). Other studies have addressed the unusual sluggishness of such an economic rebound (Gali *et al.* 2012; Stock and Watson, 2012). In contrast to their historical record and to their advanced competitors, emerging market economies have been more resilient to the GFC (Gourinchas and Obstfeld, 2012; Dominguez *et al.*, 2012). It then seems difficult to find a single law of motion of economic aftermath after a financial crisis. If recoveries are not all the same, how many shapes can be distinguished, what are their salient features, and which factors are likely to send useful warning signals about these recoveries?

Curiously, discussions about recoveries have often been reduced to the occurrence of some bounce-back effect on domestic activity given the ad hoc V-U-L classification of recovery paths (Hong and Tornell, 2005, for example). However, the response of output to a financial crisis may behave differently. Economies can either bounce back so they overshoot their precrisis activity peak (Calvo *et al.*, 2006; Bussière *et al.*, 2012) or witness very protracted recessions such as Japan's lost decades (Reinhart and Rogoff, 2009, 2014). Following Cerra and Saxena (2008), substantial efforts have been made to assess the aftermath of financial turmoil. Recently, Romer and Romer (2018) have pointed to the prominent role of fiscal and monetary policy spaces in dampening and shortening the output losses from such financial crises. Focusing on Japanese and Italian records, the above authors explain deep and protracted recessions by the lack of such policy instruments.

## *Overview*

With a complementary view, we go beyond a crude “peak-to-trough-to-peak” analysis to empirically assess the whole dynamics of economic recoveries around a financial crisis. The purpose of our study is twofold. First, we show that the usual V-U-L classification is too restrictive to capture all the ways that domestic output did or did not bounce back in the face of a financial shock. Second, we discuss factors that may explain the observed heterogeneity. In particular, the shape of recovery depends on the state of the economy before and after its financial turmoil.

To do so, we study a sample of 104 developing and advanced countries with annual macroeconomic data spanning forty years, that is, from 1973 to 2017. We perform data analysis using a neural network devoted to the nonlinear projection of complex datasets, namely, a self-organizing map or SOM (for an overview, see Kohonen, 2013). This approach has the advantage of avoiding any assumptions about the shape and number of existing profiles. The latter has proven to be a powerful visual device for the early detection of financial crises (Sarlin and Peltonen, 2013) or systemic risk in the banking system (Kolari and Sanz, 2017). Finally, following Bussière and Fratzscher (2006), we estimate a multinomial logit model to search for the determinants of the identified shapes of recovery.

## *Related literature*

The first empirical studies have questioned the extent of economic recovery without considering its own dynamics. The first attempts consisted of static comparisons between the pre- and the postcrisis macroeconomic performances in the short run (Park and Lee, 2003; Hong and Tornell, 2005; Gupta *et al.*, 2007). They have focused on the delay and the strength with which the economic rebound followed the recession trough in developing countries.

Another approach has been to study the postcrisis dynamics of output in the medium run, as initially done by Cerra and Saxena (2008). They proposed a dynamic panel setting, where a

dummy variable accounted for a specific kind of crisis (Kannan et al., 2014; Bussière et al., 2012; Furceri and Zdzienicka, 2012; Kannan, 2012). However, the shapes of the estimated responses to shock are still of secondary importance. Since they depend nonlinearly on the model's deep parameters, they are also subject to misspecification bias (Killian and Kim, 2011).

Our main empirical findings are threefold. *First*, here, we show how the SOM allows one to identify the familiar V-U-L patterns, but we show that these patterns are far less frequent than what is often assumed in the literature. Our mapping identifies a fourth S-shaped pattern that is as frequent as the V-one. Generalizing Bussière et al.'s (2012) findings, this profile is neither specific to currency collapses nor to developing countries. Moreover, it occurs in approximately one-fourth of cases, thus adding substantially to Hong and Tornell's (2005) classification. A fifth path of the output gap looks similar to a D or a "doomed" recovery, so the economic downturn now follows the financial crisis with no sign of any reversal. Such a profile accounts for 18% of all the events under study. A sixth and final path, labeled M, exhibits two mild consecutive rebounds of activity. These unusual dynamics share some features with Reinhart and Rogoff's (2014) double-dip recessions, but there are few instances of this kind (4% of the 276 events in our sample). *Second*, consistent with the literature, the empirical evidence provided here stresses the key role played by macroeconomic imbalances in the path to recovery. According to our results, both preventive and curative policy measures may boost the recovery in times of a financial crisis. Countercyclical variations in domestic credit and liquidity help economies being more resilient. A fiscal stimulus through public spending prevents domestic activity from bouncing back when it comes after the collapse rather than before it. An economy could recover more easily after a financial crisis if it becomes more open to foreign trade or if its currency gains purchasing power, no matter the exchange rate regime.

The article is structured as follows. Section 2 describes our sample and provides *prima facie* evidence on the dynamics of the output gap around crisis events. We also underline the usefulness of self-organizing maps (SOMs) in the search for common features amid hundreds of episodes of economic recovery. Section 3 describes the new profiles identified by the SOM. Section 4 shows how the frequency of recovery styles depends on the features of the financial crises, countries and the sub-period under study. Section 5 uses a multinomial logit model to find the main factors of each path to recovery. Section 6 concludes the paper.

## 2. RESILIENCE TO FINANCIAL CRISES: *PRIMA FACIE* EVIDENCE AND A MAPPING METHODOLOGY

We first describe our dataset and the definition of crisis events. Next, we provide preliminary evidence on the dynamics of the per capita output gap around crisis episodes. Finally, we describe the self-organizing map (SOM) methodology as a powerful tool to identify the main profiles of economic activity in the context of financial turmoil.

### *2.1 Data and definition of crisis episodes*

The empirical analysis is based on a sample of 104 countries. Eighty-two of these countries are developing economies, and the remaining 22 are advanced according to the World Bank classification. The database consists of annual macroeconomic and financial indicators from 1973 to 2017. They come from the IMF International Financial Statistics, the World Bank World Development Indicators, and the OECD and BIS databases. Our study thus includes the great financial crisis of 2008. Events beyond 2008 come from the latest version of Laeven and Valencia's (2018) database.

Several methods have been proposed for dating crisis events. For this reason, we use three alternative chronologies of financial crises to assess the robustness of the identified profiles of

the output recoveries. Our benchmark chronology of financial crises comes from Gourinchas and Obstfeld (2012), who provided a consistent database of various types of crises: currency collapses, systemic banking events, and sovereign debt defaults (or rescheduling). We also consider the datasets of Reinhart and Rogoff (2009) and of Laeven and Valencia (2013) as alternatives. There is no account of stock market crashes or sudden stop phenomena in our sample. According to Frankel and Rose's (1996) criteria, a currency crisis occurs in a developing country when its currency depreciates vis-à-vis the US dollar at least 25% in a given year, which corresponds to at least 10% depreciation compared to the previous year. For OECD members, a currency crisis is identified based on two sets of criteria, as defined by Bordo *et al.* (2001): (i) a change in parity, a switch to greater floating or an international rescue package, and (ii) an index of exchange market pressure involving "abnormal" variations in the interest rate, the foreign exchange reserves, and the currency rate. Systemic banking crises are episodes of financial distress, urging a policy response. This is in the spirit of the definition given by Laeven and Valencia (2013). Finally, defaults on external debt are dated according to the methodology developed by Reinhart and Rogoff (2009). A debt crisis occurs when lenders incur losses from nonpayment, repudiation or the restructuring of debt. Given the lack of reliable information on domestic debt problems, we did not account for them.

We identify 276 crisis events in our sample, among which 55 involve a systemic banking crisis, 31 involve an external debt default, and 146 involve a currency collapse. They are also 44 twin or triple crises. Only the starting year of each crisis is considered here: 11% of the events occurred in the 1970s, 41% in the 1980s, 28% in the 1990s and 20% in the 2000s.

Unsurprisingly, four in five of the events under study occurred in developing countries. All sovereign debt defaults, except for the Greek one in 2012, are registered in the latter group. These global figures do not account, however, for the strong variation in the



vulnerability of countries. For example, Mexico experienced 4 currency collapses, 2 banking panics and 1 default on its external debt. In contrast, the United States was “only” subject to the 2008 great financial crisis. As a whole, Central and Latin American countries faced more than one hundred financial crises from 1973 to 2017. This is three times more than the events recorded in Asia and Pacific in our sample.

## 2.2. Stylized facts about recoveries

A preliminary step to study the recovery process is to run a dating algorithm of the turning points in the annual series of output gaps. As is widely recommended (e.g., Reinhart and Rogoff, 2014), we built per capita ratios on the basis of the population data series from the World Bank. We followed Gourinchas and Obstfeld (2012) and Furceri and Zdzienicka (2012) by setting the smoothing parameter of the Hodrick-Prescott filter to 100. In this way, we remove the trend and avoid cycles longer than 16 years<sup>1</sup>.

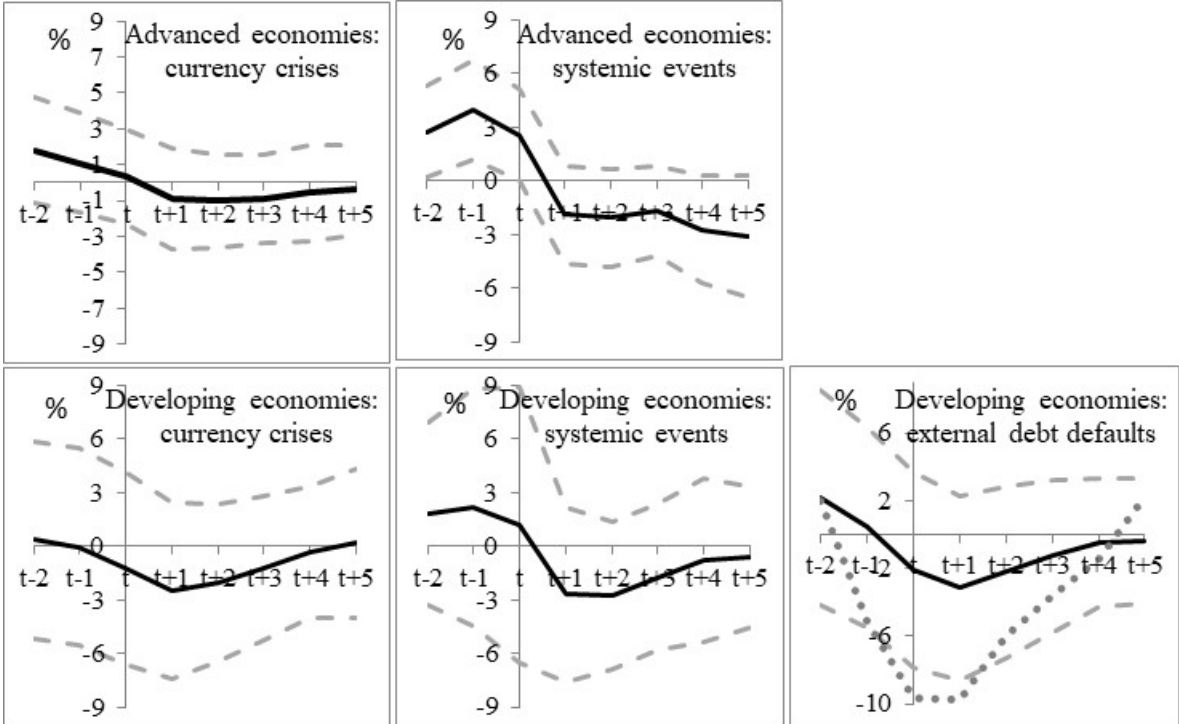
Two basic measures of economic recoveries around single crisis episodes are depicted in Figure 1: the simple average performance and its dispersion. In line with previous studies (Gourinchas and Obstfeld, 2012; Dominguez *et al.*, 2012, among others), we consider an eight-year window around a crisis occurring in year  $t$ , namely, the time interval  $[t-2, t+5]$ . The output gap (in terms of per capita real GDP) path is differentiated across three types of crises (currency, banking, and debt), given two groups of developing and advanced economies. Looking at country groups, the implied dynamics seem to exhibit familiar V-U-L shapes. A sharp decrease in the output gap generally precedes or coincides with the financial crisis, where the subsequent expansion often occurs at a more or less slow pace. In the case of currency crises, economic recovery shows a V pattern in developing countries but a U pattern

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<sup>1</sup> Results were rather robust to three alternative filter methods in Balcilar’s *mFilter* package of the R software, namely the Baxter-King, the Butterworth, and the Christiano-Fitzgerald trend-cycle decompositions.

in advanced economies. Indeed, after an exchange rate crisis (left two panels of Figure 1), developing countries face a fall in per capita output as large as their advanced partners (-2.86% against -2.79%), but their economic rebound is four times stronger (+2.71 against 0.63%).

Figure 1. Output gap behavior during single crises (per capita real GDP, annual, 1973-2017)



Note: Sample average (solid black line) with its one standard deviation confidence interval (dashed gray lines). The dotted gray line depicts the Greek default in 2012 (lower right panel).

After a banking crisis (middle panels of Figure 1), developing countries seem again more resilient than the advanced countries. On average, the former experience a U-shaped recovery with a two-year trough, whereas activity stalls in the latter as a costly L pattern. This is in line with results from impulse response analyses (Cerra and Saxena (2008); Romer and Romer (2017) and studies of the 2008 GFC (Dominguez *et al.*, 2012; Gourinchas and Obstfeld, 2012). The recovery process looks somewhat mixed during external debt defaults, suggesting either a U or an L shape. However, the sizable and lengthy economic slowdown

during the Greek default in 2012 differs from those observed on average in the developing group. This *prima facie* evidence supports Friedman's (1993) bounce-back hypothesis: the more severe the recession, the stronger the output bounces back to its long-run level.

Nevertheless, that descriptive analysis suffers from at least two major caveats. First, the overall average could potentially hide strong differences across countries and crises over time. Previous studies have already stressed heterogeneity in postcrisis macroeconomic performance, in particular Cerra and Saxena (2008). For example, some developing economies subject to a currency crisis with a sudden flight of foreign capital have recovered soon and fast despite persistent credit shortage, while others have failed to do so (Calvo *et al.*, 2006). Next, not all economic recoveries might fall into the V-U-L classification. Other patterns of output have been found by Bussière *et al.* (2012) and Reinhart and Rogoff (2014). The first authors have argued that so-called "standard" currency crises in developing countries often lead to an S profile: a mild recession occurs before the collapse, then a quick and strong recovery follows. In the second study, the worst systemic banking crises in the two last centuries often led to unusually severe recessions featured by a double-dip phenomenon looking like an asymmetric M path. Moreover, "other" ways of recovery than V or U were noted by Hong and Tornell (2005). Unfortunately, they did not describe them further.

For these reasons, and given the substantial heterogeneity in our sample, it is useful to provide an unconstrained and easily readable classification of the various ways that economies may recover after a financial crash. The next subsection details our statistical approach.

### *2.3 Identifying clusters and their neighborhood-given data complexity: Self-organizing maps*

One purpose of our statistical analysis is to go beyond the well-known V-U-L classification to provide a more complete typology of the main profiles characterizing output

recoveries. Importantly, we want to avoid putting any restrictions on the expected profiles. There is no assumption about the varieties of shape, the duration and magnitude of the recession and expansion phases or even the net gains and losses of output in the medium run. One methodology seems to be particularly well suited for achieving a clustering of recoveries, given their common features: self-organizing maps (SOMs). The mapping of financial risks has been performed with the SOM technique as an alternative way of building early warning systems (Sarlin and Peltonen, 2013). However, to our knowledge, no such warning mechanism is available to signal a more or less long and painful recovery process for an economy. Our aim is thus to bridge this gap.

An SOM is a special kind of neural network (Kohonen, 2013, for an appraisal). It builds a grid where the units are connected with a neighborhood relationship to reveal more or less homogeneous groups in a dataset. The data or patterns that look alike are gathered in the same area. For our purposes, these patterns are the output gap dynamics in the years just before and after each crisis event. Unlike the raw statistics drawn in Figure 1, SOMs have the ability to take into account the complex properties of datasets. There is no need to put constraints on either the origins of the distance factor(s) or on the number of main clusters and their features. An SOM can be seen as a nonparametric regression method that has the ability to account for nonlinear relationships.

Basically, an SOM is a regular grid of cartographical units. Each unit  $x_i$  is represented by a vector of weights  $\omega = (\omega_1, \dots, \omega_n)$ , where  $n$  is equal to the dimension of the input vector. Here, the unit  $x_i$  is the observed path of (per capita) real output gap around the financial crisis event  $i$  that occurred in a given country during a given year. The units are connected together through a neighborhood relation. Such a mapping aims at preserving the topological relationships between units. This property matters for the time paths to economic recovery under study, which implies that neighbors or similar recovery profiles in the input space (the

raw data) will be mapped as close units in the output space. In this way, the raw time series of output gaps are represented by “models”. These models are the local averages of the data, such that they keep the differences or ‘distance’ between the recorded recoveries unchanged.

An SOM is trained using an iterative procedure. At each iteration, an input vector  $x$  is usually randomly chosen. During the training phase, units are spread all around the input space. All distances between the  $x$  vector and the weighting vectors  $w_i$  are then calculated. The number of iterations must be at least 500 times the number of neurons in the output layer. At the outset of training, the weight vectors must be initialized using either a random or linear initialization method. The random assignment of weight (or *codebook*) vectors has been performed here.

The SOM algorithm is based on a competitive and unsupervised learning procedure: the R package “som” has been used for that purpose (Yan, 2016). The mapping is self-organizing since each input vector is matched with one neuron in the SOM. The unit  $c$  is the best matching unit (BMU): it ensures the closest match to the submitted input pattern  $x$  according to:

$$\|x - w_c\| = \min_{w_i} \|x - w_i\|, \quad (1)$$

where the double vertical bars refer to the Euclidian distance. Once BMU  $c$  is found, all vectors in the neighborhood of the BMU are then updated using the following formula:

$$w_i(t + 1) = w_i(t) + \alpha(t)h_{c,i}(t)(x(t) - w_i(t)), \quad (2)$$

where  $t$  denotes time, and  $\alpha(t)$  denotes the time-decreasing learning rate to achieve the convergence and stability of the resulting mapping of the recovery shapes (our units here) according to the iterative clustering procedure.

A standard choice for the neighborhood function  $h_{c,i}(t)$  is the Gaussian density centered on the BMU  $c$  defined by:

$$h_{c,i} = \exp(-\|r_c - r_i\|^2 / 2\sigma^2), \quad (3)$$

where  $r_c$  and  $r_i$  are the respective locations of units  $c$  and  $i$  on the grid. Similar to  $\alpha(t)$ , the standard deviation  $\sigma(t)$  is assumed to be a monotonically decreasing function with time. At each step of this iterative procedure, the weight vector of the BMU and the neighboring neurons are updated to mimic the input pattern.

A common way to view the resulting classification from an SOM is to split a two-dimensional space into a finite number of “regions”, with each region being associated with a set of points. Let us start from a set of various trajectories of real activity around crisis periods. The classification procedure would work iteratively, according to the selection and learning processes described in the preceding equations (2) and (3). That mapping method is now applied to identify the main profiles of recovery in GDP growth in the event of a financial crash.

### 3. COSTLY FINANCIAL CRISES: ECONOMIC SLOWDOWN AND WHAT NEXT?

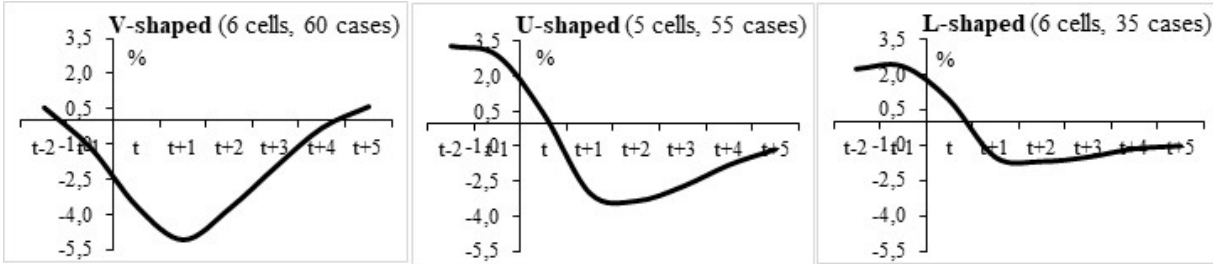
We applied the above clustering method to the output gap dynamics. Our mapping identifies the traditional V-U-L paths as well as the two other paths—labeled S and M—recently observed in previous works. One should also worry about D-shaped elusive recoveries.

#### *3.1 What can we learn from the standard V-U-L classification of recoveries?*

We performed an SOM on 104 countries from 1973 to 2017. The resulting 5-by-5 grid reveals the usual “alphabet” of recoveries in times of financial crisis. Each profile in Figure 2

below is the average of the close best matching units weighted by the number of events in the cells that are neighbors. To save space, the full grid is left as supplementary material.

Figure 2. The V, U and L paths identified by the self-organizing map (left to right, real per capita GDP gap in percent, 104 countries, 276 financial crises, 1973-2017)



Note: Year *t* refers to the crisis event. The output gap is nil along the x-axis.

Our mapping of the output gap dynamics provides support for the bounce-back effect in a V or U fashion, whereas the absence of a rebound has an L shape. As identified by the SOM, however, they barely account for 55% of all crises, even after including their neighborhood. The left panel of Figure 2 shows a V-shaped recovery: per capita output falls nearly 5% below its potential before it returns to its long-run trend in three years. In the middle panel, a U profile implies a milder recession trough followed by a looser and delayed economic rebound. The right panel is representative of L-shaped dynamics, with lasting economic recession and little sign of rebound.

The results from the SOM in Figure 2 give a more precise idea about both the common and the distinctive features of the identified V-U-L paths. The identified best matching unit by the SOM for a V shape implies a three-year delay for the output gap to become positive again from the recession trough, as it was two years before the crisis (left panel of Figure 2). The duration of a full V-shaped recovery is shorter than that assumed by Hong and Tornell (2005).

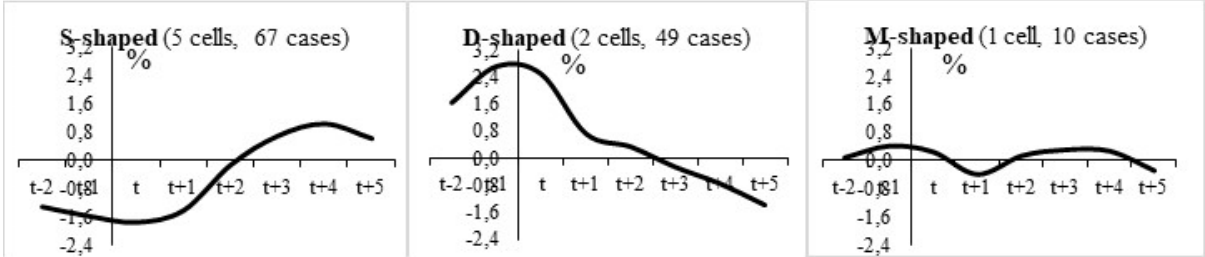
That gap appears even larger during U-shaped recoveries: countries have to wait more than five years for their per capita GDP to reach its long-run level.

We are now going to discuss the recovery process, considering the new shapes identified by the SOM that differ markedly from the well-known V-U-L shapes.

3.2 A broader family of postcrisis dynamics: the new S-D-M profiles of output recovery

Our SOM’s unsupervised classification approach finds three new recovery paths, “S”, “D”, and “M”. They did not appear from the descriptive statistics of per capita real output gap in Figure 1. As in Figure 2, the weighted average of the representative profiles in the map’s cells of the same neighborhood are depicted in Figure 3 below.

Figure 3. The new S, D, M recovery paths identified by the self-organizing map (left to right, real per capita GDP gap, 104 countries, 276 financial crises, 1973-2017)



Note: The date  $t$  on the x-axis again refers to the year of the crisis event.

The S profile implies a moderate economic slowdown in crisis times. A vigorous recovery then occurs, followed by a renewed period of weakness (left panel of Figure 3). This fourth pattern is observed in 23% of all 276 episodes under study. Bussière *et al.* (2012) also found a similar S-shaped profile. The curve they depicted is less marked than what our SOM finds. As these authors show, the S profile is also less likely during “persistent” (large and long) currency collapses in developing countries. Our findings tend to support the authors’ view since the negative gap vanishes within three years (left panel of Figure 3).



D-shaped recoveries refer to episodes of *doomed* reductions in the negative output gap. They happen after a delayed economic slowdown, in comparison with other scenarios. Such a recovery pattern concerns 18% of the 276 financial crises under study. In that situation, a country is still experiencing economic growth above its trend when the crisis erupts (see the precrisis peak in the middle panel of Figure 3). However, the country cannot avoid a very long decline in economic activity. We tried to extend the time window without finding any sign of reversal, even eight years after the occurrence of a crisis. This looks similar to the “lost decade” syndrome. However, in our sample, 75% of the financial crises followed by a D-shaped recovery occurred before 1995. Elusive D-shaped recoveries seem to have prevailed in Spain during its systemic banking crisis in 1977 and during the currency peg collapse of the Belgian franc in 1980. These crises, such as the currency crash in Venezuela in 1995 or the twin currency and banking crises in Thailand in 1997, mainly concerned developing countries.

Finally, an M-shaped recovery occurred only 10 times in the forty years under review. The latest episode concerned the Australian currency turmoil in 2000. This specific pattern shares similarities with the double-dip phenomenon recently stressed by Reinhart and Rogoff (2014). The right panel of Figure 3 shows a first limited economic rebound before the per capita output falls again below its potential value. This situation should call for a small second bounce-back effect. The cumulative loss of per capita output is 0.7% of its potential level on average since the crisis year for an M-shaped recovery. The corresponding loss in the first five years from the crisis rises to 14.7% of potential (V), 12.1% (U), 5.9% (L), 3.3% (S), and 2.1% (D).

To test for the robustness of our results, we built new SOMs using the alternative chronologies of financial crises until 2008 provided by Laeven and Valencia (2013) and by

Reinhart and Rogoff (2011). The overall picture is the same as regards the patterns of recovery and their frequency of occurrence (please see the supplementary material).

The next section provides further evidence on the economic aftermath of financial crises to account for the heterogeneity in our sample.

#### 4. SENSITIVITY OF SOM CLUSTERING TO SAMPLE HETEROGENEITY

We apply the SOM method to different subsamples, based on the origin of the financial crisis, the country level of development, the country's location, and the time-varying degree of financial liberalization.

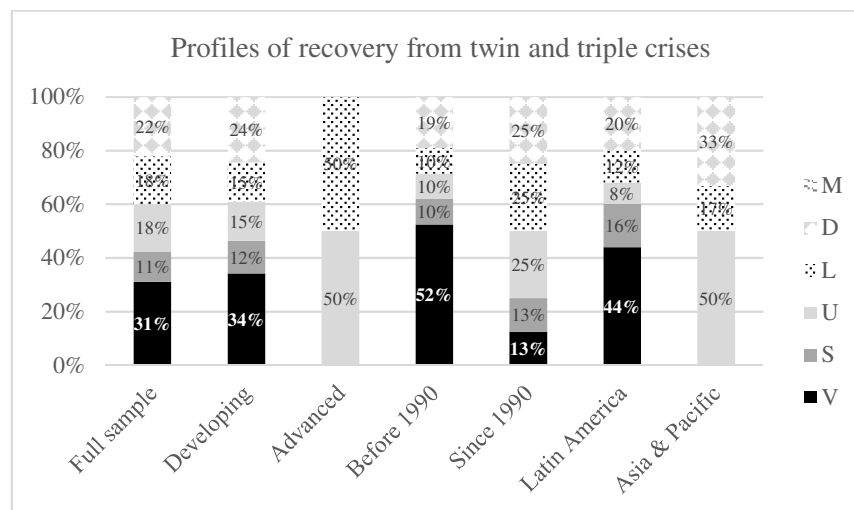
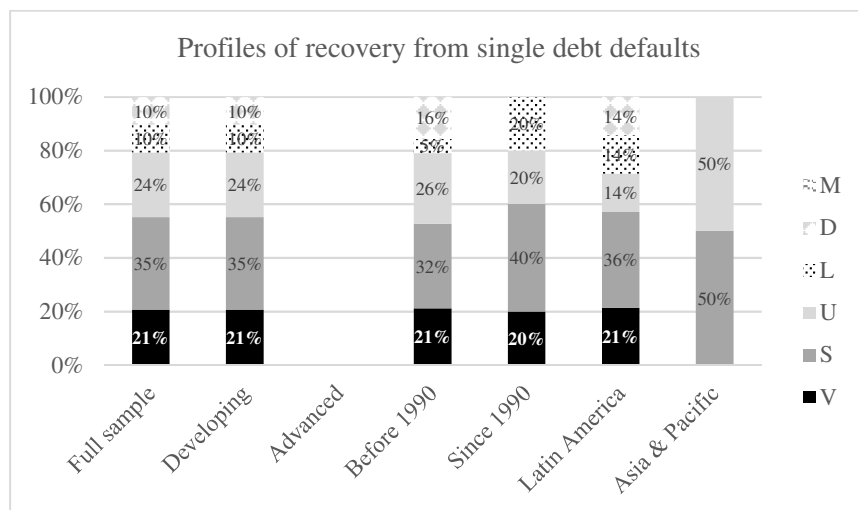
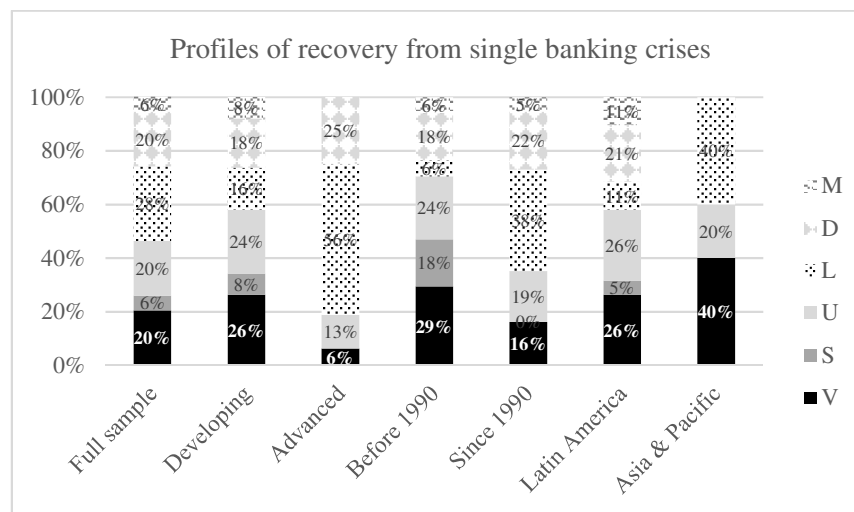
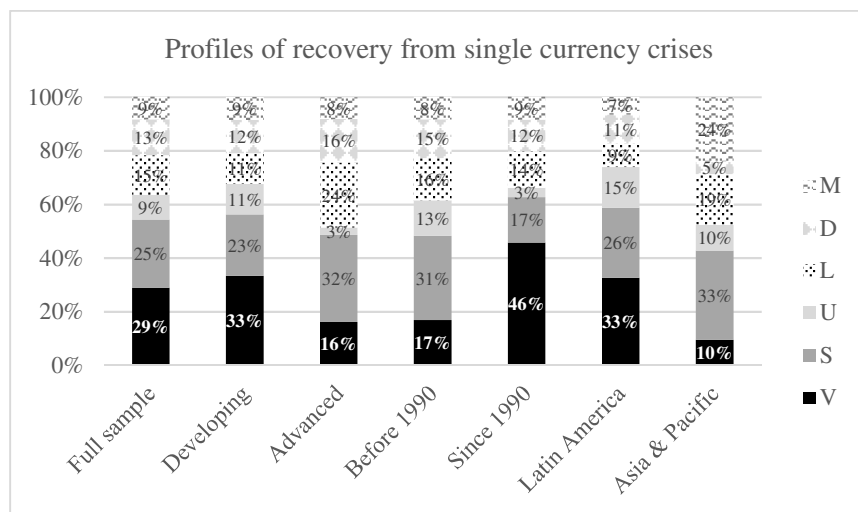
##### *4.1 How do recovery shapes differ with the type of financial crisis?*

For the four kinds of financial crisis under study, Figure 4 below indicates the frequency at which the six identified profiles occurred according to each subsample. Ratios measure the frequency of a particular profile according to a given type of financial crisis. As it reads, 29% of the 146 single currency crises in the full sample led to a V-shaped recovery. Vertical bars of the histograms distinguish recoveries during which economic activity bounced back (V-S-U) from those showing no sign of once-for-all rebound (L-D-M) during the time span.

When a currency crisis occurs, the output gap bounces back in 63% of the 142 instances (top left panel of Figure 4). That crises are growth-enhancing is consistent with Park and Lee's (2003) conclusions. However, Gupta *et al.* (2007) stressed that exchange rate collapses tend to be more contractionary in emerging market economies than in other developing countries. To check this, we have used the IMF's classification of countries. Recoveries exhibiting a bouncing back (V, S or U) appear more frequent in the first group than in the second group (63% against 50%). Our findings thus undermine Gupta *et al.*'s conclusions. Per capita output bounces back with an S shape in another one-fourth of instances. This evidence

supports Bussière *et al.*'s (2012) findings from “standard” and “large” currency collapses amid a hundred developing countries over the period 1960-2006. What is new here is that such an S profile is not specific to currency crashes or to the developing world (see Figure 4). Indeed, an S shape is the most frequent profile describing debt default, whereas doomed recoveries are relatively rare in that case (10% of D and 10% of L types recoveries).

Figure 4. Distribution of recovery profiles in full sample and subgroups



In the event of a systemic banking crisis, a V-type recovery is less likely than it is after a currency collapse (top right panel of Figure 4). A distinctive feature is that banking system failures are followed by painful elusive recoveries where output fails to bounce back in nearly half of the instances (D 20%, L 28%). In another one in five cases, there is a delayed soft rebound as the output gap follows a U path. There is overwhelming evidence that more time is needed, on average, for an economy to recover from a banking crisis.

Finally, twin or triple crises lead to an economic rebound after a severe contraction of output in 60% of occurrences. Since nine in ten of them concern developing countries, the prevalence of V- and S-shaped recoveries gives support to the view that crises have cleansing effects that boost growth (Calvo *et al.*, 2006, Bussière *et. al.*, 2012). However, one size does not fit all according to our SOM results in Figure 4 above.

#### *4.2 Economic recoveries by level of development and geographical area*

A next check is to assess how the distribution of recovery profiles may vary with the development level of individual countries. Figure 4 above reveals strong discrepancies between developing and advanced country groups. V profiles are indeed much more frequent in emerging markets. Developing countries are thus prone to faster recoveries than advanced ones. The greater resiliency of emerging market economies seems independent from the financial crisis at play. Currency crises are often associated with fast recoveries, especially in Indonesia in 1993, Brazil in 1999, India in 1991 or Paraguay in 1998. S-shaped recoveries are the most frequent during sovereign debt defaults. Figure 4 also shows that U-shaped output dynamics are as likely as V ones in a banking crisis in developing countries. Nevertheless, protracted recessions yielding an L or a D path to recovery are frequent when the domestic banking system breaks down and/or when the external debt is unsustainable, which occurred in Ecuador in 1981 and 2000 and in Mexico in 1994. The unusually sluggish catch-up of the

output gap also occurred in 6 out of 9 twinned currency and systemic banking crises in developing countries.

In the case of advanced economies, our mapping confirms that a “severe financial crash” is often associated with an L- or a D-shaped recovery. This is in line with Reinhart and Rogoff (2009). It is also consistent with the idea that systemic moral hazard issues may lead to costly disruptions in mature financial systems (Ranci re *et al.*, 2008). To illustrate this, the United Kingdom recorded two L scenarios of poor macroeconomic performance during its pound collapse in 1989 and the 2008 subprime crisis. Like the UK and with the noticeable exception of Ireland, the eleven members of the euro area in our sample experienced a recovery without a noticeable rebound in their output gap, having either an L or a D path. Sharing the same currency does not preclude divergent paths in response to a large common financial shock. An L-shaped recovery is found by our mapping for the US economy, a result consistent with Gali *et al.* (2012) and Camacho *et al.* (2011).

Regarding the issue of country heterogeneity, one may finally wonder whether the path to economic recovery could depend on the geographical region subject to financial crises. Regional patterns can matter because of high trade or financial linkages and possible contagious crises among neighbor countries. Given the number of instances, we focus on two regions: Latin America and Asia and Pacific (at the end of the histograms in Figure 4).

The overall picture is that Asian economies have been, on average, less resilient than Latin American countries, despite a much lower number of crisis episodes during 1973-2017. That generalizes Bussiere *et al.*'s (2012) conclusion, as it prevails for a broader set of financial crises. L recoveries of the output gap are more frequent in Asia than in Latin America. They are observed primarily in advanced economies in the Pacific, such as Japan and New Zealand. In contrast, with the exception of the banking crisis, V recoveries are more frequent in Latin America than in the Asian region. For example, Argentina, Brazil or Chile

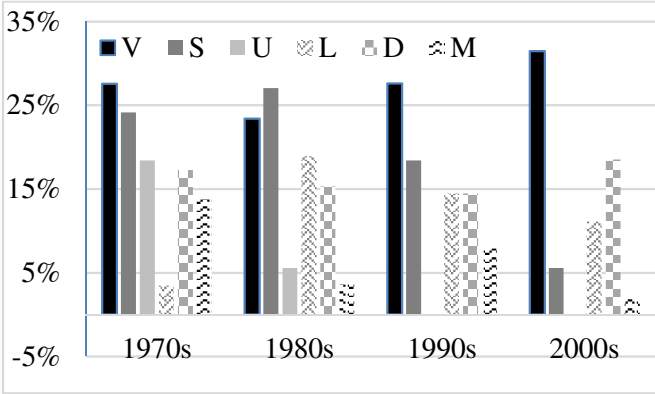
have been subject to V-type recoveries more than once. Some of them, such as Argentina, have also suffered long-lasting recoveries. In eight of the 14 instances, Central and South American economies that defaulted on their debt have bounced back quite strongly with S-shaped profiles in greater proportion than with V-shaped profiles. S-shaped recoveries have been more frequent among countries under the financial assistance of the IMF. It helped limit damage to the economy, according to Park and Lee (2003).

#### *4.3 Economic recoveries during times of financial globalization/fragmentation*

A third major issue is the extent to which more developed capital markets and financial institutions may influence the shape of business cycles during a financial crisis. According to Gupta *et al.* (2007), the relationship between postcrisis economic performance and crisis occurrence has not changed markedly from the sixties to the nineties. That view has been challenged by Bussière *et al.* (2012). To obtain a more precise idea, we have distinguished recoveries following “early” financial crises before 1990 from “recent” collapses.

Regarding systemic banking disasters, L-shaped recoveries have become more frequent than in the past, especially within the OECD group. What has markedly changed is that S profiles have completely disappeared. Conversely, our mapping shows a remarkable change in the strength of the output recovery in the case of currency crises. Looking at Figure 4, V paths accounted for 46% of the recoveries during 1990-2017 but only 17% of them before 1990. The resilience to currency crises has improved in recent years, mostly amid developing countries.

Figure 5. Time-varying distribution of output recoveries by decades.



Following Bussière *et al.* (2012), we also checked for changes over decades from the 1970s to the 2000s. Figure 5 above shows the relative stability of proportions of V-shaped and D-shaped profiles of the per capita output gap, which contrasts with the sizable changes in the remaining four types of recoveries. A first major shift is the decreasing importance of soft rebounds of the economic activity leading to U paths in the wake of a financial crash. This has happened essentially at the expense of a larger share of episodes of protracted recessions of an L kind. Our results support Bussière *et al.*'s (2012) conclusion about changes in the logic of crises or in the adjustment of macroeconomic imbalances rather than Gupta *et al.*'s (2007) view of a stable relationship. One thus has to worry about the macroeconomic conditions around crisis times.

In a final step, we rely on a discrete dependent variable model to find some macroeconomic conditions that may influence the path of economic recovery after a financial crisis.

5. WHAT MAY EXPLAIN THE ECONOMIC AFTERMATH OF FINANCIAL CRISES?

It matters to know if the shape of economic activity in countries facing a financial crisis depends on the severity of macroeconomic disequilibria. First, we describe our approach



based on the early warning systems of financial crises. Second, we discuss both domestic and external factors that help predict the shape of the economic recovery.

### *5.1 Empirical methodology*

We want to identify some of the macroeconomic factors that may signal the occurrence of each of the six V-S-U-L-D-M shapes of economic recovery. Given our findings in section 4, we have split our sample in various ways to account for specific features according to the origin of the financial crisis, countries' level of development, and possible changes in global markets since the 1990s. To our knowledge, with the exception of Hong and Tornell (2005), no other paper has sought to identify the specific determinants of the various recovery profiles around crisis times. Here we go beyond the former study as it distinguished only three types of recovery dynamics, namely Vs, Us and the 'rest' of them. The econometric methodology relies mostly on a discrete dependent variable model. It matters to know what may influence the probability for the recovery process to follow a given path around a financial crisis. Binomial discrete-choice models would be natural candidates to study each profile of output gap separately. A major drawback is however that, under the alternative (to a V path for example), it would gather profiles of very different kinds (either S or L shapes).

A way to circumvent this shortcoming is to estimate a multinomial logit model. The categories of output profile identified by the above SOM are modeled as the possible outcomes of a discrete dependent variable<sup>2</sup>. We are able to find the main factors explaining each of the V-U-L-S-D profiles. We had no choice but to drop the M-shaped recoveries from our econometric analysis because they occurred 10 times only: 2 during a banking crisis, and

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<sup>2</sup> In a previous version of the paper, we have implemented a recursive partitioning method to find the relevant signals and their threshold values. Domestic credit, liquidity, and trade openness appeared as trigger factors of a bounce back. However, as questioned by one referee, it proved hard to get clear-cut decision rules.

none at all in an external debt default. Our framework relates to Bussière and Fratzscher (2006) who showed its relevance to find early warning signals of financial crises as it reduces the bias from omitting influential categories.

We have implemented the multinomial regression method by considering the annual data of several macroeconomic indicators for our set of 104 countries during 1973-2017. These data are supposed to account for both domestic and external imbalances in the real and financial sides of an economy. We use the World Bank statistics on the following variables: a consumer price-based inflation rate, GDP ratios in terms of domestic liquidity, credit to the private sector, government public spending growth, currency misalignments as the percentage deviation of the real effective exchange rate from its long-run mean level, and the GDP ratios of the current account balance and of trade flows. Our estimates are based on two-year averages of each signaling variable before  $[t-2, t-1]$  and after  $[t+1, t+2]$  a crisis event in year  $t$ . Due to a lack of data, we had to exclude other indicators like interest rates, public debt and fiscal imbalance, private consumption, capital accumulation, unit labor cost, and foreign capital flows. Summary statistics are reported in Table 1 below.

### *5.2 Macroeconomic signals of recovery paths*

For consistency purposes, we adopted an iterative top-down approach by dropping nonsignificant variables. We then proceeded to the reversed bottom-up selection of these factors. On this basis, we ran three multinomial logit regressions to account for possible specific features arising from how, where, and when the financial crisis occurred and the subsequent recovery took place. The regression model is written as follows:

$$\ln\left(\frac{p_{ik}}{p_{vk}}\right) = \sum_{k=1}^n \beta_{ik} X_i 1_k + u_{ik}, \quad (4)$$

where  $p_{ik}$  is the probability of recovery with shape  $i=\{S, U, L, D\}$  during the crisis event  $k$ .

Table 1. Descriptive statistics for the economic determinants of output recoveries (273 crises, 1973-2017)

Recovery profile	Statistic	Credit (%GDP)		Liquidity (%GDP)		Public spending growth (%)		CPI inflation rate (%)		Current account (%GDP)		Currency misalignment (%)		Trade openness (%GDP)	
		Before crisis	After crisis	Before crisis	After crisis	Before crisis	After crisis	Before crisis	After crisis	Before crisis	After crisis	Before crisis	After crisis	Before crisis	After crisis
V	Min.	1.43	1.58	15.1	9.39	-17.1	-7.66	1.29	-3.77	-109.7	-24.0	-57.9	-55.6	17.9	18.2
	1st Q.	16.1	14.1	31.7	34.5	2.10	0.84	5.21	2.89	-4.25	-4.36	-31.9	-33.0	43.9	47.4
	<b>Median</b>	<b>25.5</b>	<b>21.0</b>	<b>42.8</b>	<b>43.0</b>	<b>3.21</b>	<b>2.09</b>	<b>8.48</b>	<b>6.51</b>	<b>-2.38</b>	<b>-2.12</b>	<b>-26.6</b>	<b>-27.5</b>	<b>57.0</b>	<b>58.0</b>
	Mean	33.5	30.9	46.3	47.5	4.22	2.72	24.4	29.6	-3.48	-2.21	-2.59	-17.1	63.9	65.2
	3rd Q.	43.7	43.6	57.3	56.7	5.56	4.15	11.7	12.1	0.43	0.021	1.79	2.55	77.1	75.8
	Max.	120.3	116.8	164.7	113.6	47.6	11.2	692.4	1,071.0	17.8	22.6	651.8	21.7	160.7	155.5
S	Min.	3.98	6.05	9.37	9.24	-7.99	-14.6	0.008	0.022	-17.5	-12.1	-42.9	-49.5	19.0	23.3
	1st Q.	16.2	14.1	22.1	23.1	1.31	1.08	5.34	3.18	-4.59	-5.08	-31.9	-33.0	39.5	38.9
	<b>Median</b>	<b>21.1</b>	<b>20.8</b>	<b>30.8</b>	<b>36.2</b>	<b>3.00</b>	<b>3.28</b>	<b>9.95</b>	<b>8.89</b>	<b>-2.09</b>	<b>-1.58</b>	<b>-15.0</b>	<b>-17.8</b>	<b>46.7</b>	<b>49.2</b>
	Mean	30.8	29.3	37.5	40.0	3.00	3.18	22.1	111.7	-2.78	-1.91	-14.8	-6.37	52.8	55.7
	3rd Q.	37.3	32.8	49.3	53.1	4.65	5.96	23.4	12.9	-0.854	-0.071	-0.568	-2.72	58.8	63.2
	Max.	134.1	117.9	94.7	102.5	27.6	19.9	241.5	5,440.2	7.68	8.41	22.0	491.9	126.9	136.0
U	Min.	7.4	12.3	8.2	9.52	-1.54	-2.96	0.122	0.533	-19.1	-18.7	-44.3	-42.1	20.6	22.4
	1st Q.	27.7	23.9	28.9	30.5	1.59	2.29	2.79	3.23	-3.47	-4.53	-31.9	-33.0	49.0	48.2
	<b>Median</b>	<b>38.8</b>	<b>41.7</b>	<b>37.2</b>	<b>37.3</b>	<b>3.31</b>	<b>3.94</b>	<b>8.36</b>	<b>6.48</b>	<b>-1.17</b>	<b>-2.23</b>	<b>-20.7</b>	<b>-13.5</b>	<b>60.1</b>	<b>54.9</b>
	Mean	53.4	54.5	45.6	46.9	3.65	4.19	14.9	12.6	-0.775	-2.31	-17.0	-16.0	73.6	64.4
	3rd Q.	58.6	73.3	54.1	49.4	5.95	6.05	16.6	12.6	2.96	-0.076	-4.63	-6.0	77.3	77.2
	Max.	290.4	222.1	119.6	138.3	9.93	13.1	107.2	61.8	14.6	7.83	20.4	20.7	214.5	145.4
L	Min.	12.4	13.4	11.0	12.2	-4.11	-5.86	-0.017	0.014	-7.25	-18.2	-31.9	-35.0	14.4	17.2
	1st Q.	26.0	25.1	27.4	30.7	1.29	1.19	1.78	3.01	-3.03	-4.04	-28.6	-33.0	44.9	43.5
	<b>Median</b>	<b>51.3</b>	<b>48.3</b>	<b>42.8</b>	<b>44.3</b>	<b>2.27</b>	<b>2.68</b>	<b>4.79</b>	<b>4.10</b>	<b>-0.854</b>	<b>-2.12</b>	<b>-5.69</b>	<b>-5.44</b>	<b>60.5</b>	<b>49.8</b>
	Mean	67.8	74.1	57.1	58.6	2.36	3.17	102.9	20.5	0.125	-1.28	-8.25	-12.0	65.1	57.8
	3rd Q.	98.0	109.5	69.6	61.8	3.67	4.67	11.9	14.5	2.44	1.32	5.67	1.03	78.4	65.1
	Max.	202.0	226.2	197.5	209.9	6.58	15.0	3,945.6	376.4	15.0	16.7	50.0	23.1	203.2	169.6
D	Min.	9.05	9.93	12.6	12.1	-17.4	-12.66	5.0e-02	1.02	-29.0	-19.1	-46.3	-49.09	12.9	14.2
	1st Q.	22.2	16.7	22.9	23.7	0.22	1.87	1.86	2.80	-2.35	-2.35	-31.9	-33.01	41.3	35.1
	<b>Median</b>	<b>38.0</b>	<b>41.7</b>	<b>34.5</b>	<b>34.6</b>	<b>1.52</b>	<b>3.35</b>	<b>5.94</b>	<b>6.24</b>	<b>0.002</b>	<b>-0.534</b>	<b>-25.3</b>	<b>-33.01</b>	<b>50.8</b>	<b>51.7</b>
	Mean	57.4	58.8	43.1	42.4	1.43	10.88	73.7	88.60	0.289	0.293	-18.7	-18.95	63.5	54.5
	3rd Q.	79.3	86.3	53.6	47.4	4.02	5.70	12.9	12.49	3.80	3.20	-4.68	-4.06	82.4	65.3
	Max.	206.3	207.1	149.5	154.3	9.96	270.81	2,032.8	1,690.3	14.0	15.6	16.4	27.9	157.6	145.3

The V-shaped recovery is the benchmark scenario, with probability  $p_V$ . Parameters  $\beta_{ik}$  capture the interaction effects between the macroeconomic factor  $X_i$  and the dummy variable  $1_k$  controlling for the occurrence of some event  $k$  (crisis origin, country development, or timing of crisis event). The random variable  $u_{ik}$  is an error term. Given the large number of interaction variables, we decomposed the estimation into three steps according to the crisis type, the country's status and the sample period. We performed the Hausman test to check for the independence of irrelevant alternatives (IIA) hypothesis. The results lead to the nonrejection of the IIA hypothesis, supporting the multinomial logit approach. The following discussion is based on the average marginal effects in Table 2 below.

Table 2 can be viewed as a heat map and summarizes the way marginal effects influence the probability of the output recovery having one of the identified shapes by our SOM. The variables on the left (right) side of Table 2 are the two-year averages before (after) the crisis event. For a given subsample (crisis type, countries' development or period), a rise in an economic aggregate may have either a positive (+) or negative (-) influence on the probability of an economic recovery with a given shape. The gray cells in the table highlight significant results at the 10 percent level or less. Table A in the appendix presents the estimated average marginal effects from the multinomial logit model.

The light gray cells refer to favorable cases, namely, those implying either a greater probability of the economy recovering swiftly in a V, S or U form or a lower chance of the output gap following an L or D path. The dark gray cells signal an increasing risk of suffering a severe recession after a financial crisis. The uncolored cells include statistically nonsignificant results.

The estimated marginal effects from the multinomial logit models convey interesting lessons about the likely economic factors favoring a bounce-back of domestic activity during the financial crisis' aftermath.

Table 2. Signs of the marginal effects on the probability occurrence of a given recovery profile (multinomial logit estimates)

<b>BEFORE CRISIS</b>		Soft recovery			Delayed recovery		<b>AFTER CRISIS</b>		Soft recovery			Delayed recovery	
Indicator	Subsample	V	S	U	L	D	Subsample	V	S	U	L	D	
Credit	Currency collapse	+	-	-	+	+							
	Banking crisis	+	-	-	+	-	Banking crisis	-	+	+	-	-	
	Advanced country	-	-	-	+	+	Developing country	-	-	+	+	+	
	Developing country	+	+	-	-	+	Pre-1990 period	-	-	+	+	+	
Liquidity	Banking crisis	-	+	-	+	-	Banking crisis	+	-	+	-	+	
	Debt default	+	+	+	-	+	Developing country	+	-	+	+	-	
	Post-1990 period	-	-	+	+	-							
Public spending	Banking crisis	+	+	+	-	-	Debt default	-	-	-	+	-	
	Developing country	+	-	-	+	+	Banking crisis	+	+	+	-	+	
Inflation	Pre-1990 period	+	-	-	+	+							
	Currency collapse	+	-	-	+	-	Debt default	+	+	+	-	+	
Currency misalignment	Banking crisis	+	+	+	-	-							
	Pre-1990 period	-	+	-	+	+							
	Currency collapse	-	-	-	+	-	Currency collapse	+	+	+	-	-	
Openness	Pre-1990 period	-	+	-	+	+	Debt default	-	+	+	+	-	
							Pre-1990 period	+	-	+	+	-	
							Pre-1990 period	-	+	-	+	+	

Note: The light (dark) gray cells refer to a significant rise (reduction) in the probability of a bounce-back scenario or the reverse in terms of a recovery process without rebound at the 10 percent level or less. Otherwise, the estimated effects are not significant from zero.

Overall, our results show evidence of two sets of determinants that may influence the likelihood of a real per capita output gap following a given path. Indeed, economic resilience may depend on preventive measures like on curative measures.

First, early warning signals of financial crises can play a role in shaping the subsequent path to economic recovery. These factors are part of the macroeconomic surveillance scoreboard and macroprudential policies, as they reflect disequilibria that may lead to severe disruptions in the financial system.

*At the domestic level*, economic activity is less likely to bounce back when credit growth accelerates in the two years before a financial crash. This negative impact on U-shaped recoveries is significant only for systemic banking crises or currency collapses. Then, an accelerating credit-to-GDP ratio elevates the risk of experiencing a severe recession so that the output gap dynamics have an L-shaped profile. Thus, a countercyclical stance of the domestic credit policy deters not only the occurrence of a financial crash but also the danger of the economy being trapped in the recession. Similarly, an excess of domestic liquidity, before a banking crisis or during the post-1990 period, lowers the chances of recovering swiftly from a situation of depressed economic activity: the probability of experiencing a U-shaped path shrinks, while a persistent L-shaped stall becomes more likely. Our results suggest that the countercyclical management of domestic liquidity by central bankers may improve the country's economic resilience to a large financial shock, which would add to the positive effects of smoothing credit fluctuations over the cycle. However, such negative effects of precrisis liquidity on recovery strength do not prevail before a debt default.

In addition, an expansionary fiscal policy before a disruption in the banking system coincides with stronger resilience in economic activity after that event. On the one hand, a V-shaped recovery or an S-shaped recovery is more likely when public spending grows at a faster pace

before such a crisis. On the other hand, there is a lower probability of no rebound at all during the crisis' aftermath such that the resulting profile is L-shaped. A precrisis fiscal stimulus thus seems to improve the economic resilience to a banking crisis. A delay may be required for the fiscal stimulus to boost real activity. Regardless of the crisis type, a surge in domestic inflation before the collapse has a more mixed effect on the recovery process because that makes either a V-type rebound or a D-shaped path more likely. This is only partly consistent with Bussière et al.'s (2012) findings, which suggest that precrisis inflation weakens the recovery process after a currency collapse in developing economies.

Let us now consider the influence of *cross-border relationships* on the eve of a financial crisis. First, changes in the degree of real currency misalignment play a major role in the recovery profile, as revealed in Table 2. When the currency appreciates in real terms, it lowers the probability of having a recovery with an L- or D-shaped profile in the years that follow a banking crisis. Perhaps more disturbing, the impact of currency appreciation on the probability of an L-shaped profile depends on whether the country experiences a banking crisis or a currency crisis: it is negative in the first case but positive in the second one. Once again, the deterring effect on scenarios of persistent recession could result from an adjustment of the real exchange rate, which could also boost foreign demand for home goods. Without such a correction, it would be more difficult for the economy to recover swiftly. Currency misalignment prior to a crisis has little influence on the chances for postcrisis activity to bounce back. The only exception is the positive effect of an overvalued currency on witnessing an S-shaped recovery during a banking crisis. A similar positive effect on S-type rebounds seems to have been at play in the 1970s-1980s. Real appreciation also led to more frequent L-shaped profiles but fewer U-shaped paths before 1990. Sign instability among marginal effects across crisis events may be related to time shifts. Unlike what is found during the first subperiod, precrisis misalignments no longer seem to play a role over the period 1990-2017 (see Table 2).



As already pointed out in the literature, those shifts may reflect changes in the logic of financial crises.

Greater trade openness before a financial crisis may lower the probability of a fast V-shaped recovery, as it does for D-shaped paths when the currency regime collapses. The evidence is mixed given the positive probability of an L-shaped profile. There is no statistical evidence of a role played by precrisis current account disequilibria in shaping the output profile. Overall, the new era of globalization since the 1990s has not coincided with a growing influence of external factors on output growth performance in times of financial crisis.

Next, a second group of determinants of an output recovery with a given SOM-identified shape relates to the adjustment process that follows the financial crash. In line with Hong and Tornell (2005) and Gupta et al. (2007), we assess the role of the previous indicators that are averaged over the first two years next to the crisis event (see the right panel of Table 2). These additional variables inform about the context under which an economic rebound takes place or not in response to the crisis. These new indicators may also reflect how domestic policies may help an economy withstand the crisis.

*On the domestic side*, sign reversals in the estimated marginal effects are often observed in comparison with the influence of the precrisis state of the economy, which holds true, in particular, for domestic credit and liquidity. The per capita output gap is prone to bounce back with an S or U shape when credit expands after a banking crisis. Interestingly, Claessens et al. (2009) reached a similar conclusion, although they disregarded the exact shape it would yield. Moreover, credit contraction relative to GDP favors an exit from the financial crisis with a lengthy recession such as an L-shaped profile. In accordance with Hong and Tornell (2005), those effects are no longer significant during currency crises, and they have no influence in the case of debt defaults.

Similar conclusions hold for liquidity just after a banking crisis and, more generally, for developing countries. There are two exceptions. First, the liquidity's marginal effect is negative on the probability of exiting a crisis with an S-shaped profile. Second, other results lack statistical significance. Postcrisis liquidity has a mixed impact on economic activity in the empirical literature: it is found to be negative during the 2008 banking crisis by Ambrosius (2017), positive according to Park and Lee's (2003) study on the Asian currency crises in the 1990s, and unreliable by Bussière and Fratzscher (2006) amid a large set of developing countries over three decades.

Postcrisis inflation has a more ambiguous influence on the probability of recovery without rebound than does public spending. Actually, a surge in inflation deters an L-shaped profile of the output gap, whereas it makes a D-shaped profile more likely. This only partially confirms the idea that price and wage flexibility plays a decisive role in the adjustment process in times of crisis. As argued by Calvo et al. (2006), steep recoveries with depressed credit and investment may occur if price disinflation and lower real wages follow the recession trough, thus improving the competitiveness of domestic firms.

The postcrisis path in public expenditures sends a clearer message than the inflation path: higher government spending tends to lower the prospect of a fast recovery looking similar to a V or an S, while there is a higher risk for an L-type sluggish recession. This negative influence on the probability of bouncing back from the recession trough is consistent with Hong and Tornell (2005), but it is at odds with Ambrosius (2017). This negative impact on postcrisis output growth can be viewed as a lack of evidence of the expected Keynesian multiplier effect in crisis times. Given the empirical evidence provided by Romer and Romer (2018), economic resilience heavily depends on the fiscal and monetary policy space. Our result may reflect strong crowding-out mechanisms when debt leverage is already high, lagged effects of fiscal impulses, a lack of enough fiscal space or a combination.

*Regarding foreign relations*, changes in the first years of the crisis' aftermath have a more significant impact on the occurrence of the identified recovery scenarios than changes before the turmoil. A real currency appreciation subsequent to a debt default deters a sluggish L-shaped recession and helps lead to an economic rebound, regardless of the shape of output gap dynamics. This positive contribution conflicts with the same positive impact on a D-shaped profile that implies a prolonged downturn of domestic activity. The latter effect has already been noted in previous studies (Ambrosius, 2017; Bussière and Fratzscher, 2006; Park and Lee, 2003).

Though it appears slightly more convincing on statistical grounds in Table 2, trade openness has mixed effects on the way in which an economy recovers from a financial crash. In most cases, except banking crises, a rise in postcrisis trade intensity favors a bounce back of per capita output in the form of a V- or U-shaped profile. In addition, an elusive D-shaped recovery becomes less likely. This relationship disappeared in the post-1990 period. At the bottom right of Table 2, postcrisis current account disequilibria have no clear impact on the likelihood of the SOM profiles of recovery, given their opposite influence on strong S-shaped rebounds and mild U-shaped rebounds.

In summary, our results highlight the decisive role played by domestic policies designed either to promote fast economic recoveries or to prevent protracted recessions. In this regard, the postcrisis expansion of credit and, perhaps less clearly, a rise in liquidity would make economies more resilient to a financial crash. Once again, those policies should not turn procyclical, especially before such a collapse. In contrast, domestic fiscal policy based on government spending seems to be less powerful at deterring a persistent economic downturn during the crisis' aftermath, while a fiscal stimulus prior to the collapse would add to economic resilience. Next, the more open to foreign trade a country is after a financial crisis, the better it

withstands the resulting trough of activity. Finally, the economy seems to recover more swiftly when domestic currency value strengthens after a debt default or before a banking crisis.

As a final remark, one may also question whether the exchange rate regime has any influence on the recovery process. To verify this, we used Ilzetzi et al.'s (2019) classification of de facto currency regimes. We observe that an economic rebound is almost as frequent when the financial shock occurs under a peg as under a float (59% versus 66%, respectively, please see table A.7 in the supplementary material). Our finding challenges Tsangarides's (2012) view of the stronger resilience to the 2008 crisis of floaters than peggers: there is no convincing evidence of such an asymmetric effect here.

## 6. CONCLUSION

The purpose of our study was to go beyond the basic V-U-L classification of recovery profiles, utilizing data on past economic and financial crises for a large sample of countries and crises and over a long time span.

Using a dataset of 104 emerging and advanced countries covering 1973-2017 and implementing a self-organizing map, we drew a more complete typology of output recoveries by finding three additional patterns surrounding financial crises: S, D, and M. These new patterns of recovery appear, respectively, in 23%, 18% and 4% of the 276 financial crisis episodes under study. By comparison, the V, U, and L shapes account for 22%, 20% and 13% of the instances, respectively. This implies that at least two in five output recoveries are excluded from the standard classification that is prominent in the existing literature. However, recovery profiles are heterogeneous since they vary across countries and over time.

In a final step, we estimated a multinomial logit model to determine what kind of macroeconomic imbalances could predict the occurrence of the identified recovery paths. Credit

expansion, real currency appreciation, a GDP share of government spending going downward and, to a lesser extent, rising liquidity, resurgent inflation or greater trade openness in the postcrisis period make strong recoveries with V, S or U shape more likely. In contrast, these factors **tend to** favor elusive L or D recoveries if they occur before the financial turmoil. The exchange rate regime does not seem to shape the recovery process during a financial crisis.

These results call for a deeper investigation in two directions. First, output gap dynamics may only be one piece of the whole economic process. As suggested by previous studies, it would be interesting to focus on additional features of the recovery process. Financial crises in recent years have raised concerns about jobless and creditless recoveries (Reinhart and Rogoff, 2009; Kannan, 2012; Stock and Watson, 2012; Gali *et al.*, 2012). Because their policy implication are still debated (Ambrosius, 2017; Romer and Romer, 2018), it would call for further investigation. Second, an in-depth analysis of the recoveries from the European sovereign debt crises would be helpful, although it would call for post-2017 data over a broader range of potential trigger factors of the recovery shape.

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## Appendix

Table A. Estimated average marginal effects from multinomial logit models

By crisis type	V	S	U	L	D
<i>Precrisis indicators</i>					
Credit * Currency	0.0039 [0.56]	-0.0019 [0.70]	<b>-0.0089</b> [ <b>0.03</b> ]	<b>0.0065</b> [ <b>0.05</b> ]	0.0004 [0.92]
Credit * Banking	0.0025 [0.84]	-0.0038 [0.72]	<b>-0.0161</b> [ <b>0.05</b> ]	<b>0.0212</b> [ <b>0.05</b> ]	-0.0038 [0.63]
Liquidity * Banking	-0.0572 [0.14]	<b>0.0536</b> [ <b>0.03</b> ]	<b>-0.0373</b> [ <b>&lt;0.01</b> ]	<b>0.0438</b> [ <b>0.08</b> ]	-0.0030 [0.80]
Liquidity * Debt	<b>0.0537</b> [ <b>&lt;0.01</b> ]	<b>0.0335</b> [ <b>&lt;0.01</b> ]	0.0051 [0.42]	<b>-0.1190</b> [ <b>&lt;0.01</b> ]	<b>0.0267</b> [ <b>&lt;0.01</b> ]
Spending * Banking	<b>0.2108</b> [ <b>0.02</b> ]	<b>0.1889</b> [ <b>0.01</b> ]	0.0162 [0.78]	<b>-0.3899</b> [ <b>&lt;0.01</b> ]	-0.0261 [0.66]
Misalignment * Currency	<0.0001 [0.99]	-0.0001 [0.97]	-0.0032 [0.25]	<b>0.0052</b> [ <b>&lt;0.01</b> ]	-0.0020 [0.37]
Misalignment * Banking	0.0089 [0.23]	<b>0.0185</b> [ <b>&lt;0.01</b> ]	0.0003 [0.96]	<b>-0.0180</b> [ <b>&lt;0.01</b> ]	<b>-0.0098</b> [ <b>0.02</b> ]
Openness * Currency	<b>-0.0139</b> [ <b>0.01</b> ]	-0.0095 [0.24]	-0.0011 [0.87]	<b>0.0079</b> [ <b>0.05</b> ]	<b>-0.0166</b> [ <b>0.02</b> ]
<i>Postcrisis indicators</i>					
Credit * Banking	-0.0089 [0.56]	<b>0.0184</b> [ <b>0.10</b> ]	<b>0.0196</b> [ <b>0.01</b> ]	<b>-0.0285</b> [ <b>&lt;0.01</b> ]	-0.0006 [0.95]
Liquidity * Banking	0.0477 [0.12]	<b>-0.0750</b> [ <b>&lt;0.01</b> ]	<b>0.0317</b> [ <b>0.01</b> ]	-0.0114 [0.60]	0.0069 [0.54]
Inflation * Banking	0.0243 [0.17]	0.0217 [0.23]	<b>0.0191</b> [ <b>0.02</b> ]	<b>-0.0859</b> [ <b>0.05</b> ]	<b>0.0207</b> [ <b>0.09</b> ]
Spending & Debt	<b>-0.1323</b> [ <b>0.01</b> ]	<b>-0.2110</b> [ <b>&lt;0.01</b> ]	-0.0518 [0.14]	<b>0.4384</b> [ <b>&lt;0.01</b> ]	-0.0434 [0.31]
Misalignment * Debt	<b>0.0258</b> [ <b>0.01</b> ]	<b>0.0441</b> [ <b>&lt;0.01</b> ]	<b>0.0126</b> [ <b>0.02</b> ]	<b>-0.0985</b> [ <b>&lt;0.01</b> ]	<b>0.0159</b> [ <b>0.08</b> ]
Openness * Currency	<b>0.0159</b> [ <b>&lt;0.01</b> ]	0.0092 [0.24]	0.0028 [0.66]	-0.0071 [0.11]	<b>-0.0208</b> [ <b>0.02</b> ]
Openness * Debt	<b>-0.0172</b> [ <b>0.07</b> ]	0.0090 [0.29]	<b>0.0076</b> [ <b>0.07</b> ]	0.0050 [0.74]	-0.0044 [0.56]

By development level	V	S	U	L	D
<i>Precrisis indicators</i>					
Credit * Advanced	-0.0006 [0.73]	-0.0027 [0.24]	-0.0014 [0.61]	<b>0.0038</b> [< <b>0.01</b> ]	0.0009 [0.51]
Credit * Developing	0.0044 [0.23]	0.0023 [0.46]	<b>-0.0072</b> [< <b>0.01</b> ]	-0.0003 [0.92]	0.0007 [0.74]
Inflation * Developing	<b>0.0009</b> [ <b>0.10</b> ]	-0.0014 [0.19]	-0.0002 [0.70]	0.0001 [0.85]	<b>0.0006</b> [ <b>0.08</b> ]
<i>Postcrisis indicators</i>					
Credit * Developing	-0.0055 [0.21]	-0.0032 [0.33]	<b>0.0071</b> [< <b>0.01</b> ]	0.0008 [0.84]	0.0008 [0.75]
Liquidity * Developing	<b>0.0045</b> [ <b>0.05</b> ]	-0.0033 [0.21]	0.0002 [0.94]	0.0019 [0.34]	-0.0032 [0.16]
By period	V	S	U	L	D
<i>Precrisis indicators</i>					
Liquidity * Post90	-0.0010 [0.67]	-0.0036 [0.42]	0.0006 [0.77]	<b>0.0049</b> [ <b>0.01</b> ]	-0.0009 [0.82]
Inflation * Pre90	<b>0.0009</b> [ <b>0.06</b> ]	-0.0010 [0.28]	-0.0003 [0.49]	0.0002 [0.57]	0.0002 [0.61]
Openness * Pre90	<b>-0.0104</b> [ <b>0.10</b> ]	0.0072 [0.25]	-0.0099 [0.28]	0.0006 [0.93]	0.0125 [0.18]
Misalignment * Pre90	-0.0017 [0.70]	<b>0.0050</b> [ <b>0.10</b> ]	<b>-0.0089</b> [< <b>0.01</b> ]	<b>0.0051</b> [ <b>0.05</b> ]	0.0006 [0.76]
<i>Postcrisis indicators</i>					
Credit * Pre90	-0.0044 [0.11]	<b>-0.0037</b> [ <b>0.10</b> ]	0.0016 [0.35]	0.0008 [0.50]	<b>0.0057</b> [ <b>0.03</b> ]
Current account * Pre90	-0.0047 [0.66]	<b>0.0136</b> [ <b>0.09</b> ]	<b>-0.0175</b> [< <b>0.01</b> ]	0.0020 [0.80]	0.0066 [0.35]
Openness * Pre90	<b>0.0113</b> [ <b>0.09</b> ]	-0.0046 [0.51]	0.0096 [0.28]	0.0033 [0.67]	<b>-0.0196</b> [ <b>0.08</b> ]

Note: The point estimates of the marginal effects are reported with their corresponding p-values in brackets based on the z-statistic. Bold cases signal statistical significance at the 10 percent level or less.