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The Ugly and the Bad: Banking and Housing Crises Strangle Output Permanently, Ordinary Recessions Do Not

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Abstract:
This paper provides empirical evidence suggesting that in industrial countries, recessions that are associated with either banking crises or housing crises dampen output far more than ordinary recessions. Using a parametric panel framework that allows for a bounceback of the level of output in the course of the cyclical recovery, we find that ordinary recessions are followed by strong recoveries that make up for almost all of the preceding shortfall in output. This bounceback tends to be significantly smaller following recessions associated with banking crises or housing crises. Our paper corroborates the practice of focusing exclusively on severe crises used in an emerging macroeconomic literature and integrates it with the earlier literature on recessions and recoveries.

Keywords: Business cycle; banking crisis; housing crisis; panel data; asymmetry; persistence

JEL classification: E32, C33

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1 Introduction

The Great Recession of 2008/2009 has renewed interest in the analysis of business cycle fluctuations. In particular, the analysis of the shape of recessions and subsequent recoveries, leading to the question whether recessions have permanent effects, has been received greater attention. While there has been some consensus that recessions in general are usually followed by particularly strong recoveries and thus do not have permanent effects on output, a growing literature concludes that this is not the case with recessions associated with severe economic crises. On the contrary such recessions depress output permanently.

This result was already documented by Kaminsky and Reinhart (1999), who found, based on a panel of countries, that recessions associated with financial crises systematically turn out to have particularly severe long-lasting effects. Similarly Cerra and Saxena (2005) showed that six Asian countries suffered permanent output losses from the Asian crisis beginning in 1997. However, despite case studies concerning the financially driven decade-long slump in Japan and the banking crises in the Nordic countries in the 1990s, it was the Great Recession of 2008/2009 that brought the analysis of recessions back into the focus of macroeconomic research and subsequently led to the hypothesis that not all recessions are alike, even in industrialized countries.

A number of recent studies on recessions associated with severe crises and the following recoveries, indeed, have come to this assessment. Starting from the proposition that severe crises break away from the ordinary, linear course of events, these studies abandon linear empirical methods of analysis. In an effort to separate the extraordinary courses of events from the ordinary courses of events (Cecchetti et al. 2009), they typically start by identifying periods of severe crises, which are usually banking, financial, housing, currency, or political crises. They proceed by determining similarities and typical patterns between these periods. Sparked partly by Reinhart's and Rogoff's (2008) attempt to draw lessons for the course of the US financial crises from historical episodes with financial crises in other countries across the last centuries, a number of recent studies have investigated recessions associated with severe crises and their aftermath (Reinhart and Rogoff 2009a and 2009b, Cecchetti et al. 2009, Haugh et al. 2009). The general finding of these studies is that severe crises usually trigger deep and long-lasting recessions. While this literature only dealt indirectly with long-term effects, such effects were explicitly investigated in a series of papers (Boyd et al. 2005, Cerra and Saxena 2008, Furceri and Mourougane 2009, IMF 2009b). They find that severe crises, on average, do indeed dampen the level of output permanently.

While this finding is in line with the earlier literature initiated by the work of Nelson and Plosser (1982), Campbell and Mankiw (1987), and Hamilton (1989), which finds that recessions have large permanent effects on output, it challenges the consensus of the more recent empirical business cycle literature. The more recent literature finds that recessions in the United States are followed by particularly strong recoveries and thus have only small or even no permanent effects on the level of output. Beaudry and Koop (1993) showed empirically for the United States that once nonlinear effects are allowed for, evidence can be found that recessions are followed by a bounceback of GDP—or alternatively by quarters with particular high growth rates of GDP—that quickly brings GDP back to its pre-recession level and usually does not dampen output permanently. The finding that recoveries following recessions are particularly strong and exhibit on average significantly higher growth rates of GDP than expansions was confirmed by Sichel (1994) and Kim et al. (2005), among others. While there is strong evidence for this finding in the United States, the evidence for other countries is mixed. Balke and Wynne (1996) find evidence for strong recoveries following recessions for the G-7 countries as an aggregate. However, Bradley and Jansen (1997), who applied the approach of Beaudry and Koop (1993) to the G-7 countries, find evidence for strong recoveries only for the United States, Italy and to a lesser degree for Germany. Kim et al. (2005) find the bounceback effect to be much smaller for several other industrial countries.

In this study, we integrate the empirical business cycle literature with the literature on recessions associated with severe crises. In particular, we explicitly evaluate the strength of recoveries following recessions associated with severe crises compared to ordinary recessions that are not associated with severe crises. This enables us to draw conclusions about the long-term effects of these both kinds of recessions in a second step. To differentiate between ordinary recessions and recessions associated with severe crises, we define banking crises and housing crises as severe crises and all recessions that were not associated with these crises as ordinary recessions. While banking crises have been frequently analyzed in the literature on severe crises, housing crises have been much less frequently analyzed, and not at all in the literature concerning the long-run effects of severe crises. However, housing crises have been proved to have severe consequences when they are associated with recessions (Claessens et al. 2009). We do not include currency crises, equity price busts, or political crises in our sample of severe crises, as the assessment of the literature seems to be that these types of crises have relatively mild consequences, on average, compared to banking crises and housing crises (see, e.g., Cerra and Saxena 2008, Claessens et al. 2009, Reinhart and Rogoff 2009b). Our study follows Claessens et al. (2009) and IMF (2009a) and exclusively focuses on recessions and recoveries in industrial countries. We find that ordinary recessions and recessions associated with severe crises differ sharply in terms of the subsequent recovery. While ordinary recessions are usually followed by strong recoveries, recoveries following recessions associated with severe crises are not particularly strong. Consequently, the latter lead to large permanent output losses. Even though recoveries following ordinary recessions are stronger the deeper the recession was, we also find that ordinary recessions can lead to permanent output losses. However, these losses turn out to be of a much smaller magnitude than in the case of recessions associated with severe crises. In a series of tests, we prove our main results to be robust with respect to several modifications of our baseline model. Overall, we show that the findings in the literature that indicate that severe crises have large permanent effects and the findings in the literature that indicate that recessions are followed by strong recoveries can be reconciled by differentiating between ordinary recessions and recessions associated with severe economic crises.

The structure of the remaining paper is as follows. Section 2 presents our estimation strategy. Section 3 describes the data set. Section 4 presents our estimation results and illustrates them graphically. Section 5 reports the results of several robustness checks and Section 6 summarizes the results and concludes.

2 Methodology

As is common in the literature on the long-run effects of severe crises, we rely on an autoregressive panel model of GDP growth. To account for nonlinear dynamics following recessions—independently whether they are ordinary or associated with severe crises—we augment the model by the current-depth of recessions (cdr) term introduced by Beaudry and Koop (1993). The cdr term is defined as the deviation of current GDP from its former maximum:

$$cdr_t = \max(y_{t-j})_{j\geq 0} - y_t, \tag{2}$$

where $\max(y_{t-j})_{j\geq 0}$ refers to the peak of log real GDP until year *t*. When real GDP falls below its former maximum or alternatively when real GDP growth is negative, the cdr term becomes positive; otherwise, it is equal to zero. Therefore, during recessions, cdr_t usually becomes positive until the output loss is regained. During expansions cdr_t is usually equal to zero.

By using the cdr term, we deviate from the existing literature on severe crises initiated by Cerra and Saxena (2008) and largely inspired by Romer and Romer (1989), which estimates long-run effects by means of dummy variables that take the value one during phases of severe crises. Thereby, we focus exclusively on the recovery phase and do not try to estimate the average depth of severe crises in terms of GDP by means of dummy variables, but rather interpret economic crises as shocks that can have very different sizes. Moreover, the approach of Beaudry and Koop (1993) is more flexible than using dummy variables, since it allows the recovery to evolve more strongly the deeper the recession was. Finally, we do not have to predetermine how many lags of the dummy variable to include to estimate the strength of the recovery phase, since the length of the recovery phase as investigated here is determined automatically and it ends when GDP reaches its former maximum.

For a panel dataset with *i* countries and *t* years of observation, the core model is given by

$$\Phi(L)\Delta y_{t,i} = \alpha_i + [\Omega(L) - 1]cdr_{t,i} + \varepsilon_{t,i}, \tag{1}$$

where Δy_t denotes real GDP growth in year *t*, the lag polynomial of Φ measures the autoregressive structure of GDP growth, and α_i accounts for country-specific fixed effects. The lag polynomial of Ω measures the impact of the cdr term. If the sum of all coefficients is positive, economic growth will on average be faster during recoveries than during expansions when the cdr term is zero.

To assess the impact of banking crises and housing crises on recoveries, we define interaction terms for banking crises, cdr^{bc}, and for housing crises, cdr^{hc}, which take on the value of the cdr term if a recession was accompanied by a banking crisis or a housing crisis and are zero otherwise. We estimate the effects of severe crises by including the interaction terms, $cdr_{t,i}^{bc}$, and, $cdr_{t,i}^{hc}$, in equation (2). The panel model then is given as

$$\Phi(L)\Delta y_{t,i} = \alpha_i + [\Omega(L)-1]cdr_{t,i} + [\Theta(L)-1]cdr_{t,i}^{bc} + [\Pi(L)-1]cdr_{t,i}^{hc} + \varepsilon_{t,i}\,, \tag{3}$$

where the lag polynomial of Θ and Π measures the impact of severe crises on the strength of the recovery. If the sum of all coefficients for the respective interaction terms is negative, the hypothesis that recoveries following recessions that were associated with severe crises are weaker will be supported.

3 Data

The panel consists of 16 OECD countries, namely Australia, Belgium, Canada, Denmark, Finland, France, Germany, Great Britain, Italy, Japan, the Netherlands, Norway, Spain, Sweden, Switzerland, and the United States. We focus exclusively on industrial countries even though the majority of severe economic crises, at least when we think about financial crises, did not occur in these countries but rather in emerging or developing countries. Emerging and developing countries, thus, provide a wealth of empirical evidence regarding the effects of severe crises. However, exploiting this evidence may come at the cost of blurring or biasing estimation results by mixing data from countries with sharply differing market structures, institutions, risk perceptions, etc. In contrast to a number of recent studies, we therefore refrain from adding data from nonindustrialized countries to our sample. The time span covered is 1970 to 2006, and the indicator we use to represent economic activity is annual real GDP as taken from the OECD's Economic Outlook (2009).

In the literature, housing crises are usually identified by real house price developments. They are indicated either by phases of sharply falling prices (Ahearne et al. 2005, Jannsen (2010), or IMF 2003) or by periods in which prices are far below their long-run trend (Detkens and Smets 2004 or Bordo and Jeanne 2002). We rely on the former identification scheme. Building on Ahearne et al. (2005), Jannsen (2010) and IMF (2003), we define a housing crisis as a period when real house prices fall by 7.5 percent or more over a period of at least four years. The starting year of the crisis is defined by the peak of real house prices within a rolling nine-year window.[1] Data on real house prices come from the Bank of International Settlements. With respect to banking crises, historical episodes with bank runs or closures of relevant financial institutions are usually used for identification. We rely on the chronology of banking crises of Reinhard and Rogoff (2009a), which in turn is based on chronologies from other sources. Throughout this paper, we define a recession as a period of negative GDP growth, this seems appropriate for industrial countries and annual data. According to this criterion, we have 41 recessions in our sample. In addition we have 29 housing crises and 16 banking crises in our sample.

The data we use for estimation is presented in figures 1 and 2. For each country in our sample, we show log real GDP and the cdr term. Since we identify 41 recessions in the sample, we can also observe 41 phases with positive cdr terms. We also indicate (with a vertical line) the years that mark the start of a banking crisis or a housing crisis. Note that several of the banking crises and housing crises were followed by recessions, as is indicated by the positive values of cdr to the right of a vertical line.

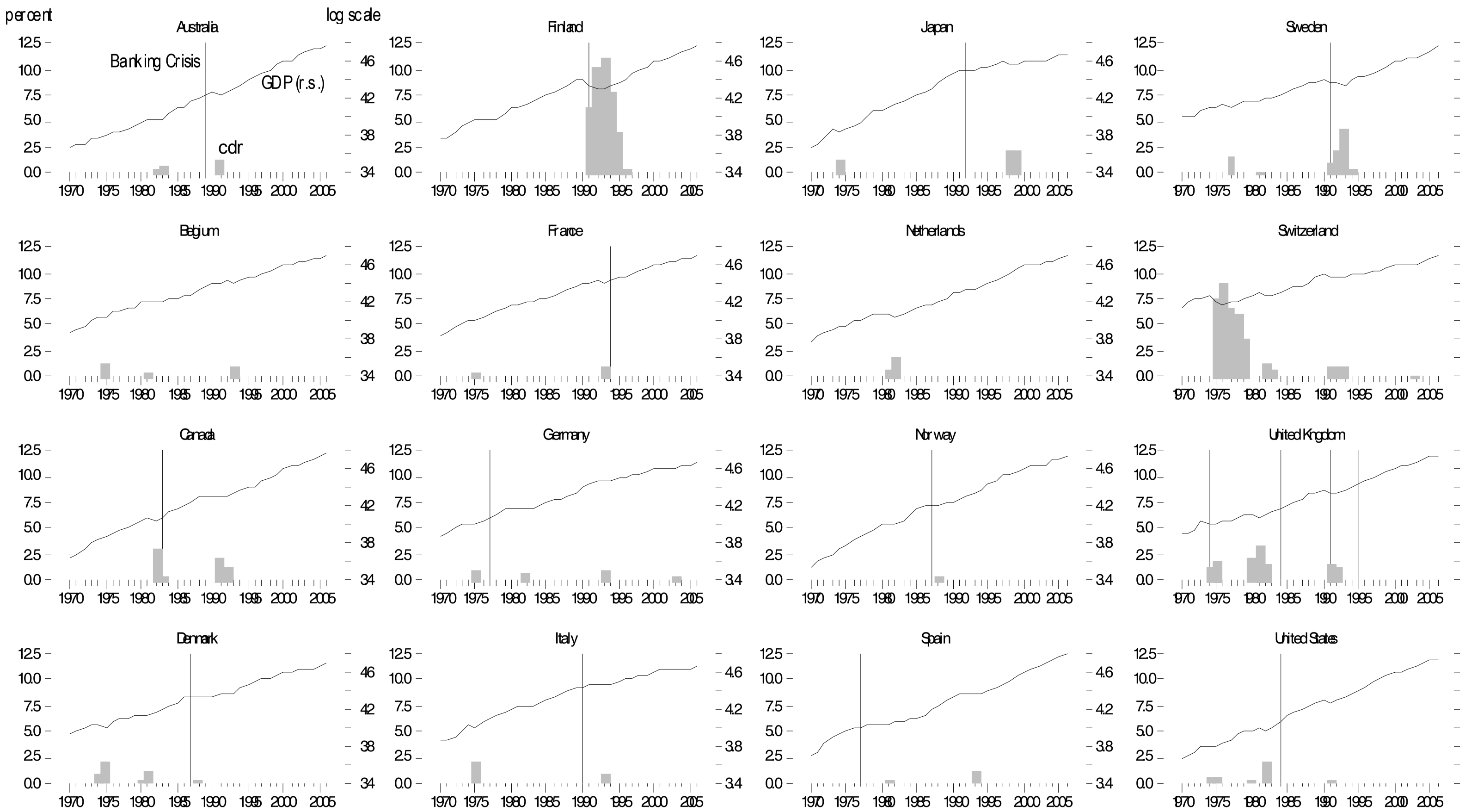
As we are interested in the existence and the strength of bounceback effects both following ordinary recessions and recessions associated with severe crises, we have to differentiate between these two types of recessions. Therefore, we consider a recession to be associated with a banking crisis or a housing crisis if it begins within a period of two years after the crisis began.[2] It turns out that eight out of the 16 banking crises and 21 out of the 29 housing crises were followed by a recession. Furthermore, seven out of eight banking crises were accompanied by a housing crisis.

The only banking crisis not accompanied by a housing crisis, according to our criteria, took place in Australia in 1989. Since real house prices in this period declined by 7.2 percent, which is considerably close to our criterion of 7.5 percent, two types of crises seem to be reflected in our sample: housing crises that were accompanied by banking crises and (pure) housing crises. In the following, the expression banking crisis denotes a banking crisis accompanied by a housing crisis, if not otherwise mentioned.

[1] The results are considerably stable with respect to the length of the rolling window and the price decline required. Below, we provide robustness checks of our results when using various dating schemes for housing crises.

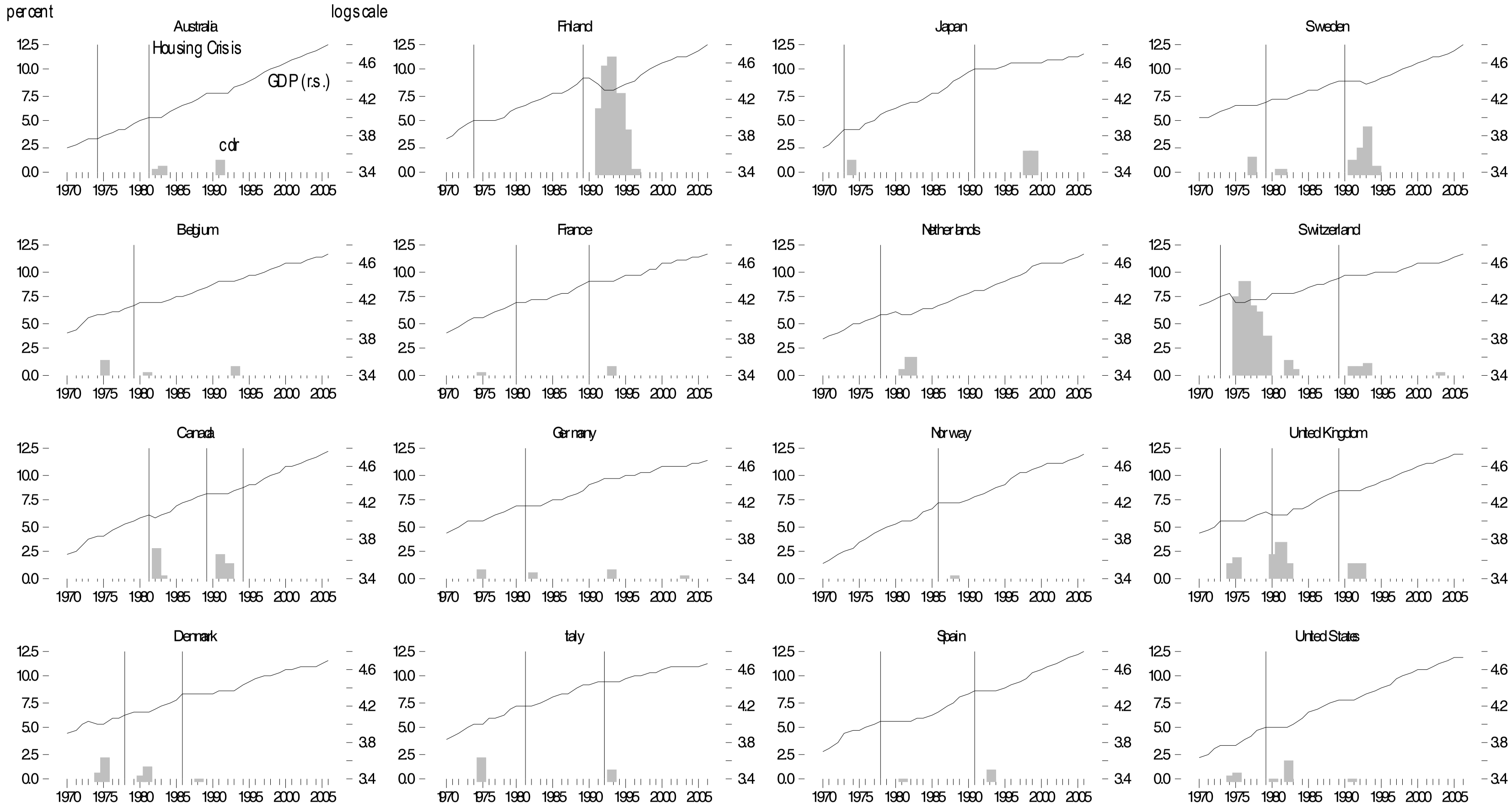
[2] We test the robustness of the results with regard to this definition in Section 5.

Figure 1:
GDP, Indicator of Current Depth of Recession and Banking Crises



Notes: Vertical lines indicate the year in which a banking crisis began.

Figure 2:
GDP, Indicator of Current Depth of Recession and Housing Crises



Notes: Vertical lines indicate the year in which a housing crisis began.

4 Results

We first discuss the estimation results. After that we proceed by assessing the dynamic effects of recessions and severe crises graphically using impulse response functions.

4.1 Estimation Results

We adopt an AR(2) process as our baseline model. Preliminary tests show that the first two lags of GDP growth are highly significant in virtually any specification, while higher lags are usually not. In the first specification, we estimate model (2) by allowing for one lag of the cdr term. We find a slightly positive parameter value, which is not significantly different from zero (Table 1). Thus, there seems to be no evidence in the data indicating that recessions in general are followed by particularly strong recoveries. Including the second lag of the cdr term does not alter this result (specification II).

Table 1:
Estimation Results

	I	II	III	IV
$\Delta y_{t-1,i}$	0.43 (9.7)	0.44 (8.6)	0.49 (10.8)	0.50 (9.8)
$\Delta y_{t-2,i}$	–0.16 (3.6)	–0.16 (3.5)	–0.17 (4.1)	–0.21 (4.3)
$\Delta cdr_{t-1,i}$	0.11 (1.4)	0.14 (1.1)	1.39 (4.7)	1.48 (4.9)
$\Delta cdr_{t-2,i}$		–0.04 (0.3)		–0.52 (1.7)
$\Delta cdr^{bc}_{t-1,i}$			–1.42 (4.7)	–1.76 (5.4)
$\Delta cdr^{bc}_{t-2,i}$				0.82 (2.4)
$\Delta cdr^{hc}_{t-1,i}$			–1.18 (3.9)	–1.17 (3.6)
$\Delta cdr^{hc}_{t-2,i}$				0.36 (1.1)
AIC	2163.0	2164.8	2143.9	2142.2
F-Test			0.79 / 0.08	0.92 / 0.24

Notes: t-values in parenthesis. First values of F-tests indicate the *p*-value of the hypothesis that the parameter values for the *cdr* terms and the banking crises interaction terms are identical. Second values refer to the housing crises interaction term *cdr* terms.

In specification III, we allow for heterogeneity among recessions and augment the first specification by the first lag of the interaction term for banking crises and housing crises. The parameter value of the cdr term, as well as the t-value, increases considerably. After an ordinary recession, GDP growth gets an extra boost, on average, of 139 percent of the overall output loss as long as GDP is below its former maximum level. Hence, in the absence of further negative shocks, GDP generally reaches its old level already after one year. When the recession was caused by a banking crisis, this effect vanishes completely and the parameter value of the interaction term becomes –1.42. When the recession was caused by a housing crisis, the parameter value is –1.18, which suggests that some bounceback effect occurs, but it is considerably weaker. The F-test confirms the hypothesis that the parameter values of cdr and the interaction term for banking crises are of equal size (p-value: 0.79). For housing crises, the evidence is somewhat weaker. The corresponding p-value is 0.08. Thus, when a recession is accompanied by one of the two types of crises, the bounceback effect observed following ordinary recessions is almost or even completely offset.

In specification IV, we augment the model by a second lag for each cdr term. It turns out that the business cycle effects in the first year following a recession are even more pronounced than in specification III. For the second year, the parameter values have the opposite sign, indicating some repercussion effect for each type of recession, with or without a severe crisis. Overall, the effects are qualitatively similar to those in specification III. Taken together, the parameter values of the first two lags of the cdr term are not significantly different from one, indicating that the output loss during an ordinary recession is completely offset in the following recovery. This is not the case when the recession was associated with a banking crisis (p-value: 0.92) or a housing crisis (p-value: 0.24).

The Akaike Information Criteria favors the specifications that include the interaction terms for banking crises and housing crises and exhibit the lowest value for the specification IV, which includes two lags of each variable. A likelihood-ratio test indicates that specification IV fits the data better than specification I (p-value: 0.00), specification II (p-value: 0.00), and specification III (p-value: 0.05).

4.2 Impulse Response Analysis

We graphically illustrate the short- and long-run effects of recessions on GDP implied by our estimates. For linear models, it is sufficient to compute a single, representative impulse response function. Unfortunately, this is not true for nonlinear models, where the shape of the impulse response function may depend on the sign and the size of the shock. Since the models estimated above are nonlinear under negative GDP shocks and we are interested only in these kind of shocks, we compute impulse response functions for negative shocks of various sizes. We begin with a size of minus one percent and proceed with integer steps up to minus nine percent.

To account for negative shocks that may hit the economy after the shock in the initial period, we employ impulse response functions in line with Potter (2000). First, we derive the steady state GDP growth of an average industrial economy in our panel. Therefore, we calculate the unconditional mean of GDP growth in our sample, which is 2.6 percent.

Consequently, only negative shocks of more than minus 2.6 percent lead to negative GDP growth rates in the initial period and thus to nonlinear dynamics. Based on the steady state, we calculate a baseline forecast in the absence of any shock in the initial period and a forecast given a negative shock. For both forecasts, we allow the economy to be hit by further shocks beginning from the second period onwards. These shocks are drawn randomly from a Gaussian distribution with zero mean and the estimated standard deviation over all residuals of the model, which is 1.7. Finally, the difference between the baseline forecast and the forecast given a shock in the initial period is calculated for a horizon of 10 periods. This process is repeated 1,000 times. The average of the differences at each point in time yields the impulse response function.

For the calculations of the impulse response functions, we employ specification IV because the pairwise LR-tests favor this as the best performing model. When simulations are run for an ordinary recession, the interaction terms between the cdr term and the severe crisis dummies are supposed to be zero and we remain with the model

$$\Delta y_t = 1.7 + 0.50\Delta y_{t-1} - 0.21\Delta y_{t-2} + 1.48 cdr_{t-1} - 0.52 cdr_{t-2} + u_t \,, \tag{4}$$

where the constant 1.7 equals the average over all country-specific fixed effects.

When the recession is associated with a banking crisis or housing crisis, the interaction terms are at work. We use the Wald test to test the hypothesis that the parameter values of the cdr term and each of the interaction terms taken together are zero and find that the hypothesis is not rejected. Therefore, we simplify the model by excluding the cdr terms until the initial recession is over. Thereby we have the same model for both, recessions associated with banking crises and recessions associated with housing crises.[3] When the economy is hit by negative shocks later on, cdr dynamics are allowed for again. Thus, impulse responses are calculated using simulations from the following equation:

$$\Delta y_t = \begin{cases} 1.7 + 0.50\Delta y_{t-1} - 0.21\Delta y_{t-2} + u_t \text{, until } cdr_t \text{ becomes zero for the first time} \\ 1.7 + 0.50\Delta y_{t-1} - 0.21\Delta y_{t-2} + 1.48 cdr_{t-1} - 0.52 cdr_{t-2} + u_t \text{, else} \end{cases} \tag{5}$$

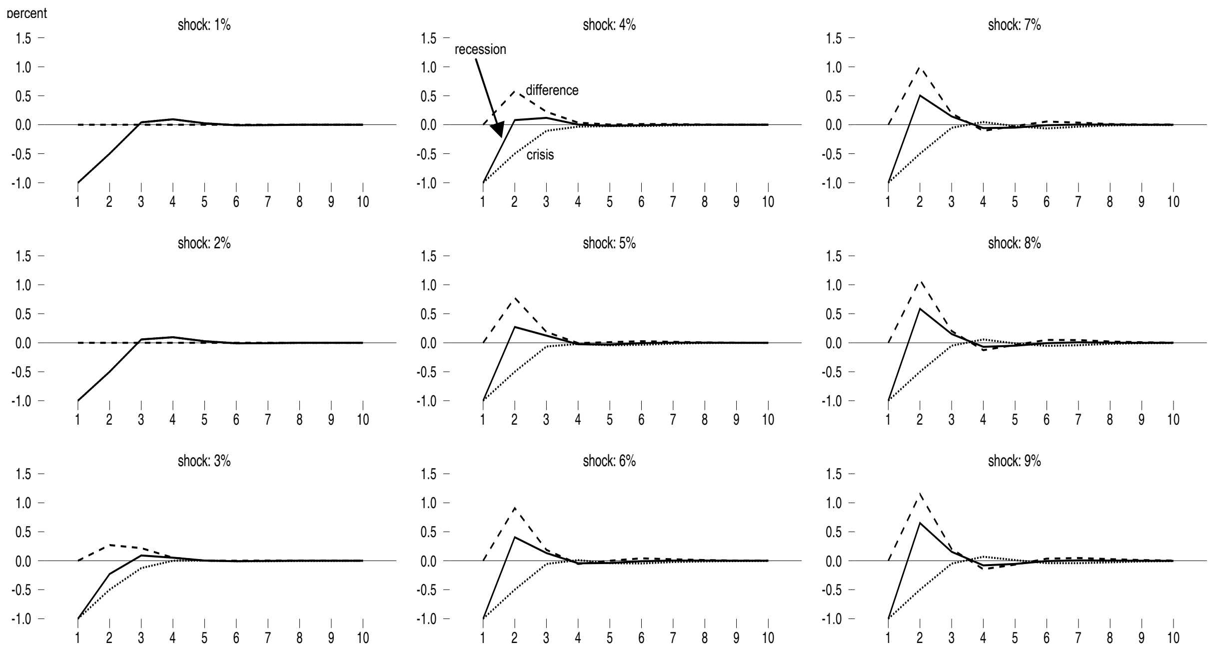
Figure 3 compares the resulting impulse response functions for GDP growth following an ordinary recession and a recession associated with a severe crisis. All impulse response functions are normalized by the absolute value of the initial shock. As mentioned before, the impulse response functions are identical for the first two shocks because GDP growth does not become negative in this case. For shocks stronger than minus two percent, GDP growth

[3] The alternative is to include either the interaction term for banking crises or for housing crises in the model. Both alternative specifications lead to virtually the same results as with model (5).

following ordinary recessions is considerably higher than following recessions associated with severe crisis in the first two years of the recovery. Furthermore, ordinary recessions lead to higher growth rates than in the baseline during the recovery and thus to a bounceback of GDP. By contrast, GDP growth in the first two years following a recession associated with a severe crisis is lower than in the baseline. Due to nonlinearity, the bounceback effect following an ordinary recession is (relatively) more pronounced the stronger the initial shock.

In terms of the level of GDP, the economy catches up to the baseline rapidly in the case of an ordinary recession (Figure 4). However, as the confidence interval indicates, GDP is still likely to remain permanently below the baseline for all considered shocks.[4] Therefore, recessions have small but permanent effects on economic activity, even if a bounceback occurs. When a recession is associated with a severe crisis, GDP permanently stays below the baseline, at roughly 1.5 times the size of the shock. Additionally, GDP in this case is always significantly lower than in the case of an ordinary recession.

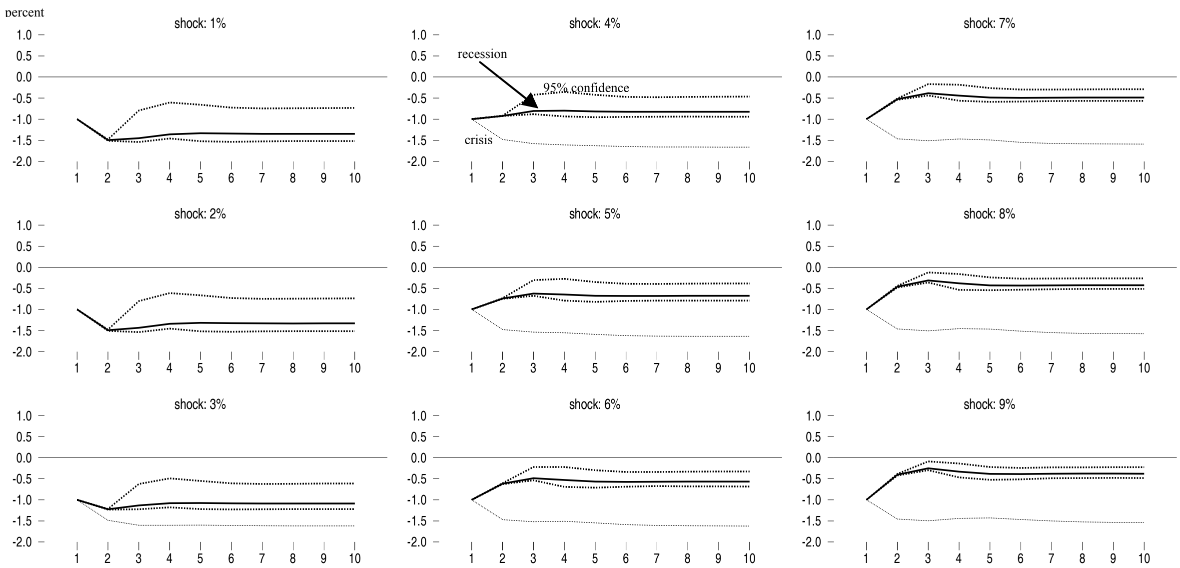
Figure 3:
GDP Growth: Deviation from Baseline



Notes: Impulse response functions are calculated as the difference to the baseline and are calculated as the mean over 1,000 bootstrap simulations. Impulse response functions are scaled by the absolute value of the respective shock.

4 Beginning with a shock of roughly minus 15 percent, the long-run GDP level is not significantly below the baseline anymore. However, shocks of this size are very unlikely to be observed in industrial countries, in particular when the recession is not associated with a banking or housing crisis.

Figure 4:
GDP Level: Deviation from Baseline

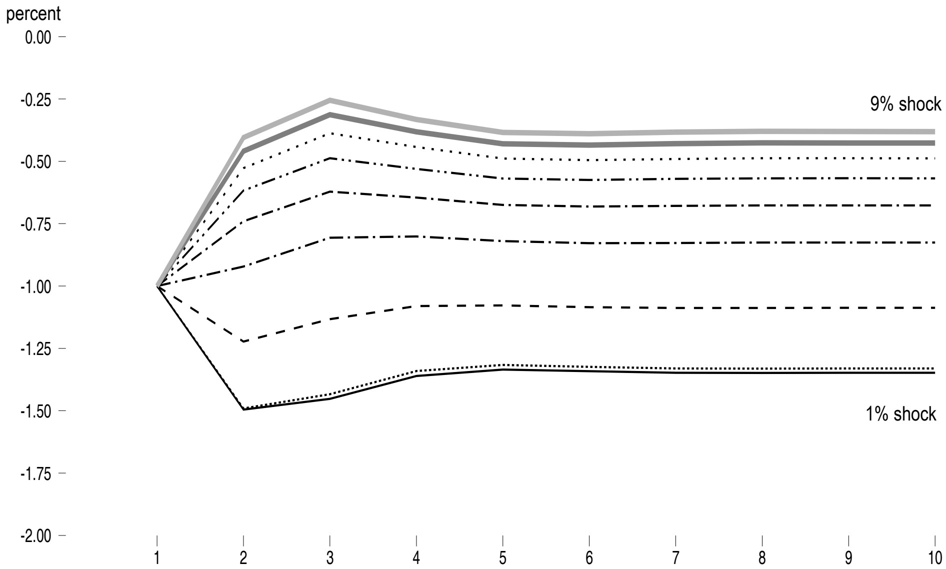


Notes: Impulse response functions are calculated as the difference to the baseline and are calculated as the mean over 1,000 bootstrap simulations. Impulse response functions are scaled by the absolute value of the respective shock.

Figure 5 compares the relative strength of the bounceback effect following ordinary recessions in terms of level of GDP for different sizes of the initial shock. It turns out that the bounceback effect becomes relatively stronger with increasing size of the negative shock. Beginning with an initial negative shock of 4 percent, the permanent effect of a recession is lower than the initial size of the shock. However, the additional "strength" of the bounceback effect diminishes with increasing size of the shock.

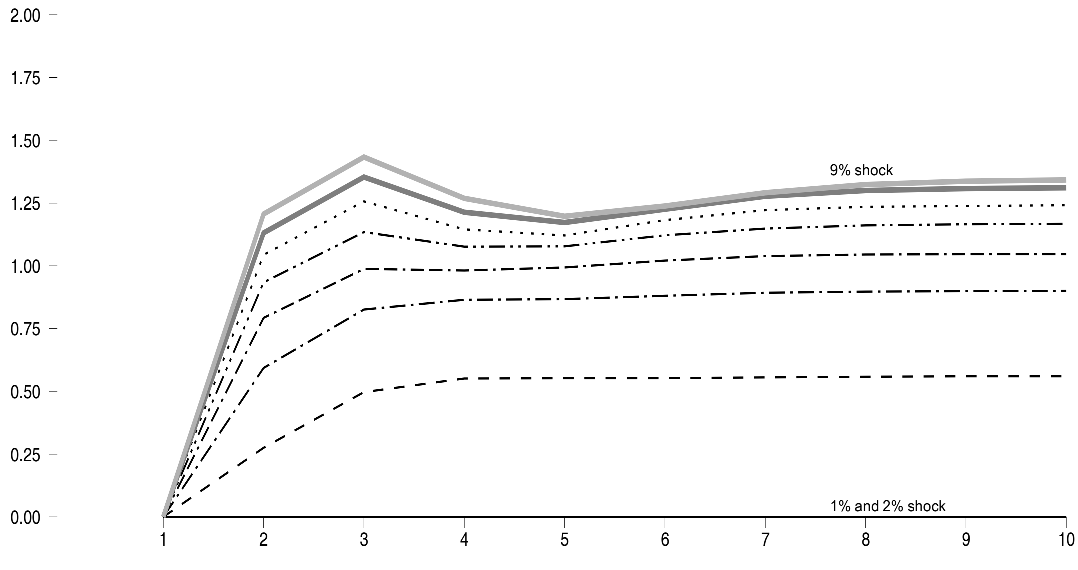
Similar patterns can be observed when comparing the recovery following an ordinary recession and a recession associated with a severe crisis (Figure 6). The recovery following an ordinary recession becomes relatively stronger with increasing size of the initial shock. Again, this effect diminishes with increasing size of the shock.

Figure 5:
GDP Level: Deviation from Baseline in the Case of a Recession



Notes: Impulse response functions are calculated as the difference to the baseline and are calculated as the mean over 1,000 bootstrap simulations. Impulse response functions are scaled by the absolute value of the respective shock.

Figure 6:
GDP Level: Deviation between an Ordinary Recession and a Recession associated with a Severe Crisis



Notes: Impulse response functions are calculated as the difference to the baseline and are calculated as the mean over 1,000 bootstrap simulations. Impulse response functions are scaled by the absolute value of the respective shock.

5 Robustness Checks

To assess the stability of our results, we perform a number of robustness checks. First, we check whether our results are driven by the influence of some outliers in our sample of recessions. Then, we check whether our results are robust when using alternative criteria for identifying housing crises. Therefore, we first perform a grid search to determine the criteria for identifying a housing crisis endogenously and second, we use alternative identification criteria for housing crises taken from the literature. In addition, we address the importance of non modelled or "global" developments for our estimation results, and we check whether the results are valid when we use quarterly data. Furthermore, we discuss the possible endogeneity of housing crises. Finally, we check whether our results are robust, when we allow for more heterogeneity between countries. Overall, our main results remain valid for all the robustness checks.

Regarding the issue of outliers, a comparison of the recessions in our sample reveals that the recession in Finland beginning in 1991 and the recession in Switzerland beginning in 1975 were, indeed, exceptionally strong in terms of length and output loss. Since both recessions were preceded by a housing crisis, and the recession in Finland was additionally associated with a banking crisis, one might argue that our results are driven mainly by these two cases. To check the robustness of our results with respect to these two potential outliers, we included dummy variables for each of the two recessions in the model. The estimation results show that the parameter value of the cdr term and the t-value increase considerably (Table 2). Thus, the results of our baseline specifications (specifications I and II) seem to be driven to some extent by these two recessions. Therefore, a bounceback effect following recessions is usually observable in the data, even when we do not account for further banking crises or housing crises in our sample. The results of the augmented specifications (III and IV), where we do account for the other crises, are still valid. The bounceback effect following an ordinary recession is much stronger than on average. When the recession is associated with a severe crisis, the bounceback is much weaker or even vanishes completely.

Table 2:
Estimation Results for Outlier Analysis

	I	II	III	IV
$\Delta y_{t-1,i}$	0.50 (10.5)	0.51 (9.6)	0.52 (10.8)	0.52 (9.9)
$\Delta y_{t-2,i}$	–0.16 (3.8)	–0.20 (3.8)	–0.17 (4.0)	–0.20 (4.0)
$\Delta cdr_{t-1,i}$	0.82 (4.1)	0.88 (4.0)	1.47 (4.9)	1.53 (5.0)
$\Delta cdr_{t-2,i}$		–0.26 (1.2)		–0.53 (1.7)
$\Delta cdr_{t-1,i}^{bc}$			–1.18 (2.9)	–1.35 (3.1)
$\Delta cdr_{t-2,i}^{bc}$				0.66 (1.5)
$\Delta cdr_{t-1,i}^{hc}$			–0.81 (2.1)	–0.90 (2.2)
$\Delta cdr_{t-2,i}^{hc}$				0.46 (1.1)
dum_{t-1}^{FN1991}	–0.86 (4.1)	–1.3 (4.7)	–0.32 (1.0)	–0.56 (1.5)
dum_{t-2}^{FN1991}				0.24 (0.6)
dum_{t-1}^{SW1975}	–0.66 (3.0)	–0.62 (2.3)	–0.49 (1.5)	–0.37 (1.0)
dum_{t-2}^{SW1975}				–0.09 (0.2)
AIC	2150.2	2149.7	2144.7	2146.3
F-Test			0.36 / 0.04	0.37 / 0.12

Notes: t-values in parenthesis. First values of F-tests indicate the *p*-value of the hypothesis that the parameter values for the *cdr* terms and the banking crises interaction terms are identical. Second values refer to the housing crises interaction term *cdr* terms. dum^{FN1991} is a dummy variable for the starting year of the recession in Finland (1991). dum^{SW1975} is a dummy variable for the starting year of the recession in Switzerland (1975).

Further, we check whether our results are driven by the ad hoc method we use to identify housing crises. Therefore, first we vary the minimum house price decline required to identify a housing crisis as well as the rolling window of years that we use to identify a housing crisis to check whether other criteria provide a better model fit than our ad hoc criteria of a minimum price decline of 7.5 percent after a price peak within a rolling window of nine years. Running a grid search over different criteria, we find very similar results compared to our ad-hoc criteria to be optimal. Second, we apply two alternative but related identification criteria proposed in the literature. When we follow the criterion of Ahearne et al. (2005), namely that all periods following price peaks within a rolling window of nine years are presumed to be housing crises, the results virtually do not change. Alternatively, when we follow the criterion of the IMF (2003), namely that only those 25 percent of price peaks followed by the strongest price declines qualify as housing crises, the bounceback effect following ordinary recessions is estimated to be considerably smaller. However, there are two reasons, why this robustness check should not be considered decisive. First, the AIC of the model when using the IMF identification criteria of housing crises is rather low. This indicates that too many "non-ordinary" recessions switched sides. Second, the moderate bounceback effect is largely driven by the fact that the housing crisis in Switzerland that began in 1975 cannot be considered one of the most severe housing crises in terms of price declines and therefore is considered to be an ordinary recession. Once we control for this recession via a dummy variable, the bounceback effect is estimated to be considerably higher again. Overall, our results are in general robust with respect to the method used to identify housing crises.[5]

Furthermore, to verify that our results are not driven by non modelled or "global" developments, we re-estimate the baseline specification using methods that allow such developments to be controlled for in different ways. Specifically, we use the following methods: estimation of the panel model with time fixed effects, incorporation of a variable that controls for global GDP growth, and estimation of a system of country-specific equations by seemingly unrelated equations. For all three methods the results are similar. The bounceback effect following an ordinary recession is estimated to be somewhat lower, but close to 100 percent of the former output loss. When the recession is associated with a severe crisis, this effect is offset to a large degree or even completely. Therefore, the baseline results are qualitatively robust to the consideration of global business cycle dynamics.[6]

An important issue when interpreting our results is whether the severe economic crises we use can be interpreted as exogenous events or whether they were triggered at least to some extent by business cycle developments. To address this issue, we concentrate exclusively on housing crises, since nearly all the banking crises in our sample that were associated with a recession were associated with a housing crisis as well. Furthermore, our identification criteria for housing crises reach four years into the future, which increases the risk that an identified housing crisis could have been triggered by a recession. We test for the robustness of the exogeneity assumption for housing crises by modifying the identification criteria of housing crises. In a first step, we require a minimum distance between the start of the housing crisis and the following recession to consider them to be associated and thereby reduce the probability that a housing crisis is triggered by an associated recession. Even if we require a minimum distance of two years between a housing crises and a recession, our results are qualitatively identical.[7] In a second step, we apply alternative identification criteria that the

[5] The detailed robustness check regarding the identification of housing crises can be found in Appendix A.

[6] The detailed robustness check regarding the influence of non modelled or "global" developments can be found in Appendix B.

[7] In contrast, to require a minimum distance between housing crises and associated recessions to ensure that housing crises are exogeneous in our model one could require a maximum distance as well to ensure that severe economic crises are related to the following recessions. According to our baseline specification, a recession is classified as being associated with a severe crisis when it occurs within two years after the beginning of the crisis. To assess the robustness of our results with respect to this classification, we check the impact of alternative definitions on the estimation results. We re-estimate the model both under the assumption that the recession occurs within one year following the outbreak of a crisis and under the assumption that it occurs within three years. While the results are robust with regard to the time window of three years, they change if we allow for a time window of only one year. The recovery following an ordinary recession is estimated to be considerably weaker than in the baseline model. Furthermore, it does not matter anymore whether the recession was associated with a housing crisis or not. The assumption that the beginning of the recession and the crisis have to lie within a time window of one year seems to be rather restrictive and in contrast to the literature on business cycle effects of housing crises (see, e.g.,

grid search in Appendix A.1 showed would lead to comparable results to our baseline identification criteria. Namely, we identify a housing crisis as a price peak within a rolling window of three years followed by a minimum price decline of 3 percent in the first year following the price peak. Even if we require a minimum distance of two years between the housing crises identified by the alternative criteria and a recession, which means we identify a housing crisis before the associated recession started, our results are qualitatively identical to our baseline results. We conclude that we can interpret housing crises as exogenous events and that our results are robust with respect to the issue of possible endogenous housing crises.[8]

Finally, we check whether our results are robust when we allow for more heterogeneity across countries. In our baseline model, we use the fixed effects model, assuming that only the average growth rate varies across countries and assuming that the other parameters are homogeneous. In a first step, we relax these assumptions by allowing the autoregressive parameters of GDP growth to vary across countries and estimate the model using the seemingly unrelated regression (SUR) method. Our results turn out to be qualitatively robust to this modification. In a second step, we allow also the parameters of the *cdr* terms to vary across countries by applying a random coefficient approach. We use the random coefficient model of Swamy (1970) and model the constant, the dynamic parameters, and the *cdr* term as random. Due to the fact that some countries did not experience crises we do not model the interaction terms as random. The recovery is again quite strong. The impact of the crises is much weaker. This result can be explained by the fact that some of the heterogeneity that is due to the crises is already captured by the random coefficient. Since the number of crises per country varies, the model can hardly discriminate between a pure crises effect and country-specific heterogeneity. It is a strong argument in favour of our main results that they prevail even in this setup.[9]

6 Conclusion

We provide empirical evidence for industrialized countries that ordinary recessions are typically followed by a strong recovery. This bounceback effect is nonlinear in the size of the negative shocks and becomes relatively stronger, the larger the shock is. In contrast, when a recession is associated with a banking crisis or a housing crisis, the bounceback of GDP will

IMF 2003, Ahearne et al. 2005, or Claessens 2009). Therefore, the results of the baseline model are reasonable with respect to consideration of alternative maximum lag lengths for the construction of the interaction term. Detailed results can be made available on request.

8 The detailed robustness check regarding the issue of exogeneity can be found in Appendix C.

9 The detailed results can be found in Appendix D.

be almost or even completely offset. Consequently, recessions associated with banking crises or housing crises lead to considerably higher permanent output losses than ordinary recessions. Our results remain valid when several robustness checks are applied.

Our results are relevant in several respects. We confirm empirical results that were obtained in the literature concerning the effects of banking crises and housing crises by using nonparametric methods, but we do so by using parametric methods, and we further provide a rationale for analyzing ordinary recessions and recessions associated with severe crises separately. In addition, we provide evidence in favor of nonlinear adjustment paths in the sense of Beaudry and Koop (1993) following ordinary recessions. By implication, theoretical business cycle models should allow for nonlinear business cycle dynamics. Moreover, policy-makers should be aware that recovery paths following recessions can be quite different from one another, necessitating different policy responses. Finally, since banking crises and housing crises can usually be recognized during or even before a recession, our results have practical implications for forecasting recessions and, in particular, for forecasting recoveries.

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8 Appendices: Robustness Check

In the Appendices, we check the robustness of our results with respect to the identification criteria for housing crises, the influence of global business cycle developments, the use of quarterly data to re-estimate some of our specifications, the assumption that severe economic crises are exogenous to the business cycle, and the assumption of homogeneity across countries.

8.1 Appendix A. Identification of Housing Crises

We check the robustness of our results with respect to the identification criteria for housing crises by running a grid search over alternative identification criteria and by using alternative identification criteria taken from the literature.

8.1.1 Appendix A.1 Endogenous Threshold for Identifying Housing Crises

In the baseline scenario, we define the starting year of a housing crisis as the peak in real house prices within a rolling window of nine years followed by a price decline of at least 7.5 percent within the subsequent four years. Even though this method provides reasonable and stable results with respect to other identification criteria used in the literature, it is rather ad hoc. Therefore, we further test the robustness of the results with respect to the identification of housing crises by determining the identification criteria for housing crises endogenously. We run a grid search over a range of possible thresholds for the required house price decline to identify a housing crisis. We do so not only in peaks of real house prices within a rolling window of nine years, but also for rolling windows of eleven, seven, five and three years.

We perform the grid search as follows. We allow the threshold variable for the minimum house price decline required to identify a housing crisis to take a value between 0 and 20 percent. The grid search is applied for steps of 0.1 percentage points. Given the identified housing crises for a certain threshold, we identify a housing crisis to be associated with a recession if it begins in the same period or within the next two years after the crisis began. Then we run our regression model and choose the threshold that results in the regression model with the lowest value for the Akaike Information Criterion (AIC). For simplicity, we compare only models that include the first lag of the *cdr* term and the interaction term. Furthermore, we do not differentiate between banking crisis that are associated with housing crises and (pure) housing crises.

Table A1
Grid Search for Best Threshold and Estimation Results

Rolling windows	11	9	7	5	3	baseline
threshold	8.7-8.9	8.7-8.9	9.7-10.6	9.7-10.6	3.0-3.1	7.5
AIC	2147,7	2141,1	2144.0	2144.2	2144.8	2141.4
no. of crises	25	28	22	20	31	29
$\Delta y_{t-1,i}$	0.49 (10.6)	0.49 (10.8)	0.50 (10.8)	0.50 (10.8)	0.49 (10.7)	0.49 (10.8)
$\Delta y_{t-2,i}$	-0.16 (3.8)	-0.16 (3.9)	-0.16 (3.7)	-0.16 (3.7)	-0.17 (4.0)	-0.16 (3.9)
$cdr_{t-1,i}$	1.05 (4.3)	1.55 (5.0)	1.38 (4.7)	1.37 (4.7)	1.52 (4.7)	1.54 (5.0)
$cdr_{t-1,i}^{\text{all}\,hc}$	-0.99 [0.00]	-1.48 [0.00])	-1.30 [0.00]	-1.29 [0.00]	-1.44 [0.02]	-1.47 (4.8)

Notes: t-values in brackets; *p*-values in square bracket; *p*-values for the interaction term were calculated by simulations with 1000 draws.

It turns out that the grid search for a rolling window of nine years leads to a threshold that is very close to our ad hoc criterion of 7.5 percent, namely a threshold between 8.7 and 8.9 percent. Further, the estimation results for both criteria are nearly indistinguishable from each other and the AICs are nearly identical (Table A1). The results for the longer and shorter rolling windows indicate that the identification criteria for a rolling window of nine years with a threshold variable between 8.7 and 8.9 percent lead to the best model in terms of the AIC. However, our estimation results are absolutely robust to changes in the rolling window.

8.1.2 Appendix A.2 Alternative Identification Criteria of Housing Crises

In the baseline model, we follow Jannsen (2010) and Aßmann et al. (2011) and define the starting year of a housing crisis as the peak of real house prices within a rolling window of nine years followed by a price decline of at least 7.5 percent within the subsequent four years. Even though these criteria provide reasonable and stable results, it is rather ad hoc. Therefore, we test the robustness of the results by modifying our identification criteria with respect to two alternative but related identification criteria applied in the literature. First, we modify our identification criterion to include all price peaks that occur within a rolling window of nine years. This is in accordance with Ahearne et al. (2005), who use a similar criterion for quarterly data. Using this modified criterion, we identify 34 housing crises in our sample. Since 29 of these 34 housing crises were already identified as crises in our baseline scenario the results are rather stable with respect to this modification (Table A2). Second, we modify our identification criteria according to IMF (2003), such that only the 25 percent most severe house price declines following one of the 34 identified price peaks are identified as a housing crisis.[10] Since the identification criteria of the IMF leave us with only 4 'pure' housing crises, for this robustness check we consider all banking crises and all housing crises in separate models, respectively.[11] Our results are qualitatively stable with respect to this modification (specification III and IV). However, the bounceback effect following ordinary recessions is estimated to be much weaker than in the baseline model.

Table A2:
Estimation Results for Alternative Housing Crises Identification Criteria

	All peaks		Most severe			
	I	II	III	IV	V	VI
$\Delta y_{t-1,i}$	0.49 (10.7)	0.50 (9.7)	0.45 (10.0)	0.46 (9.9)	0.50 (10.7)	0.48 (10.2)
$\Delta y_{t-2,i}$	–0.17 (4.1)	–0.21 (4.3)	–0.16 (3.8)	–0.16 (3.7)	–0.17 (3.9)	–0.16 (3.7)
$cdr_{t-1,i}$	1.38 (4.7)	1.47 (4.8)	0.33 (2.9)	0.30 (2.5)	1.05 (4.6)	0.73 (3.4)
$cdr_{t-2,i}$		–0.52 (1.7)				
$cdr^{bc}_{t-1,i}$	–1.41 (4.7)	–1.75 (5.4)	–0.38 (2.7)		–1.06 (4.5)	
$cdr^{bc}_{t-2,i}$		0.81 (2.4)				
$cdr^{hc}_{t-1,i}$	–1.17 (3.9)	–1.16 (3.6)				-0.69 (3.2)
$cdr^{hc}_{t-2,i}$		0.36 (1.1)				
$cdr^{all,hc}_{t-1,i}$				-0.31 (2.1)		
dum^{SW1975}_{t-1}					-0.89 (3.6)	-0.54 (2.4)
AIC	2144.1	2142.5	2157.6	2160.2	2146.3	2156.2
F-Test	0.78 / 0.07	0.92 / 0.05	0.62	0.91	0.91	0.74

Notes: t-values in parenthesis. First values of F-tests indicate the *p*-value of the hypothesis that the parameter values for the *cdr* terms and the banking crises interaction terms are identical. Second values refer to the housing crises interaction term.

For both specifications, the bounceback effect is only about a quarter of the size obtained for the baseline model, but it still vanishes completely in case of a banking crisis or a housing crisis. The moderate bounceback effect result obtained for the specifications with the most severe housing crises is largely driven by the fact that the housing crisis in Switzerland that began in 1975 cannot be considered one of the most severe housing crises in terms of price declines and therefore enters into the sample of ordinary recessions. Once we control for this recession via a dummy variable, the bounceback effect is estimated to be 100 percent of the

[10] Each of the remaining 9 housing crises was accompanied by a decline in real house prices of at least 32.5 percent.

[11] Furthermore, we consider only the mdoel with one lag of the cdr term and the interaction term to save space. The results are robust when we include also the second lag of both terms in the model.

former output loss in case we consider banking crises (specification V) or 70 percent in case we consider housing crises (specification VI).

8.2 Appendix B. Accounting for Global Factors

Country-specific business cycle dynamics are certainly influenced by the global economy (Kose et al. 2003). Therefore, one might argue that our results are driven by global or other non-modelled developments, for which we do not control in our relatively parsimonious model, rather than by domestic business cycle dynamics. We check the robustness of the results in this regard by modifying our model in three different ways: including time-fixed effects, introducing a global GDP variable, and estimating the model using the seemingly unrelated regressions (SUR) method.

8.2.1 B.1 Time Fixed Effects

One method of capturing the influence of global developments on the results is to introduce time-fixed effects. However, as this would involve estimating another 33 parameters, we do not use time fixed effects in our baseline model.

Table B1:
Estimation Results with Time Fixed Effects

	I	II	III	IV
$\Delta y_{t-1,i}$	0.43 (9.7)	0.41 (7.6)	0.46 (9.7)	0.45 (8.3)
$\Delta y_{t-2,i}$	–0,16 (–3.6)	–0.07 (1.5)	–0.10 (2.1)	–0.11 (2.2)
$cdr_{t-1,i}$	0.11 (1.4)	0.07 (0.6)	0.89 (3.4)	0.89 (3.3)
$cdr_{t-2,i}$		0.08 (0.7)		–0.27 (1.0)
$cdr^{bc}_{t-1,i}$			–0.86 (3.3)	–1.12 (3.9)
$cdr^{bc}_{t-2,i}$				0.56 (1.9)
$cdr^{hc}_{t-1,i}$			–0.65 (2.5)	–0.67 (2.4)
$cdr^{hc}_{t-2,i}$				0.25 (0.9)
AIC	1960.9	1962.3	1952.3	1951.9
F-Test			0.77 / 0.02	0.46 / 0.06

Notes: t-values in parentheses. First values of F-tests indicate the *p*-value of the hypothesis that the parameter values for the *cdr* terms and the banking crises interaction terms are identical. Second values refer to the housing crises interaction term.

The introduction of time fixed effects confirms the baseline results. While the parameter values and *t*-values are in general smaller, the results are qualitatively identical (Table B1). Ordinary recessions are followed by a bounceback effect that is now below, but close to, 100 percent of the preceding output loss. Banking crises completely offset this effect. Pure housing crises, on the other hand, weaken the bounceback effect considerably, but not as strongly.

8.3 B.2 Global GDP Variable

As a second method of controlling for the influence of the global business cycle dynamics, we include a global output variable in the baseline model. We calculate global output for each country individually as export weighted GDP growth of the other 15 countries in our sample.[12] Since the most important industrial countries are included in our sample, the calculated global variable should be a reasonable approximation of the global business cycle from the perspective of each individual country. Including the global variable Δy_t^*, the model is defined as

$$\Phi(L)\Delta y_{t,i} = \alpha_i + [\Omega(L)-1]cdr_{t,i} + [\Theta(L)-1]cdr_{t,i}^{bc} + [\Pi(L)-1]cdr_{t,i}^{hc} + \Gamma(L)\Delta y_{t,i}^* + \varepsilon_{t,i} . \quad (5)$$

We assume that each country is small compared to the world and allow therefore for contemporaneous effects of the global economy on domestic GDP growth.[13]

The global GDP variable is highly significant and improves the fit of the model considerably (Table B2). The qualitative results of the baseline model are confirmed. We can still observe a bounceback effect following an ordinary recession, even though the parameter values and *t*-values are smaller than in the baseline model. Subsequent to a banking crisis, we do not observe a particularly fast recovery. Following a housing crisis, the bounceback effect is at least considerably weaker or even completely offset.

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[12] Export data were taken from the International Financial Statistics Database of the IMF.

[13] This assumption is obviously questionable for the United States, but reasonable for the other countries in our sample. The method of calculating the global term is inspired by a growing literature that uses export-weighted or, alternatively, trade-weighted foreign variables to account for global developments (see Abeysinghe and Forbes (2001) and Pesaran et al. (2004)).

Table B2:
Estimation Results with Global Variables

	I	II	III	IV
$\Delta y_{t-1,i}$	0.47 (10.7)	0.46 (9.4)	0.50 (11.2)	0.49 (9.9)
$\Delta y_{t-2,i}$	–0,08 (2.4)	–0.08 (2.1)	–0.09 (2.7)	–0.11 (2.9)
$cdr_{t-1,i}$	0.12 (1.8)	0.10 (1.0)	0.77 (3.2)	0.82 (3.3)
$cdr_{t-2,i}$		0.02 (0.2)		–0.39 (1.6)
$cdr^{bc}_{t-1,i}$			–0.73 (3.0)	–0.99 (3.7)
$cdr^{bc}_{t-2,i}$				0.62 (2.3)
$cdr^{hc}_{t-1,i}$			–0.57 (2.3)	–0.61 (2.3)
$cdr^{hc}_{t-2,i}$				0.35 (1.3)
$\Delta y^{*}_{t,i}$	0.81 (17.0)	0.81 (17.0)	0.78 (16.4)	0.78 (16.3)
$\Delta y^{*}_{t-1,i}$	–0.33 (6.0)	–0.33 (5.9)	–0.32 (5.8)	–0.31 (5.5)
AIC	1925.0	1927.0	1919.5	1919.2
F-Test			0.68 / 0.05	0.46 / 0.11

Notes: t-values in parentheses. First values of F-tests indicate the *p*-value of the hypothesis that the parameter values for the *cdr* terms and the banking crises interaction terms are identical. Second values refer to the housing crises interaction term.

8.4 B.3 Seemingly Unrelated Regression

If global business cycle dynamics are relevant in our model, their neglect directly translates into cross-correlation of the error terms if we estimate our model country-wise using ordinary least squares. This would lead to inefficient estimation results. A direct way to address this problem is to estimate the system of equations using the seemingly unrelated regression (SUR) method, which explicitly accounts for the cross-correlation in the error terms. A disadvantage of SUR is that we have to estimate the covariance matrix and therefore additional $(16*15)/2=120$ parameters. For a dataset containing 592 observations, this is highly demanding and could lead to imprecise parameter estimates. Even though SUR seems to be an appropriate method for our estimation exercise in general, we refrain for this reason from using it for the baseline estimates. To test if there is still a common nonlinear effect concerning the recovery following a recession, we restrict the parameters of the *cdr* terms and the interaction terms such that they are equal across all the countries in our panel. Further, to make the results as comparable as possible to the panel estimation results, we also restrict the autoregressive terms such that they are equal across countries.[14]

[14] The results are qualitatively the same if we do not restrict the autoregressive terms such that they are equal.

Table B3:
Seemingly Unrelated Regression Estimation Results

	I	II	III	IV
$\Delta y_{t-1,i}$	0.40 (10.2)	0.40 (9.6)	0.41 (10.6)	0.41 (10.4)
$\Delta y_{t-2,i}$	–0,14 (3.8)	–0.14 (3.5)	–0.13 (3.5)	-0.16 (4.4)
$cdr_{t-1,i}$	0.05 (1.0)	–0.02 (0.2)	0.88 (6.2)	0.95 (6.5)
$cdr_{t-2,i}$		0.08 (1.1)		-0.55 (3.8)
$cdr^{bc}_{t-1,i}$			–0.95 (6.2)	–1.33 (8.3)
$cdr^{bc}_{t-2,i}$				0.95 (5.9)
$cdr^{hc}_{t-1,i}$			–0.75 (5.1)	–0.88 (6.1)
$cdr^{hc}_{t-2,i}$				0.54 (3.3)

Note: t-values in parentheses.

The baseline results are qualitatively confirmed by SUR estimation. The bounceback effect following ordinary recessions is estimated to be weaker than in the baseline model, but with a parameter value of 0.88 in the specification with one lag this is still high (Table B3). When a recession is associated with a crisis, the bounceback effect does not occur at all (banking crisis), or is at least considerably weaker (housing crisis).

8.5 Appendix C. Exogeneity of Housing Crises

We consider a recession to be associated with a housing crisis if it begins in the same year or within the next two years after the crisis began. It turns out that of the 20 housing crises that according to this definition are associated with a recession, only one begins in the same year as the recession. Eight housing crises started one year before the respective recession and 11 started two years before the respective recession.

Table C1:
Estimation Results for Different Minimum Distances between Housing Crises and Recessions

Minimum distance	0	1	2
no. of recessions starting in year	1	8	11
no. of crises	20	19	11
$\Delta y_{t-1,i}$	0.49 (10.8)	0.49 (10.6)	0.50 (10.6)
$\Delta y_{t-2,i}$	-0.16 (3.9)	-0.17 (3.9)	-0.18 (4.1)
$cdr_{t-1,i}$	1.54 (5.0)	1.29 (4.4)	1.03 (4.3)
$cdr^{\text{all}\,hc}_{t-1,i}$	-1.47 (4.8)	-1.21 (4.2)	-0.97 (4.0)

Note: t-values in parentheses.

Our estimation results are qualitatively robust for setting a minimum distance between a housing crisis and a recession considered to be associated. When we set a minimum distance of two years, the parameter estimate of the *cdr* term takes a value of 1.0 and is highly significant (Table C1). The bounceback effect is nearly completely offset when a recession is associated with a housing crisis.[15] A minimum distance of two years between the beginning of a housing crisis and the beginning of a recession seems to be reasonable to consider a housing crisis to be exogenous of the recessions. This is particularly true because we do not relate the recession itself to the housing crises, but rather the recoveries that start by definition in our model one year after the recession.

In Section 2, we showed that our results are robust to alternative identification criteria. In particular, we show that we receive qualitatively the same results when a housing crisis is identified as a price peak within a rolling window of three years followed by a minimum price decline of 3 percent in the first year after a house price peak. Therefore, we also run the former robustness check for housing crises identified by these alternative identification criteria. Even if we require a minimum distance of two years between the housing crises identified by the alternative criteria and a recession, that means, we identify a housing crisis before the associated recession started, our results are qualitatively identical to our baseline results. The results are again robust to alternative minimum distances between the beginning of housing crises and recessions (Table C2).

Table C2:
Estimation Results for Different Minimum Distances between Housing Crises and Recessions for an Alternative Identification Scheme of Housing Crises

Minimum distance	0	1	2
no. of recessions starting in year	1	7	10
no. of crises	18	17	10
$\Delta y_{t-1,i}$	0.49 (10.7)	0.49 (10.5)	0.49 (10.3)
$\Delta y_{t-2,i}$	-0.17 (4.0)	-0.17 (4.0)	-0.17 (4.0)
$cdr_{t-1,i}$	1.52 (4.7)	1.24 (4.0)	0.92 (3.7)
$cdr_{t-1,i}^{\text{all}\,hc}$	-1.44 (4.5)	-1.16 (3.8)	-0.86 (3.4)

Note: t-values in parentheses.

[15] The results do not change when the three housing crises for which the recession starts three years after the crises began are included in the interaction term.

8.6 Appendix D. Heteorgeneity

We test for the robustness of our results when we allow for more heterogeneity across countries by allowing the autoregressive parameters of GDP growth to vary across countries and additionally by allowing the parameters of the *cdr* term to vary across countries by means of the random coefficient approach.

8.6.1 Appendix D.1 Heterogeneity of the Autoregressive Parameters of GDP Growth

In our baseline model, we allow only the average growth rates to vary across countries, while the parameters for lagged GDP growth are assumed to be homogeneous. Even though, these assumptions can be justified by the empirical circumstances, i.e., using annual data and including only industrial countries in the panel, they are apparently rather strong. In a first step, we check whether these assumptions are crucial for our estimation results by allowing the autoregressive parameters of GDP growth to vary across countries. We estimate our model as a system of equations using SUR and restrict only the parameters of the *cdr* terms and the interaction terms to be homogeneous across countries.
Compared to the estimation results based on SUR with the autoregressive parameters restricted to be equal across countries, the parameter estimates for the *cdr* terms and the interaction terms are slightly lower (Table D1). However, our baseline results are qualitatively confirmed.

Table D1:
Seemingly Unrelated Regression Estimation Results

	I	II	III	IV
$cdr_{t-1,i}$	0.04 (0.6)	0.11 (1.2)	0.76 (5.0)	0.84 (5.2)
$cdr_{t-2,i}$		-0.08 (0.9)		-0.31 (2.0)
$cdr^{bc}_{t-1,i}$			–0.83 (4.8)	–1.06 (5.2)
$cdr^{bc}_{t-2,i}$				0.47 (2.6)
$cdr^{hc}_{t-1,i}$			–0.67 (4.4)	–0.68 (4.1)
$cdr^{hc}_{t-2,i}$				0.22 (1.3)

Note: t-values in parentheses.

8.6.2 Appendix D.2 Random Coefficient Model

A fixed effects model restricts the dynamic parameter and the parameters of the *cdr*-terms and the crises to be equal among all countries. It might be assumed that the autoregressive dynamics may be heterogeneous between countries. Further, Bradley and Jansen (1997) and Kim et al. (2005) argue that the *cdr* effect and the bounceback effects are heterogeneous between countries, too. Note that the crisis specification we propose provides a first step in explaining the latter form of heterogeneity. Since recessions and crises are rare events, a different number of crises may explain seemingly country specific differences in the post-recession period. However, it cannot be denied that beyond this explained heterogeneity, further country-specific impacts concerning the post-recession periods can exist. To deal with this issue, we additionally apply the random coefficient model proposed by Swamy (1970). We do a Bayesian analysis for the random coefficient model, since the FGLS approach as proposed by Swamy (1970) performs weakly in smaller samples such as ours. We estimate the posterior distributions using the Gibbs Sampler and assume Gaussian priors with zero mean and a variance of 10 for all mean parameters and an exponential prior for each variance parameter. The posterior means as well as the 95 % confidence bands show results in accordance to those from the fixed effects model (Table D2). The mean of the first *cdr* parameter is well above one, while the mean of the coefficient of crisis variable is clearly negative.

Table D2:
Estimation Results for Random Coefficient Model

	mean	std. dev.	2.5 percentile	97.5 percentile
constant	1.558	0.217	1.129	1.984
$\Delta y_{t-1,i}$	0.522	0.109	0.321	0.736
$\Delta y_{t-2,i}$	-0.206	0.099	-0.401	-0.010
$cdr_{t-1,i}$	1.483	0.370	0.754	2.216
$cdr_{t-2,i}$	-0.310	0.365	-1.025	0.419
$cdr_{t-1,i}^{all,hc}$	-0.869	0.440	-1.746	-0.008
$cdr_{t-2,i}^{all,hc}$	0.368	0.434	-0.498	1.210

Our main results prevail also when estimating the model with this approach, since it would presumably be hard to disentangle the heterogeneity captured by the random coefficient of the *cdr* terms and the heterogeneity between countries that is due to differing number of crises hitting the economies.