Severe Economic Crises and the Business Cycle

An Empirical Analysis

Inaugural-Dissertation

zur Erlangung des akademischen Grades eines Doktors

der Wirtschafts- und Sozialwissenschaften

der Wirtschafts- und Sozialwissenschaftlichen Fakultät

der Christian-Albrechts-Universität zu Kiel

vorgelegt von

Diplom-Volkswirt Nils Jannsen

Niebüll

Kiel 2011

Gedruckt mit Genehmigung der

der Wirtschafts- und Sozialwissenschaftlichen Fakultät

der Christian-Albrechts-Universität zu Kiel

Dekan: Prof. Dr. Roman Liesenfeld

Erstberichterstattender: Prof. Dr. Joachim Scheide

Zweitberichterstattender: Prof. Dr. Helmut Herwartz

Tag der Abgabe der Arbeit: 23. Dezember 2011

Tag der Disputation: 31. Mai 2012

Contents

List of Tables

List of Figures

1 Introduction

In this dissertation, I analyze the business cycle effects of severe economic crises, such as financial crises or housing crises. The dissertation is a collection of five papers. It contributes to the empirical literature on the effects of severe economic crises. The results found are particularly relevant for economic policy and macroeconomic forecasting, and in some cases they also may serve as the empirical foundation for theoretical business cycle models.

In the literature, the effects of severe economic crises and in particular the effects of financial crises have been analyzed by several authors. Well-known early examples are Kaminsky and Reinhart (1999) and Bordo et al. (2001). The onset of the Great Recession of 2008/2009 has increased the interest in the analysis of the effects of such crises considerably. A series of papers finds that financial crises lead to particularly deep and long-lasting recessions (see, e.g., Reinhart and Rogoff 2008 and 2009a, IMF 2009a, Cecchetti et al. 2009). Moreover, there is strong evidence that such crises also have considerable long-run effects on GDP (see, e.g., Cerra and Saxena 2008, Furceri and Mourougane 2009, IMF 2009b). Since the Great Recession has been mainly perceived to have been triggered by a financial crisis, most of the papers analyzing the effects of severe economic crises have focused on the financial crises. However, even though the financial crisis was preceded by a housing crisis in the United States, the more recent literature on the effects on housing crises is relatively scarce. A notable exception is Claessens et al. (2009), who show that housing crises lead to particularly deep and long-lasting recessions as well.

This dissertation contributes to the literature in several dimensions. It has a special focus on housing crises, which have been analyzed in the literature much less frequently than financial crises, and on the business cycle effects and possible international spillover effects of housing crises (Chapter 2). Moreover, it analyzes the economic conditions under which housing crises are particularly costly (Chapter 4). It proposes a method of dealing with the problem of heterogeneity in the sample that frequently occurs when the effects of severe economic crises are analyzed (Chapter 3). Finally, it analyzes the strength of recoveries following recessions associated with severe economic recessions compared to ordinary recessions (Chapter 5). In this context, it analyzes the relevance of international synchronization of recessions and recoveries for the strength of recessions and for the strength and the dynamics of recoveries (Chapter 6).

Review of Chapter 2: National and International Business Cycle Effects of Housing Crises

In this chapter, I analyze the national and international business cycle effects of housing crises empirically. While most of the recent literature on the effects of severe economic crises focus on financial crises (or banking crises), the literature on the effects of housing crises is relatively scarce. I contribute to the literature by reexamining the effects of housing crises using a sample of historical housing crises for 15 industrial countries and analyze whether they generated international spillover effects.

As regards the national effects of housing crises, I analyze the typical behavior of several macroeconomic variables (e.g., GDP, the output gap, private consumption, or residential investment) during historical housing crises. I find that housing crises usually lead to long-lasting recessions and have the most severe effects in the first two years. When comparing the results for the historical housing crises with more recent housing crises that began in the years 2006 and 2007 in the United States, the United Kingdom, France, and Spain I show that the more recent housing crises were followed by exceptionally strong recessions in terms of GDP growth. However, when comparing the results in terms of the output gap, I find that the more recent crises were very similar to the historical housing crises, with the United States as a notable exception.

As regards the international spillover effects, I show by means of a panel data model that housing crises in general have significant negative international spillover effects. Further, I use a international business cycle model to perform a case study for the four more recent housing crises. I show that if these four housing crises had evolved like a normal historical housing crisis in terms of GDP growth, they would have led to significant negative international spillover effects in nearly all other countries in the sample. However, the model is not able to explain the strength of the recessions observed in the other countries in the sample in the years 2008 and 2009.

Review of Chapter 3: Estimating the Shape of Economic Crises under Heterogeneity

In this chapter (joint work with Jonas Dovern), we propose a method of dealing with heterogeneity in a sample of severe economic crises. Analyses of severe economic crises usually have to rely on large samples because they are rare events. This raises the problem of heterogeneity that can occur in the sample, for example, when macroeconomic conditions, institutions, or economic policy regimes differ considerably across countries or over time. Heterogeneity in the sample may bias the results.

We propose using two measures of heterogeneity, namely the time dependent mean and the time dependent volatility of GDP growth, to account for heterogeneity in a sample of severe economic crises. Our proposal is backed by strong empirical and theoretical evidence that differences in macroeconomic institutions or economic policies are reflected in the mean and the volatility of GDP growth. We use two related approaches to illustrate the relevance of our proposal that have been frequently used to analyze severe economic crises, namely estimating the costs of severe economic crises and estimating the shape of severe economic crises. In most of our analysis, we use a sample of 40 countries, including industrial and developing countries as well as emerging economies, and focus on the effects of financial crises.

The first approach frequently used in the literature to analyze the effects of severe economic crises is to estimate their costs. It captures the effects of severe economic crises—usually in terms of GDP—in a single scalar measure. We use six different measures of costs that are taken from the literature and show that our measures of heterogeneity usually can help significantly to explain the estimated costs. We show further that the correlation of the six cost measures increases once we account for heterogeneity. Finally, we demonstrate that using the suggested measures to account for heterogeneity improves forecasting accuracy when performing a (quasi) out-of-sample forecasting exercise.

The second approach frequently used in the literature to analyze the effects of severe economic crises is to estimate their shape. This method calculates the average of particular variables before, during, and after severe economic crises in the sample. We show that the estimated shape of financial crises is much less dependent on the available sample of crises when we account for heterogeneity with our suggested measures. The gains of accounting for heterogeneity are smaller when we estimate the shape of housing crises. However, this result supports our hypothesis that our suggested method is particularly useful with samples that exhibit a considerable degree of heterogeneity, but less useful with samples that exhibit a lower degree of heterogeneity, because the sample of housing crises is much more homogeneous than the sample of financial crises (see Chapter 2). Finally, we compare the shape of financial crises with the shape of housing crises. When we do not account for heterogeneity in the samples, we find that the shape in terms of GDP growth of both types of crises is similar. However, once we account for heterogeneity, we find that housing crises are considerably more severe than financial crises.

Review of Chapter 4: Costs of Housing Crises—International Evidence

In this chapter (joint work with Christian Aßmann and Jens Boysen-Hogrefe), we analyze the economic conditions under which housing crises are particularly costly. The literature on the effects of housing crises finds that housing crises usually cause deep and long-lasting recessions, but also shows that this finding is subject to remarkable uncertainty (see, e.g., Chapter 2). Moreover, this literature is usually silent on the links between the housing market and overall economic activity. We suggest three possible links between the housing market and overall economic activity and test empirically whether they are particularly important for the costs that a housing crisis causes.

The first two links we take from the literature that analyzes the links between the housing market and overall economic activity in general. Even though some of the empirical results in the literature are contradictory, there is some evidence that the housing market influences overall economic activity via wealth effects and via the construction sector. The third possible link is the link via the banking sector, since activity in the housing market usually goes hand in hand with a high degree of leverage financed by the banking sector. This link became obvious during the Great Recession of 2008/2009, which originated in the housing market in the United States, and which in turn affected the financial sector considerably.

We construct interaction terms between proxies that capture the relevance of these links and a housing crisis indicator and estimate the relevance of the three links in a panel model that includes 16 industrial countries. We find strong evidence for the relevance of the banking sector link. Housing crises that are associated with banking crises lead to significantly lower GDP growth in the first two years of a crisis. In addition, we find some evidence for the relevance of the link via wealth effects. Housing crises that occur in countries with a high homeownership rate lead to lower GDP growth rates. However, models that control for the relevance of wealth effects do not explain the variation in the data better than models that do not. Finally, we find no evidence for the relevance of the link via the construction sector. Housing crises that occur in countries with a large construction sector relative to overall economic activity do not lead to lower GDP growth rates during the first two years of a crisis. Our results are robust when we choose alternative identification criteria for housing crises and when we control for the possibly endogeneity of housing crises.

Review of Chapter 5: The Ugly and the Bad: Banking and Housing Crises Strangle Output Permanently, Ordinary Recessions Do Not

In this chapter (joint work with Jens Boysen-Hogrefe and Carsten-Patrick Meier), we estimate the strength of recoveries following recessions. The results in the literature on the strength of recoveries are ambiguous. While some of the literature finds that recoveries following recessions—in particular in the United States—are considerably strong, some of the literature implies that recoveries following recessions associated with severe economic crises are weak. We reconcile the contradicting results of the literature by differentiating between different types of recessions.

We differentiate between recessions associated with banking or housing crises and recessions that are not associated with such crises (ordinary recessions) and estimate the strength of following recoveries using a panel model. The panel model includes 16 industrial countries. To estimate the strength of recoveries, we include a current-depth-of-recession term—taken from the literature—in our model that takes positive values during recessions and is equal to zero otherwise. We find that recoveries following ordinary recessions are particularly strong and are stronger the deeper the preceding recession was. We do not find evidence that recoveries following recessions associated with severe economic crises are particularly strong. Consequently, the permanent effects of ordinary recessions on GDP are considerably smaller than the permanent effects of recessions associated with severe economic crises. This result is robust when we use alternative identification criteria for housing crises, when we include additional variables that control for the influence of a global business cycle, or when we control for outliers in our sample. Moreover, our results are not driven by the possible endogeneity of housing crises.

Review of Chapter 6: International Recessions, Crises, and the Dynamics of Recoveries

In this chapter, I analyze the relevance of international synchronization of recessions and recoveries for the strength of recessions and the strength and the dynamics of recoveries. While there is a rich literature that analyzes international business cycle synchronization, the literature on the relevance of international synchronization during recessions and recoveries is relatively scarce. Overall, there is some evidence that internationally synchronized recessions are deeper and longer than other recessions and that the following recoveries are more sluggish than other recoveries. I contribute to the literature by providing additional stylized facts on the relevance of international synchronization of recessions and recoveries. In particular, I differentiate between ordinary recessions and recessions associated with severe economic crises.

First, I analyze the relevance of international synchronization during recessions. Several measures are used to estimate the degree of international synchronization. Overall, the results are sensitive to the measure that is used to estimate the degree of international synchronization and to outliers in the sample. I find some evidence that internationally synchronized recessions are stronger in terms of GDP growth. Countries hit by severe economic crises tend to be more vulnerable to internationally synchronized recessions. Ordinary recessions seem to have larger international spillover effects. There is only limited evidence that the degree of international synchronization has to pass a certain threshold to become relevant for the strength of a recession.

Second, I analyze the relevance of international synchronization for the strength and the dynamics of recoveries. For this purpose, I augment the model of Boysen-Hogrefe et al. (2010) (see Chapter 5) using an open economy model and estimate it using a panel model. Based on the estimation results, I build a stylized two-region model consisting of a small open economy and a large rest-of-the-world economy. The two-region model is used to run simulations when one or both regions are in a recovery following an ordinary recession or alternatively following a recession associated with a severe economic crisis. The results of Boysen-Hogrefe et al. (2010) are largely confirmed for the open economy model. Moreover, I find that recoveries that are internationally synchronized tend to be stronger than recoveries that are not internationally synchronized. However, a country benefits only from international synchronized recoveries when the foreign recoveries following ordinary recessions. The benefits are larger when the country itself country itself is hit by a severe economic crisis.

References

Aßmann, C., J. Boysen-Hogrefe and N. Jannsen (2011). Costs of Housing Crises: International Evidence. Bulletin of Economic Research, forthcoming.

Bordo, M., B. Eichengreen, D. Klingebiel and M.S. Martinez-Peria (2001). Is the Crises Problem Growing More Severe? *Ecocomic Policy* 16 (32): 53–82.

Boysen-Hogrefe, J., N. Jannsen and C.-P. Meier (2010). The Ugly and the Bad: Banking and Housing Crises Strangle Output Permanently, Ordinary Recessions Do Not. Kiel Working Papers 1586, Kiel Institute for the World Economy.

Cerra, V., and S.C. Saxena (2008). Growth Dynamics: The Myth of Economic Recovery. *American Economic Review* 98 (1): 439–457.

Cecchetti, S.G., M. Kohler and C. Upper (2009). Financial Crises and Economic Activity. NBER Working Paper 15379. National Bureau of Economic Research, Cambridge, MA.

Claessens, S., M.A. Kose, and M.E. Terrones (2009). What Happens During Recessions, Crunches and Busts? *Economic Policy* 24 (60): 653–700.

Dovern, J. and N. Jannsen (2009). Estimating the Shape of Economic Crises Under Heterogeneity. Kiel Working Papers 1520, Kiel Institute for the World Economy.

Furceri, D., and A. Mourougane (2009). The Effect of Financial Crises on Potential Output. OECD Economics Department Working Papers 699. Organization for Economic Cooperation and Development, Paris.

IMF (International Monetary Fund) (2009a). From Recession to Recovery: How Soon and How Strong? *World Economic Outlook*. April. Washington, D.C.

IMF (International Monetary Fund) (2009b). What's The Damage? Medium-Term Output Dynamics After Financial Crises. *World Economic Outlook*. October. Washington, D.C.

Jannsen, N. (2010). National and International Business Cycle Effects of Housing Crises. *Applied Economics Quarterly* 56 (2): 175–206.

Jannsen, N. (2011). International Recessions, Crises, and the Dynamics of Recoveries. Mimeo.

Kaminski, G.L., and C.M. Reinhart (1999). The Twin Crises: The Causes of Banking and Balance-of-Payments Problems. *American Economic Review* 89 (3): 473–500.

Reinhart, C.M., and K.S. Rogoff (2008). Is the 2007 US Subprime Crises so Different? An International Historical Comparison. *American Economic Review* 98 (2): 339–344.

Reinhart, C.M., and K.S. Rogoff (2009a). *This Time is Different: Eight Centuries of Financial Folly*. Princeton.

Reinhart, C.M., and K.S. Rogoff (2009b). The Aftermath of Financial Crises. NBER Working Paper 14656. National Bureau of Economic Research, Cambridge, MA.

2 National and International Business Cycle Effects of Housing Crises[1]

2.1 Introduction

Developments in the housing market can have an enormous influence on the business cycle of a country. Housing wealth accounts for a big share of overall private household wealth, so that large movements in house prices influence the overall wealth of private households dramatically. Also, owning houses or residential apartments usually goes along with high leverage. Moreover, the residential construction sector has been proved to be highly important for the overall economy. Leamer (2007) demonstrates for the United States that recessions have frequently been preceded by downswings in residential construction. Therefore, housing crises defined as exceptionally strong downswings in the housing market should have the potential to depress the economic activity of a country considerably.

This is, indeed, the assessment of a number of studies. The IMF (2003) shows that housing crises in industrial countries between 1960 and 2002 led, on average, to severe recessions, albeit there was a considerable degree of heterogeneity between housing crises. Further, housing crises are usually followed by long-lasting negative output gaps that need more than five years to turn positive again. This result was confirmed by Ahearne et al. (2005), who used a similar approach. Related studies that investigate the consequences of asset price busts in general but also differentiate between equity price busts and housing crises confirm these results. For instance, Jonung et al. (2006) find that a strong decline in asset prices usually has long-lasting negative effects on GDP growth and the output gap. Further, Detken and Smets (2004) show that asset price busts causing an above average loss in output usually go along with a previous above average asset price increase. Finally, Bordo and Jeanne (2002) find that boom and bust cycles occur more frequently in housing markets than in stock markets. Studies that compare the consequences of housing market crises with equity price busts usually conclude that housing market crises are followed, on average, by more severe recessions, in terms of length of the recession and output loss.

The onset of the Great Recession of 2008/2009 brought the analysis of the consequences of severe economic crises back into the focus of macroeconomic research. The consequences of severe economic crises were analyzed in a series of papers initiated mainly by the work of Reinhart and Rogoff (2008). Overall, these papers conclude that severe economic crises are

[1] This Chapter is based on the paper: N. Jannsen (2010). National and International Business Cycle Effects of Housing Crises. Applied Economics Quarterly, 56(2): 175-206.

followed by particularly long-lasting and deep recessions (see, e.g., Reinhart and Rogoff 2009a and 2009b, Claessens et al. 2008, Cecchetti et al. 2009) that lead to permanent output losses (Cerra and Saxena et al. 2008, IMF 2009b, Furceri and Mourougane 2009).

Since the Great Recession of 2008/2009 was mainly perceived to be a financial crisis, the literature focuses in general on financial or banking crises. However, the financial crisis in the United States was preceded by a boom and bust cycle in the housing market, which strongly affected the financial sector. Other countries, such as the United Kingdom and Spain, also suffered from housing crises in 2008/2009. Given these, it is reasonable to build not only on the experience of historical financial crises but also on the experience of historical housing crises to gain further insights into the behavior of the economy during the Great Recession and thereafter.

One exception in the current literature is Claessens et al. (2008), who compare the consequences of housing crises with those of credit crunches and equity price busts. They find that housing crises are followed, on average, by recessions that are roughly as severe as recessions triggered by credit crunches, whereas the consequences of equity price busts are considerably milder. We start from this observation and try to investigate the role of housing crises during the Great Recession of 2008/2009 against the background of the historical experience concerning housing crises. Therefore, we first re-examine the evidence on the consequences of such crises in industrial countries that has been presented by the IMF (2003) and the literature that followed. Then we put the recent experience in countries that were hit by housing crises, such as the United States or Spain, into a historical perspective. We find that these housing crises were followed by exceptionally strong recessions. Based on these findings, we test whether housing crises have the potential to lead to significant negative spillover effects to other countries. First, we make the general point that housing crises have significant negative spillover effects by applying a panel model. Then, we affirm this result by applying an international business cycle model. We show that the housing crises that occurred in several industrial countries beginning in 2006 and 2007 are able to explain a significant downturn in many industrial countries, in particular in Europe. However, according to our international business cycle model, the housing crises are not sufficient to explain the steepness of the downturn in the winter half year 2008/2009. We conclude that even if we do not take the—compared to historical housing crises—probably exceptionally strong spillover effects to the financial sector into account, housing crises on their own played an important role during the Great Recession of 2008/2009.

The paper is structured as follows. After the introduction, Section 2.2 provides a comparison of historical housing crises with the housing crises that began in 2006 and 2007 in several industrial countries. In Section 2.3, the international spillover effects of housing crises are investigated. Section 2.3.1 illustrates the general relevance of the international spillover effects. In Section 2.3.2, the spillover effects during the Great Recession are analyzed. Section 2.4 summarizes and interprets our results.

2.2 Historical Housing Crises

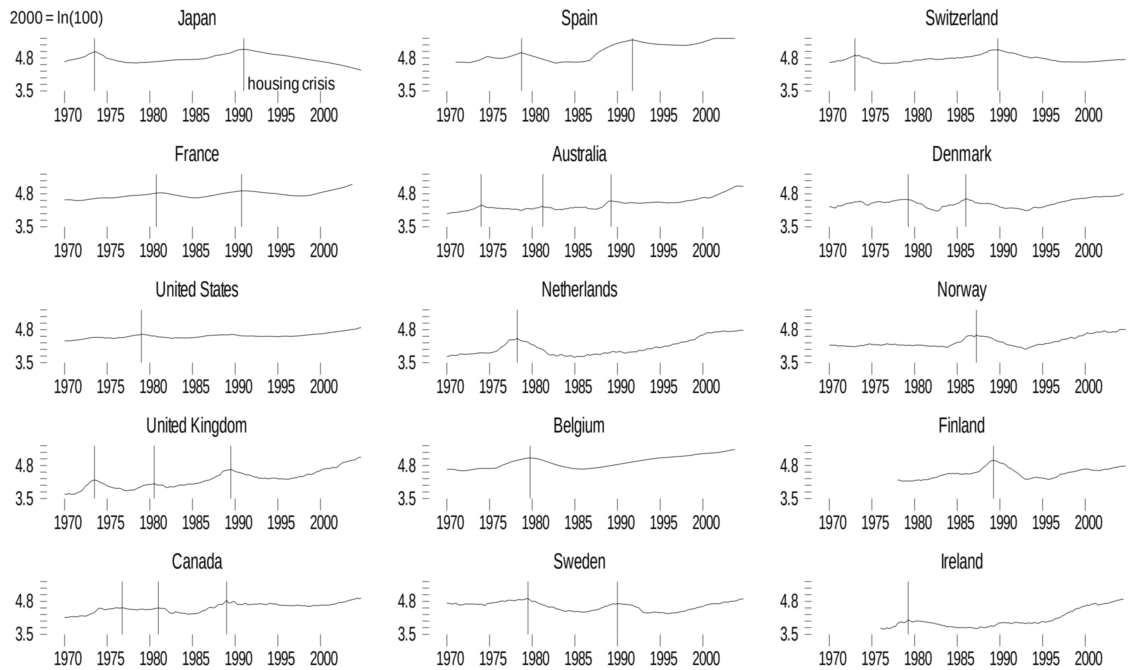
Severe economic crises, such as housing crises, are rare events and potentially lead to nonlinear dynamics that differ considerably from normal times. Thus, their effects are hard to model empirically using time-series techniques, which capture the average behavior of the economy. Therefore, nonparametric historical comparisons of a panel of countries that have faced severe economic crises have become a standard tool for assessing the impact of such severe crises on the business cycle in the literature on housing crises (see, e.g., IMF 2003) as well as in the literature on financial crises (see, e.g., Reinhart and Rogoff 2008, Claessens et al. 2008). To make our historical comparison, we first define a housing crisis using two criteria and then analyze the typical behavior of macroeconomic variables during a crisis. Finally, we compare the housing crises beginning in 2006 and 2007 in four industrial countries with historical patterns.

2.2.1 Methodology for Identifying Housing Crises

Basically two methods are used in the current literature to identify housing crises. One looks for deviations from the trend in house prices (Detkens and Smets 2004 or Bordo and Jeanne 2002), while the other one looks for turning points in price movements and regards strong price declines as crises (Ahearne et al. 2005 or IMF 2003). In the following, we draw on an approach related to the latter by using two criteria to define a housing crisis. Namely, we define the start of a housing crisis as the peak in house prices within a rolling window of eight years, followed by a price decline from the peak of at least 7.5 percent during the next four years. In doing so, we deviate from the existing literature. While Ahearne et al. (2005) analyze economic trends around in peaks in house prices identified in a moving window of six years, we impose a restriction on the size of the price decrease following the price peak, since we are interested more in crises than in cyclical movements. The IMF (2003) identifies only 25 percent of the most severe price declines following price peaks as housing crises, which limits the number of housing crises identified considerably.

Using our definition and a dataset of 15 industrial countries with quarterly data for real house prices between 1970 and 2004, we identify 27 housing crises.[2] Our approach is robust to moderate modifications of both criteria. When we relax our criteria and interpret, in analogy to Ahearne (2005), each identified turn in house prices as a housing crisis, we identify 30 housing crises. When we tighten our criteria and interpret only those price peaks as the beginning of housing crises that were followed of a price decline of at least 15 percent, then we remain with 18 identified housing crises.[3]

Figure 2.1:
Real House Prices in Selected Countries



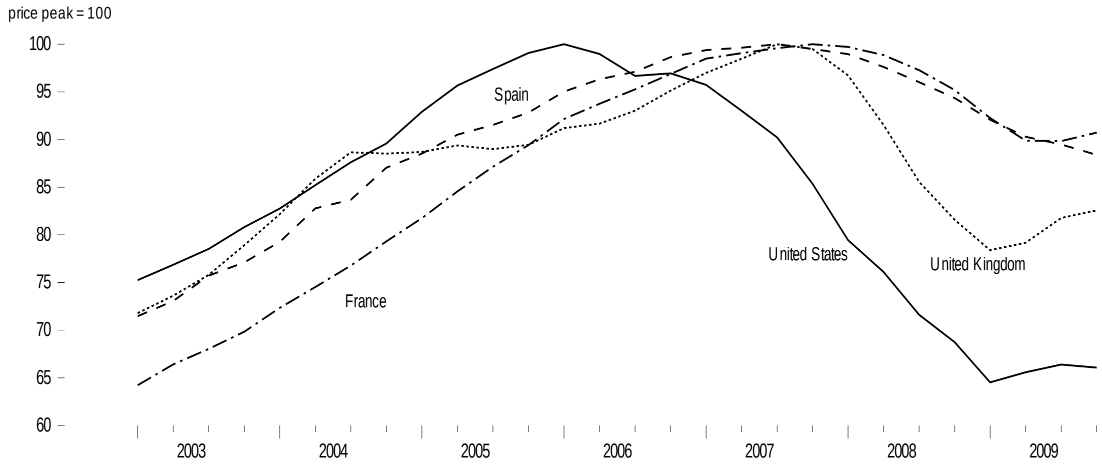
Most of the crises took place during the 1970s and 1980s. During the last 20 years, no housing crisis can be observed in the dataset. Moreover, housing crises seem to cluster within certain time periods. For instance, eight countries faced housing crises in the period from 1989 to 1991, while seven countries were affected in the period from 1979 to 1981, and four in the period from 1973 to 1974. Further, the United States, while fulfilling the above-mentioned criteria for a housing crisis in 1979, were also confronted with decreasing real house prices in 1973 (with a price decrease of 4.3 percent) and in 1989 (with a price decrease of 7.3 percent).

[2] The dataset consists of data for Great Britain, Canada, Spain, Australia, Netherlands, Belgium, Sweden, Switzerland, Denmark, Norway, Finland, and Ireland and was kindly provided by the Bank for International Settlements (BIS). Quarterly house prices in France and the United States as well as land prices in Japan were added from national sources (see Appendix A).

[3] The robustness of the results with respect to the identification criteria for housing crises is tested in Appendix B.

In the following, we compare the typical economic development during historical crises with more recent developments in countries hit by a housing crisis. We consider the following four countries: the United States, Great Britain, Spain, and France. Figure 2.2 illustrates that these countries faced a housing crisis beginning in 2006 or 2007 according to our criteria.[4] While the United States reached the price peak already in the first quarter of 2006, the price peaks in the other three countries occurred at the end of 2007; in Great Britain and Spain in the third quarter and in France in the fourth quarter of 2007.

Figure 2.2:
Real House Prices in Selected Countries from 2003 to 2008



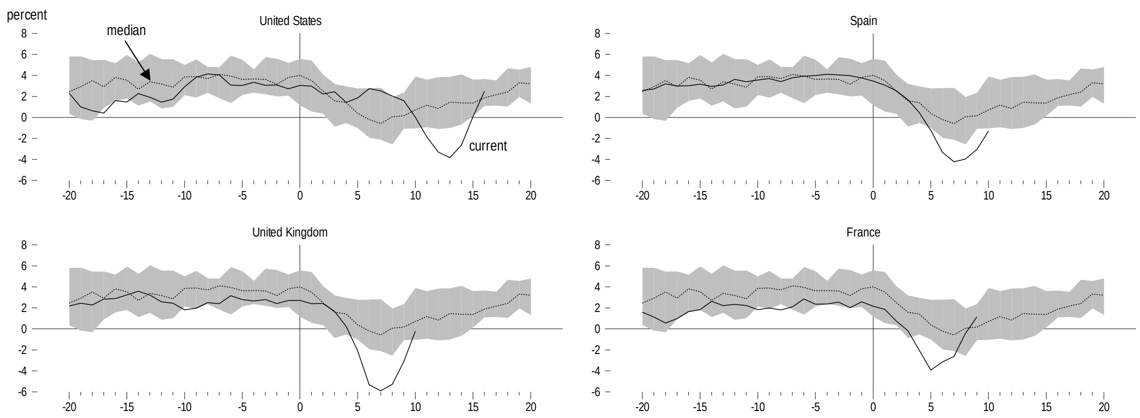
2.2.2 Historical Comparison

To extract the typical business cycle behavior of economies during housing crises, we derive the median values of several macroeconomic variables within a time span running from 20 quarters before a crisis to 20 quarters after the onset of a housing crisis, based on the 27 identified historical crises. In the following figures, the quarter in which the price peak occurred is set to zero, so that quarter one is the first quarter with declining house prices. Figure 2.3 shows that GDP growth declines sharply, on average, at the beginning of the housing crisis and requires more than four years to reach the old level again. The trough is usually reached five to eight quarters after the price peak. The shaded area around the median value marks the one standard error band over all crises. The figure shows that GDP

[4] Until the first quarter of 2010, our criteria are matched only exactly in case of the United States. For the other three countries, we assume that house prices will not exceed their peak value within four years. Also, some other countries, such as Ireland, are affected by shrinking house prices or even housing crises. Here we focus on the economically most important countries.

growth during housing crises is surrounded by remarkable uncertainty. Housing crises that were not followed by a quarter of negative GDP growth are just as possible as housing crises followed by an even stronger decline in GDP growth. However, even if the uncertainty surrounding the business cycle fluctuations during housing crises is taken into account, the assessment is that housing crises are followed by a considerable weakening of GDP growth. Since most of the historical housing crises took place in the 1970s and 1980s, when macroeconomic conditions differed crucially from today's conditions, it seems sensible to adjust GDP for its trend. The deviation of trend reveals a pronounced business cycle pattern in which it peaks contemporaneously with house prices which is followed by a long-lasting bust with a negative deviation of trend for a period of five years (Figure 2.4).[5]

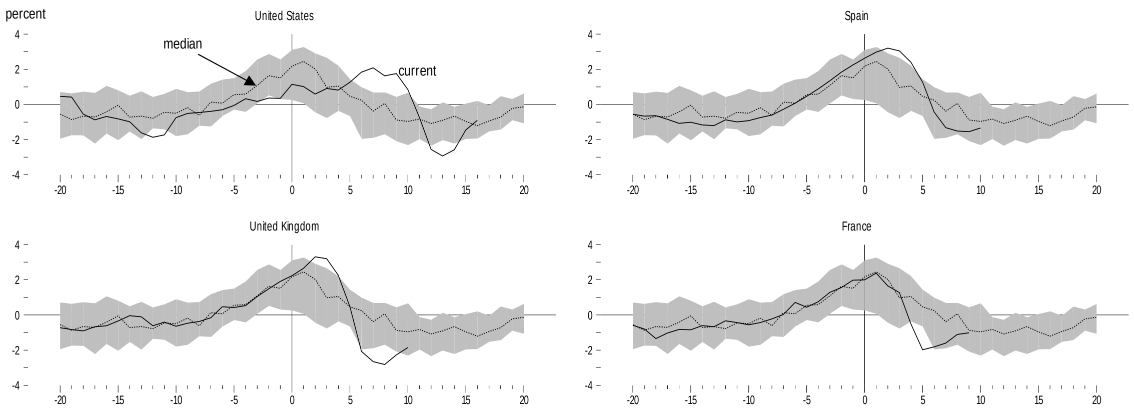
Figure 2.3:
Gross Domestic Product during a Housing Crisis



Notes: Percentage change, year to year; includes data up to the first quarter 2010; shaded area marks the one-standard-error confidence band.

[5] The trend was estimated with the Hodrick-Prescott filter based on all available data for GDP from the first quarter 1970 up to the fourth quarter 2009 with a standard value of 1600 for lambda. To estimate the most recent values for the output gap, the GDP time series were extended using forecasts of autoregressive models to lessen the end-point bias problem.

Figure 2.4:
Output Gap during a Housing Crisis



Notes: Calculated based on a Hodrick-Prescott filter with a value of 1600 for lambda; includes data up to the first quarter 2010; shaded area marks the one-standard-error confidence band.

On a yearly basis, GDP growth reaches its lowest level in the second year after the price peak with an average growth rate of 0.1 percent (Table 2.1). This is far below the average growth rate of all the considered countries, which amounts to 2.0 percent. At –1.1 percent, the output gap reaches its lowest value in the second and third year of the crisis.

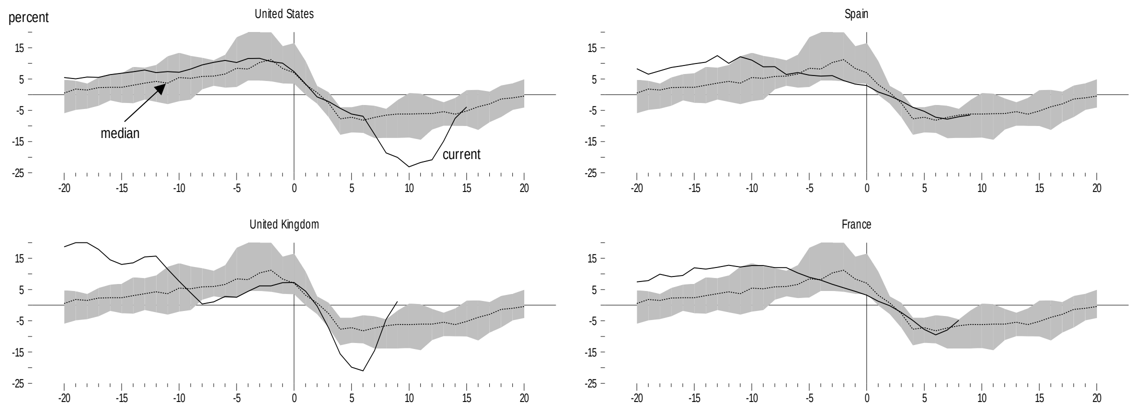
Table 2.1:
Average Growth Rates of GDP and Average Output Gap during a Housing Crisis[a]

Year	Real domestic product[b]			Average output gap[c]		
	Median	Lower quantile	Upper quantile	Median	Lower quantile	Upper quantile
–4	3.3	1.1	5.8	–0.5	–1.2	0.2
–3	3.4	1.5	5.7	–0.4	–1.4	0.5
–2	4.1	1.5	6.2	0.2	–0.3	1.2
–1	4.1	2.0	6.1	1.7	1.1	2.5
0	2.3	0.2	4.5	1.8	0.4	2.6
1	0.1	–2.4	2.4	–0.1	–1.2	0.7
2	1.0	–1.7	3.5	–1.1	–1.9	–0.2
3	1.7	–0.2	3.7	–1.1	–1.9	–0.4
4	3.3	1.6	4.8	–0.5	–1.1	0.0

[a]Housing crisis starts in the first quarter of year 0. — [b]Growth rates calculated on the basis of yearly averages of quarterly GDP in levels. — [c]Yearly average over quarterly values.

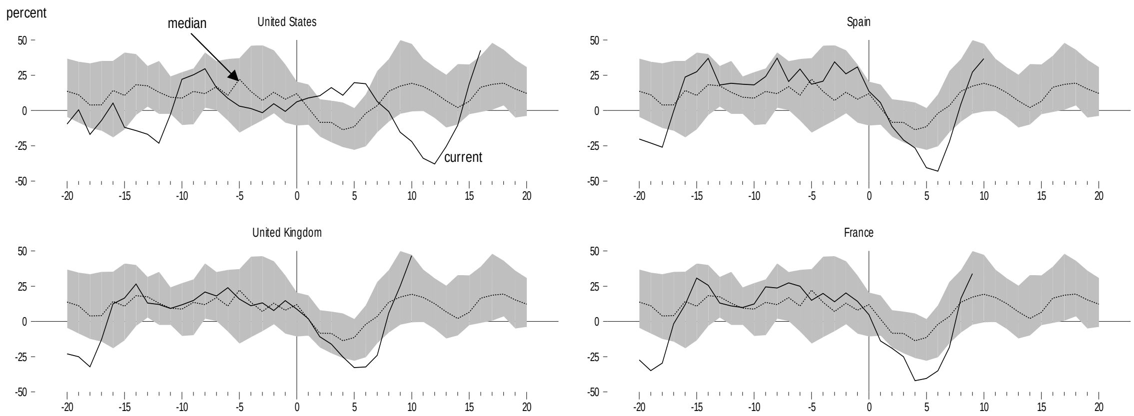
Additionally, the results suggest that an increase in house prices previous to a crisis could stimulate the economy and contribute to an upswing ahead of the crisis, since the output gap increases notably before the crisis.[6] The monetary and financial indicators react significantly to housing crisis as well. On average, real house prices deteriorate sharply at the beginning of a housing crisis (Figure 2.5), by even more than is induced by the criteria that were chosen to define a housing crisis. Further, share prices decline considerably at the beginning of a housing crisis (Figure 2.6). They drop by 15 percent, on average, within the first year.

Figure 2.5:
Real House Prices during a Housing Crisis



Notes: Percentage change, year to year; includes data up to the first quarter 2010; shaded area marks the one-standard-error confidence band.

Figure 2.6:
Nominal Share Prices during a Housing Crisis

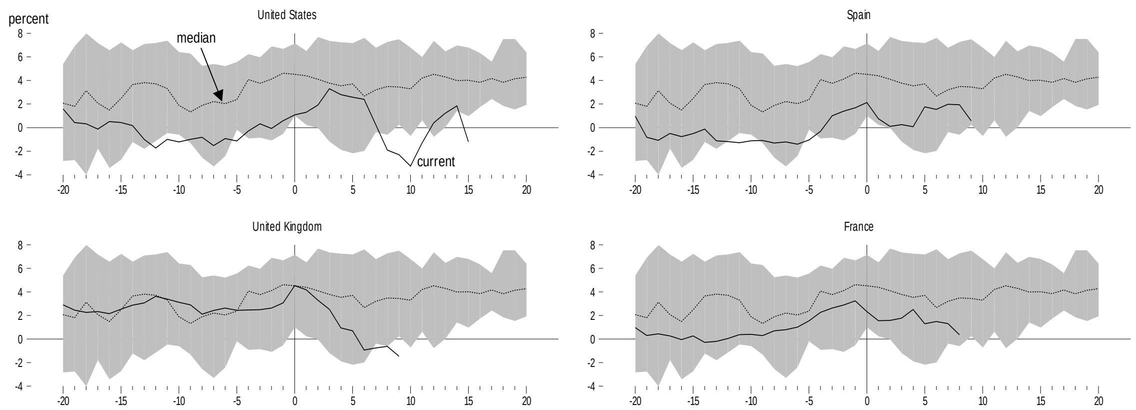


Notes: Percentage change, year to year; includes data up to the first quarter 2010; shaded area marks the one-standard-error confidence band.

[6] While the output gap is well suited to capture the dynamics of the business cycle, it is not necessarily well suited to calculate the costs of a housing crisis compared with the gains of a housing boom that usually takes place before the crisis, because for a longer time span, by definition, the output gap adds up to zero and thus is biased to the result of no costs.

Volatility seems to increase significantly as the crisis surges; however, the uncertainty surrounding share price development is extremely high. The short-run real interest rate starts to rise roughly two years before house prices reach their peak (Figure 2.7). One explanation for this could be that central banks tighten monetary policy to dampen a boom that was to some extent induced by rising house prices. Right after the turning point, when the crisis becomes visible, monetary policy is eased.

Figure 2.7:
Real Interest Rates during a Housing Crisis



Notes: Calculated as the difference between short-term interest rate and year-to-year percentage change of the headline consumer price index; includes data up to the first quarter 2010; shaded area marks the one-standard-error confidence band.

A comparison of the historically typical business cycle pattern during a housing crisis with the current patterns in the United States and in the three European countries shows that GDP growth in all four countries was significantly below average for several months. Even if we take into account that GDP growth in the United States, the United Kingdom, and France before the housing crises was already below the historical average, growth in these countries during the housing crisis was exceptionally weak. While GDP growth in the three European countries loses momentum roughly when the historical comparison suggests, the downturn in the United States occurs with a delay of about 1.5 years.

Concerning the onset of the downturn in comparison to the historical experience, the output gap exhibits a similar pattern to GDP growth: while the downturn in the three European countries is in line with the historical comparison, it began in the United States with some delay. Even though the swing between the peak and the trough of the output gap is relatively large in all four countries and in particular in the United Kingdom and Spain, the output gap indicates that the downturn is more in line with the historical experience when compared to GDP growth. While the United States, the United Kingdom, and France are likely to have passed the trough by the fourth quarter 2009, this assessment cannot be made for Spain.

The increase in real interest rates starts in all of our four underlying countries about two years prior to the price peak. In the United States, the real interest rate begins to decline four quarters after the price peak and turns negative after two years. In the European countries, the real interest rates fall at the beginning of the crisis. However, this is mainly due to a commodity price hike at that time, which led to an acceleration of the inflation rate. The nominal interest rates do not start to decline until the fourth quarter 2008 in these countries. In the United States, Spain, and France, we can also observe long-lasting phases of very low or even negative real interest rates before the price peak, but also in the United Kingdom real interest rates were relatively accommodative in the pre-crisis phase. At the same time, house prices increased significantly above average in these countries, which indicates a close relationship between house prices and monetary conditions. However, in the United Kingdom, where the real interest rate was in line with the historical comparison, we can observe exceptionally strong house price increases in this period as well. During the crisis, the house price declines in the United Kingdom and, with some delay, in the United States are particularly strong, while the price declines in Spain and France are, on average, roughly as strong as during previous housing crises. Share prices decrease at the beginning of the housing crisis in the three European countries and with some delay in the United States. The magnitude of this decrease is roughly in line with the historical comparison. During the last observable quarters share prices start to increase again in all four countries.

2.3 International Business Cycle Effects of Housing Crises

The previous section provided evidence that housing crises usually go hand in hand with long-lasting and deep recessions on the national level. This result gives rise to the hypothesis that housing crises may lead to significant negative spillover effects to other countries. We test this hypothesis by means of two approaches. First, we extend the panel model approach introduced by Cerra and Saxena (2008) to estimate the effects of severe economic crises by adding a variable that captures the onset of housing crises in foreign countries. Second, we use a parsimonious international business cycle model and impose the typical business cycle pattern during housing crises on countries suffering from such crises during the Great

Recession of 2008/2009. Further, we use the latter approach to estimate to what extent housing crises can explain negative spillover effects to other countries in this period.

2.3.1 Panel Model Approach

Cerra and Saxena (2008) use a panel model to estimate the impact of severe economic crises, such as banking crises or currency crises, on GDP. Therefore, they construct qualitative indicators of severe economic crises in the spirit of Romer and Romer (1989), who introduced a similar approach to capture the effects of monetary policy shocks on output. Then they extend an autoregressive panel model by these indicators and are thereby able to estimate the impact of severe economic crises on output. The baseline model is given by

$$\Delta y_{i,t} = c_i + \sum_{j=1}^{m} \alpha_j \Delta y_{i,t-j} + \sum_{j=1}^{m} \beta_j d_{i,t-j} + u_{i,t} \,, \tag{2.1}$$

where $\Delta y_{i,t}$ is GDP growth of country *i* in year *t*, $d_{i,t}$ is a dummy variable that takes the value of one when a severe economic crisis, in our case a housing crises, begins in country *i*, and c_i captures country fixed effects.[7] Since we are interested in the international spillover effects of housing crises, we extend the baseline model by a variable that captures the occurrence of housing crises in foreign countries. Obviously, the size of the countries suffering from housing crises is relevant for the strength of international spillover effects. Therefore, we construct an individual export-weighted foreign housing crises measure, $d^*_{i,t}$, for all countries, *i*, by multiplying the domestic housing crises indicator, $d_{k,t}$, with the respective export weight of country *k* for country $i, w_{ik,t}$, and adding up over all *p* countries in our sample:

$$d^*_{i,t} = \sum_{k=1}^{p} w_{ik,t} \cdot d_{k,t} \;. \tag{2.2}$$

The variable $d^*_{i,t}$ takes the value of zero when no trading partner of country *i* is facing a housing crisis and a value of one when all trading partners of country *i* are facing a housing crisis; therefore, this variable is usually expected to take values much smaller than one.

[7] We deviate from the baseline model of Cerra and Saxena (2008) in two aspects. First, while Cerra and Saxena (2008) set the dummy variable equal to one for the whole period of a severe crisis, we set the dummy variable equal to one only for the first year of a housing crisis, since we have not identified the end of a housing crisis. Second, we do not allow for a contemporaneous effect of the housing crises on GDP growth, because the analysis in Section 2 revealed that, given our identification criteria, we usually do not have to expect a strong decline in GDP growth before the second year of a housing crisis.

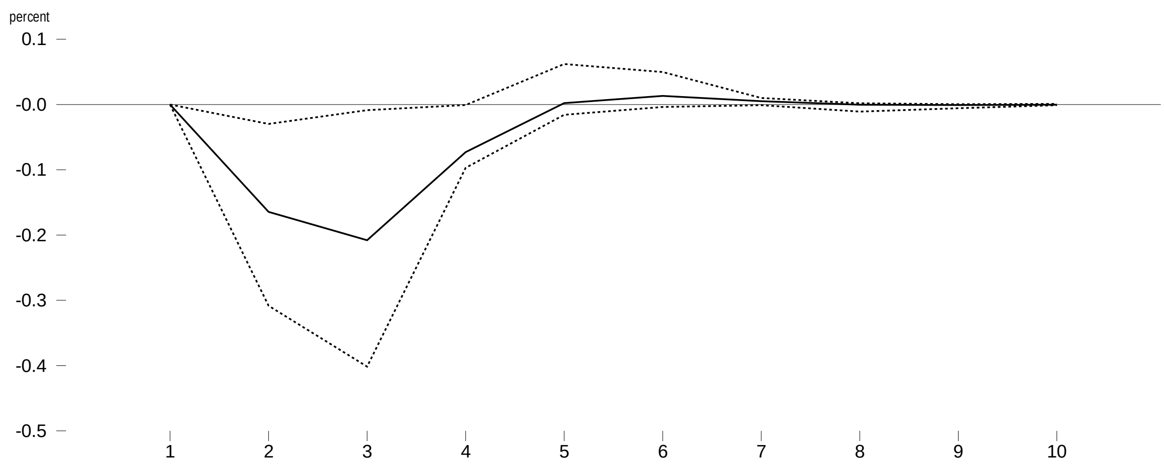
Extending the baseline model (2.1) by the foreign housing crises variable $d^*_{i,t}$ yields to the model

$$\Delta y_{i,t} = c_i + \sum_{j=1}^{m} \alpha_j \Delta y_{i,t-j} + \sum_{j=1}^{m} \beta_j d_{i,t-j} + \sum_{j=1}^{m} \gamma_j d^*_{i,t-j} + u_{i,t} \ . \qquad (2.3)$$

We estimate this model for a panel of the 15 countries for which we identified housing crises in Section 2.2. By keeping the dummy variable, $d_{k,t}$, in the model, we control for the effects of domestic housing crises, which seems appropriate, since the analysis in Section 2.2 revealed that housing crises frequently occurred at the same time in several countries. We choose a lag length of $m = 2$, since lags of a higher order are insignificant at the five percent level.

Figure 2.8 shows the effects on GDP growth for a country if ten percent of its trading partners were suffering from a housing crisis ($d^*_{i,t} = 0.1$). On average, foreign housing crises reduce domestic GDP growth for four years. The confidence bands show the 95 percent significance level drawn from one thousand Monte Carlo simulations. The strongest effect is estimated for the second year after the onset of foreign housing crises, with a decline in GDP growth of roughly half a percentage point.

Figure 2.8:
Effects of Foreign Housing Crises on Domestic GDP Growth



Note: Dashed lines mark the 95 percent confidence bands based on 1,000 draws from a Monte Carlo simulation.

2.3.2 International Business Cycle Model

As a second approach to determine the relevance of international business cycle effects of housing crises, we adopt a multi-country model. Usually, the estimation of multi-country models in a VAR framework with an increasing number of countries soon becomes infeasible due to the exponentially increasing numbers of parameters. Therefore, the empirical investigation of international transmission mechanisms concentrated for a long time only on models that include a very limited number of countries or on bilateral models. Abeysinghe (2001a), Abeysinghe (2001b), and Abeysinghe and Forbes (2001) introduced an approach that makes the estimation of multi-country models in a VAR framework feasible. Basically, they use trade weights to aggregate foreign GDP growth—or other variables of interest—from the domestic perspective to single variables and thereby reduce the number of variables to be estimated dramatically. Using a similar approach, Pesaran et al. (2004) developed a Global VAR model that includes more macroeconomic variables than the former models and accounts for cointegration relationships. In a series of papers, this model has been used, for example, to investigate the international linkages of the Euro Area (Dees et al. 2007) or to run counterfactual simulations (Pesaran et al. 2007).

Here, we stick to a model that includes only GDP growth and therefore is more in line with the approach of Abeysinghe and Forbes (2001), which is sufficient for our purpose to obtain rough estimates of international spillover effects of housing crises by imposing the typical GDP growth path during housing crises that was developed in Section 2.2. We are aware that this simulation strategy is by far not costless. In particular, we implicitly deny the importance of transmission channels other than the trade channel and do not model the housing crises explicitly. However, by using this highly stylized simulation method we can circumvent—in the spirit of the analysis in Section 2.2—the problems that arise when modeling housing crises dynamics and are able to straightforwardly obtain the results we are interested in.

Model Description

We draw on a multi-country model, that explains domestic GDP growth, $\Delta y_{i,t}$, by means of own lags and foreign GDP growth. In its most extensive form, the model is given by

$$\begin{pmatrix} 1 & -\beta_{01}w_{12,t} & \cdots & -\beta_{01}w_{1p,t} \\ -\beta_{02}w_{21,t} & 1 & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots \\ -\beta_{0p}w_{p1,t} & \cdots & \cdots & 1 \end{pmatrix} \begin{pmatrix} \Delta y_{1,t} \\ \cdots \\ \cdots \\ \Delta y_{p,t} \end{pmatrix} = \begin{pmatrix} D_{1,t} \\ \cdots \\ \cdots \\ D_{p,t} \end{pmatrix} + \sum_{j=1}^{m} \begin{pmatrix} \alpha_{j1} & \beta_{j1}w_{12,t-j} & \cdots & \beta_{j1}w_{1p,t-j} \\ \beta_{j2}w_{21,t-j} & \alpha_{j2} & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots \\ \beta_{jp}w_{p1,t-j} & \cdots & \cdots & \alpha_{jp} \end{pmatrix} \begin{pmatrix} \Delta y_{1,t-j} \\ \cdots \\ \cdots \\ \Delta y_{p,t-j} \end{pmatrix} + \begin{pmatrix} u_{1,t} \\ \cdots \\ \cdots \\ u_{p,t} \end{pmatrix}, \quad (2.4)$$

where $D_{i,t}$ describes the deterministic part of the equation and can consist of a constant and a trend term. The key feature of model (2.4) is that it allows domestic GDP to depend on the foreign GDP of all other countries included in the model and therefore provides a very flexible framework to simulate the international transmission of shocks. Estimation of the model becomes feasible by assuming that the relative importance of GDP growth in the foreign country, *k*, for GDP growth in the domestic country, *i*, is adequately described by the export share, $w_{ik,t}$, of country i to country *k*. Further, it is assumed that the foreign GDP growth elasticity of domestic GDP growth for country *i*, $\beta_{j,i}$, is equal over all *p* countries in the sample. Therefore, the individual country equations can be summarized as

$$\Delta y_{i,t} = D_{i,t} + \sum_{j=1}^{m} \alpha_{ji} \cdot \Delta y_{j,t-i} + \sum_{j=0}^{m} \beta_{ji} \cdot \Delta y^{*}_{i,t-j} + u_{i,t}\,, \quad (2.5)$$

where foreign GDP growth, $\Delta y^{*}_{i,t}$, is aggregated via the export shares, $w_{ik,t}$, over all *p* countries

$$\Delta y^{*}_{i,t} = \sum_{k=1}^{p} w_{ik,t} \cdot \Delta y_{k,t} \quad (2.6)$$

and the export shares for the country *i* sum up to unity. The implicit assumption underlying the model structure is that international transmission works mainly through the trade channel, while domestic economic activity can be explained adequately by an autoregressive process. The former assumption is rationalized by Baxter and Kouparitsas (2005), who found bilateral trade linkages to be a robust driver of business cycle comovement between countries. By allowing the weights to be time-dependent, we account for the varying importance of trading partners over time because, for example, demand in some countries grows faster than in other countries or the composition of demand changes over time. The export weights are calculated as an average over the last four quarters, such that short-term fluctuations do not influence the results.

We assume for each country that the contemporaneous foreign variable in equation (2.5) is weakly exogenous, which is basically equivalent to the small open economy assumption.[8] Based on this assumption, the model can be estimated equation by equation with the method of least squares. In this paper, we adopt a model with 25 countries, among which are the most important industrial countries.[9] The model is estimated on the basis of quarterly data from 1985:1 to 2007:4. The choice of the country sample and the estimation period was guided by the aim to include as many countries as possible in order to cover all the regions of the world on the one hand and to have sufficiently long times series for the estimation of the model on the other hand. For all 25 countries included in the model, GDP data are available beginning in 1985.[10] We estimate the model for quarterly data and allow for five lags for domestic and foreign GDP growth at maximum.

The equations are estimated with a model reduction method.[11] This estimation method reduces the uncertainty surrounding the simulation exercises and, thus, leads to smaller confidence bands.[12] We apply a testing procedure which was proposed by Brüggemann and Lütkepohl (2001), among others, and that sequentially deletes, equation by equation, the regressors with the smallest significance level until a certain threshold of the significance level is reached.[13] The threshold is set to the ten percent significance level.

[8] This is a standard assumption in the Global VAR literature and has been demonstrated frequently to hold in general (see, e.g., Dees et al. 2007).

[9] The countries are Germany, France, Netherlands, Belgium, Ireland, Portugal, Finland, Italy, Spain, Greece, United States, United Kingdom, Japan, Denmark, Norway, Sweden, Switzerland, Canada, Australia, South Africa, South Korea, Israel, Turkey, Singapore, and Mexico.

[10] The choice of 1985 as the starting year has the further advantage that it covers the period of the Great Moderation and therefore avoids possible instabilities if the model were be estimated with pre-Great Moderation data, as well.

[11] The model selection method deletes, based on the complete model with all lags, the variable with the smallest significance level until all remaining variables are significant at the ten percent level. All included deterministic terms are structurally stable at the five percent level. We test for autocorrelation in the first, second, fourth, and eighth lag of the residuals. The country equation for Greece is allowed to include the maximum number of eight lags to ensure that the residuals are free of autocorrelation. For the United Kingdom, autocorrelation is detected for the eighth lag. All other residuals are free of autocorrelation.

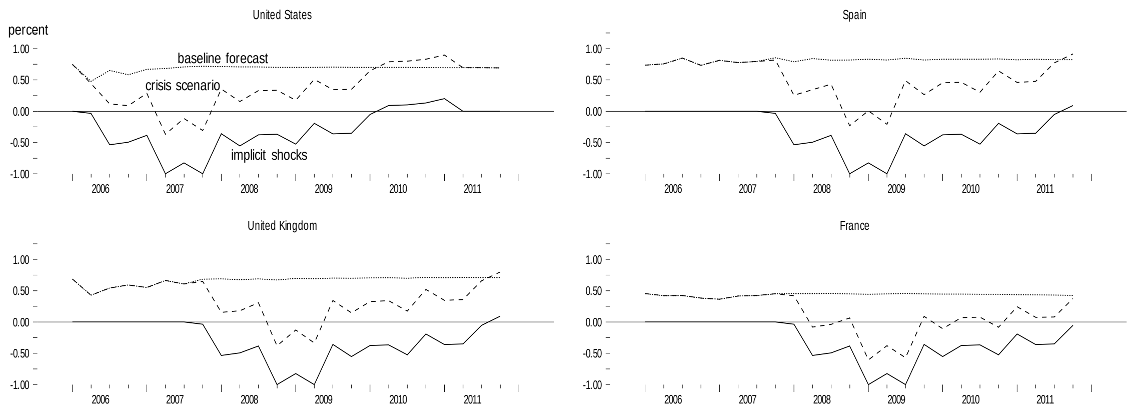
[12] Brüggemann and Lütkepohl (2001) show that model reduction methods also improve forecasting performance compared to the unrestricted model. However, they suggest that their results depend strongly on the underlying data-generating process and should not be generalized. Therefore, we test our results by providing the simulation results for the unrestricted VAR in Appendix C. In general, the test results are qualitatively identical to those of the restricted VAR.

[13] A more elaborate, but also complex, model reduction method is the PCGets method proposed by Hendry and Krolzig (2001). However, Brüggemann et al. (2001) demonstrate that for simulation exercises, the testing procedure applied here leads to comparable results.

Simulation Method

We simulate the transmission effects of housing crises in the four countries where we were able to identify a crisis according to our criteria, namely the United States, the United Kingdom, Spain, and France. Therefore, we compare a baseline scenario to a crisis scenario. The consequences of a housing crisis in the four countries for other countries are then measured by impulse response functions, calculated as the difference in GDP growth in both scenarios. The baseline scenario is the unconditional model forecast, which soon converges to the long-run average GDP growth rate (Figure 2.9). For the crisis scenario, we assume that the GDP growth in the four countries will develop as during a typical housing crisis—derived in Section 2.2—and then forecast GDP growth in the other countries conditional on this assumption.

Figure 2.9:
Baseline Forecast, Crisis Scenario, and Implicit Shocks



Instead of imposing GDP growth exactly as during historical housing crises, we calculate GDP growth for the crisis scenario in the four countries by adding the difference between GDP growth in the first period of the housing crises and GDP growth in the respective quarter, *t*, of a housing crisis ("implicit shocks") to the baseline forecast. Basically, this method yields the same patterns of GDP growth as during historical housing crises, but tries to correct somehow for different potential growth rates. This could be relevant, because many housing crises took place in the 1970s and 1980s, when macroeconomic conditions were different from today's conditions. Most notably, the potential growth rates were usually higher, such that the average GDP growth of a historical housing crisis could still be "too high" compared to the forecast of GDP growth in the baseline scenario. This method ensures a reasonable replication of the typical business cycle pattern during a historical crisis while taking into account the various trend growth rates in the 1970s and 1980s.[14]

We start the simulation in the first quarter of 2006, since the housing crises in the United States started in that quarter. The implicit shocks for the United Kingdom, Spain, and France before the beginning of housing crises are set to zero. The housing crisis in the United States is expected to have its largest negative impact in 2007. The housing crises in the three European countries are expected to have their largest negative impact in the winter half year 2008/2009. Naturally, this simulation exercise can only provide a broad measure of the international effects of housing crises. However, due to its simplicity, this method is appropriate to translate the historical comparison in Section 2.2 directly into an estimate of the strength and the length of international effects of housing crises.[15]

International Effects of Typical Housing Crises

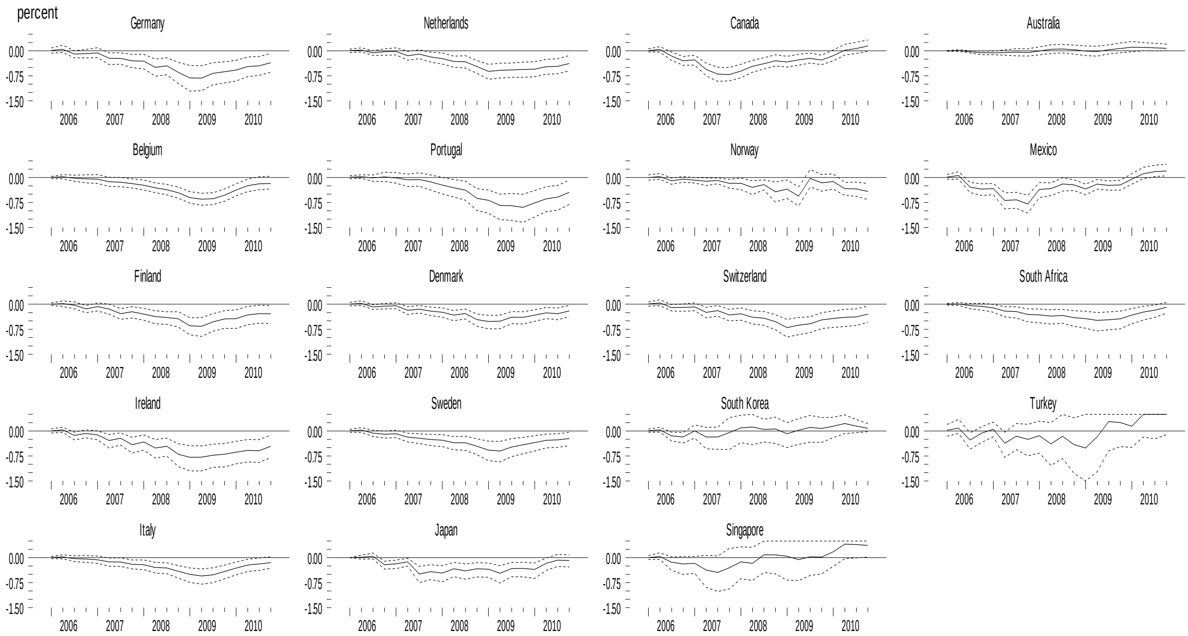
Figure 2.10 illustrates that housing crises in the United States, the United Kingdom, Spain, and France lead to a significant decline of GDP growth in most European countries.[16] Most countries face lower GDP growth rates for several years, beginning in 2007 and testing until the end of the simulation period at the end of 2010. Exceptions with only a few quarters of significant negative impact or generally small effects are South Korea, Singapore, Australia, and Turkey. The biggest decline for most of the European countries and South Africa is expected to occur between the third quarter 2008 and the first quarter 2009 and thus in the same time period as the three countries in Europe that are directly affected by a housing crisis. The housing crisis in the United States leads only to a relatively small decline in GDP growth in those countries. In contrast, Canada and Mexico are more affected by the housing crisis in United States and thus face the largest decline in GDP growth in 2007, while the crises in the European countries have only small spillover effects. Japan faces a relatively constant decline in GDP growth between the third quarter of 2007 and the end of 2009. Overall, the result obtained in Section 2.3.1, namely that housing crises potentially lead to significant international negative spillover effects, is supported.

[14] The results are qualitatively the same when we impose average GDP growth during historical housing crises in the four countries. In general, the international transmission effects are estimated to be somewhat lesser.

[15] Since the housing market is not modeled explicitly, the following results for the international transmission mechanisms hold also for comparable phases of economic downturns in the discussed countries.

[16] Estimation with the model selection method results in no significant effects of the foreign variable on GDP growth in Israel and Greece. Therefore, these countries are excluded from the figures.

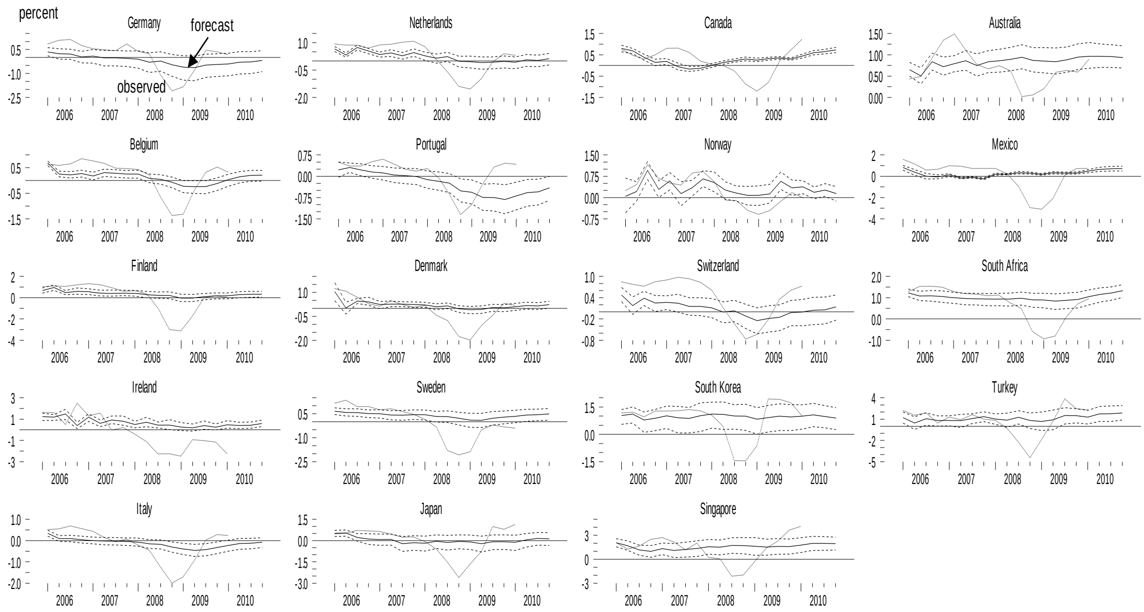
Figure 2.10:
International Impact of Housing Crises on GDP Growth



Note: Dashed lines mark the 95 percent confidence bands calculated via bootstrap simulation with 1,000 replications.

To test how well the international business cycle model can explain GDP growth during the Great Recession of 2008/2009, we ran a forecasting experiment beginning in the first quarter of 2006, given the housing crises in the United States, the United Kingdom, Spain, and France. Figure 2.11 illustrates that the model by far cannot explain the pronounced downturn of the winter half year 2009/2009, which occurred in most countries of our sample. In general, the model predicts, for most countries, a longer-lasting but less pronounced downturn than observed. Indeed, in several countries, such as Italy, Japan, and Portugal, observed GDP growth beginning in the second half of 2009 is higher than predicted by the model. While the mean forecast includes several quarters of negative GDP growth for many countries within the sample, the confidence bands indicate that in general GDP growth is expected to be significantly negative at the five percent level for very few countries, such as Italy, Belgium, and Portugal. Further, the model tends to underestimate GDP growth in the beginning of the simulation period.

Figure 2.11:
Model Prediction of GDP Growth from 2006 to 2010



Note: Dashed lines mark the 95 percent confidence bands calculated via bootstrap simulation with 1,000 replications.

One reason for this might be the unusual behavior of GDP growth in the United States compared to the historical experience. The comparison between GDP growth during historical housing crises and GDP growth during the housing crisis in the United States beginning in 2006 revealed that GDP growth in the United States is subject to a delay of roughly six quarters. However, if we account for this observation in our forecasting experiment, the results do not change dramatically. In general, the model then under-estimates GDP growth in 2006 and 2007 only to a somewhat lesser degree. Further, it explains the decline in GDP growth in the winter half year 2008/2009 somewhat better, as well, however, without being able to explain the downturn completely.[17]

During the Great Recession, international transmission mechanisms that work through the financial sector obviously played an important role. Therefore, the assumption that international transmission during housing crises works mainly through the trade channel might be too restrictive for this period. Therefore, we augment model (5) with a variable that aggregates foreign GDP growth with an indicator of financial openness and then re-estimate the model. We find that the predicted GDP growth rates of the model for nearly all countries

[17] A figure with the results can be found in Appendix D.

in our sample are higher than compared to the baseline model.[18] Hence, the augmented model fails to explain the downturn during the Great Recession.

2.4 Conclusion

A historical comparison shows that housing crises usually lead to long-lasting and deep recessions. On average, a housing crisis has the most severe effects in the first two years and particularly between the fifth and the seventh quarter after house prices have reached their peak. In a typical historical housing crisis, the output gap is not expected to close for five years. According to our identification criteria of housing crises the United States, the United Kingdom, Spain, and France are likely to have faced housing crises beginning in 2006 and 2007. These housing crises were followed by exceptionally strong recessions when compared to the historical experience. While the patterns of GDP growth and the output gap in the three European countries were quite similar to the historical comparison, the downturn in the United States seems to have started after a delay of roughly six quarters. The observation that housing crises do have the potential to trigger recessions on the national level gives rise to the hypothesis that they have negative international spillover effects, as well. We show by means of two models that emphasize the trade channel as the most important international transmission mechanism that housing crises lead to significant negative spillover effects to other countries. Further, we show that the housing crises in the United States, the United Kingdom, Spain, and France are sufficient to explain a severe downturn, in particular in European countries during the Great Recession, but fail to explain the steep downturn of the winter half year 2008/2009. Since we explicitly do not take the spillover effects of the housing sector to the financial sector into account—effects that are likely to have been much more severe during the Great Recession than during the historical crises—we demonstrate the importance of housing crises on their own during the Great Recession.

[18] A figure with the results and a more detailed explanation can be found in Appendix D.

2.5 References

Abeysinghe, T. (2001a). Estimation of Direct and Indirect Impact of Oil Price on Growth. *Economic Letters* 73: 147–153.

Abeysinghe, T. (2001b). Thai Meltdown and Transmission of Recession Within the ASEAN4 and NIE4. In S. Claessens and K. Forbes (eds.), Kluwer International Finacial Contagion Academic Publishers. Boston: 225–240.

Abeysinghe, T., K. Forbes (2001). Trade-Linkages and Output-Multiplier Effects: A Structural VAR Approach with a Focus on Asia. NBER Working Paper 8600. National Bureau of Economic Research, Cambridge, MA.

Ahearne, A.G., J. Ammer, B.M. Doyle, L.S. Kole and R.F. Martin (2005). House Prices and Monetary Policy: A Cross-Country Study. International Finance Discussion Papers 841. Board of Govonors of the Federal Reserve System, Washington, D.C.

Baxter, M., and M.A. Kouparitsas (2005). Determinants of Business Cycle Comovement: A Robust Analysis. *Journal of Monetary Economics* 52: 113–157.

Bordo, M.D., and O. Jeanne (2002). Boom-Busts in Asset Prices, Economic Instability, and Monetary Policy. NBER Working Paper 8966. National Bureau of Economic Research, Cambridge, MA.

Brüggemann, R., H.-M. Krolzig and H. Lütkepohl (2001). Comparison of Model Reduction Methods for VAR Processes, *Economic Papers* 2003-W13. Nuffield College, Oxford.

Brüggemann, R., and H. Lütkepohl (2001). Lag Selection in Subset VAR Models with an Application to a U.S. Monetary System. In Econometric Studies – A Festschrift in Honour of Joachim Frohn, edited by R. Friedmann, L. Knüppel and H. Lütkepohl. Berlin, LIT Verlag: 107–128.

Cerra, V., and S.C. Saxena (2008). Growth Dynamics: The Myth of Economic Recovery. *American Economic Review* 98: 439–457.

Cecchetti, S.G., M. Kohler and C. Upper (2009). Financial Crises and Economic Activity. NBER Working Paper 15379. National Bureau of Economic Research, Cambridge, MA.

Claessens, S., M.A. Kose and M.E. Terrones (2008). What Happens During Recessions, Crunches and Busts? IMF Working Paper 08/274. International Monetary Fund, Washigton, D.C.

Dées, S., F. Di Mauro, M.H. Pesaran and L.V. Smith (2007). Exploring the International Linkages of the Euro Area: A Global VAR Analysis. *Journal of Applied Econometrics* 22: 1–38.

Detken, C., and F. Smets (2004). Asset Price Booms and Monetary Policy. ECB Working Paper 364. European Central Bank, Frankfurt/Main.

Furceri, D., and A. Mourougane (2009). The Effect of Financial Crises on Potential Output. OECD Economics Department Working Papers 699. Organization for Economic Cooperation and Development, Paris.

Hendry, D., and H.-M. Krolzig (2001). Automatic Econometric Model Selection with PCGets. London, Timberlake Consultans Press.

IMF (International Monetary Fund) (2003). When Bubbles Burst. *World Economic Outlook*. April. Washington, D.C.: 61–94.

IMF (International Monetary Fund) (2009a). From Recession to Recovery: How Soon and How Strong? *World Economic Outlook*. April. Washington D.C.: 103–138.

IMF (International Monetary Fund) (2009b). What's The Damage? Medium-Term Output Dynamics After Financial Crises. *World Economic Outlook*. October. Washington D.C.: 121–151.

Jonung, L., L. Schuknecht and M. Tujula (2006). The Boom-Bust Cycle in Finland and Sweden 1984–1995 in an International Perspective. Working Paper 2006/13. Center of Financial Studies, Frankfurt/Main.

Lane, P.R., and G.M. Milesi-Ferretti (2007). The External Wealth of Nations Mark II: Revised and Extended Estimates of Foreign Assets and Liabilities, 1970-2004. *Journal of International Economics* 73: 223–250.

Leamer, E. (2007). Housing is the Business Cycle. NBER Working Paper 13428. National Bureau of Economic Research, Cambridge, MA.

Pesaran, M.H., T. Schuermann and S.M. Weiner (2004). Modelling Regional Interdependencies Using a Global Error-Correcting Model. *Journal of Business & Economic Statistics* 22: 129–181.

Pesaran, M.H., S.L. Smith and R. Smith (2007). What If the UK or Sweden Had Joined the Euro in 1999? An Empirical Investigation. *International Journal of Finance&Economics* 12: 55–87.

Reinhart, C.M., and K. Rogoff (2008). Is the 2007 US Subprime Crises so Different? An International Historical Comparison. *American Economic Review* 98: 339–344.

Reinhart, C.M., and K. Rogoff (2009a). *This Time is Different: Eight Centuries of Financial Folly*. Princeton University Press, Princeton, NJ.

Reinhart, C.M., and K. Rogoff (2009b). The Aftermath of Financial Crises. NBER Working Paper 14656. National Bureau of Economic Research, Cambridge, MA.

Romer, C.D., and D.H. Romer (1989). Does Monetary Policy Matter? A New Test in the Spirit of Friedman and Schwartz. *NBER Macroeconomics Annual* 4: 121–170.

2.6 Appendix A: Data Description

The real house prices used in Section 2.2 primarily for the historical comparison were taken from a dataset provided by the Bank of International Settlements. House prices for France, Spain, and Belgium were interpolated from yearly to quarterly data. House prices for the United States (House Price Index – All Transactions, Office of Federal Housing Enterprise) and land prices for Japan (Nationwide Land Price Index, Japan Real Estate Institute), deflated by consumer prices taken from the national statistical agencies, were added. All other data for the historical comparison were taken from the OECD Economic Outlook database. All current data in the figures were taken from various national sources to ensure that the most recent data were used.[19]

GDP data for the model in Section 2.4 were mainly obtained from the OECD Economic Outlook database. Data for Singapore, South Africa, and Israel were taken from the International Financial Statistics Database of the International Monetary Fund. Seasonal adjustment was performed with Census X11 for GDP data for Singapore and Israel. Bilateral export data for calculating the weights for the foreign variables were taken from the International Financial Statistics Database of the International Monetary Fund.

2.7 Appendix B: Robustness of Identification Criteria for Housing Crises

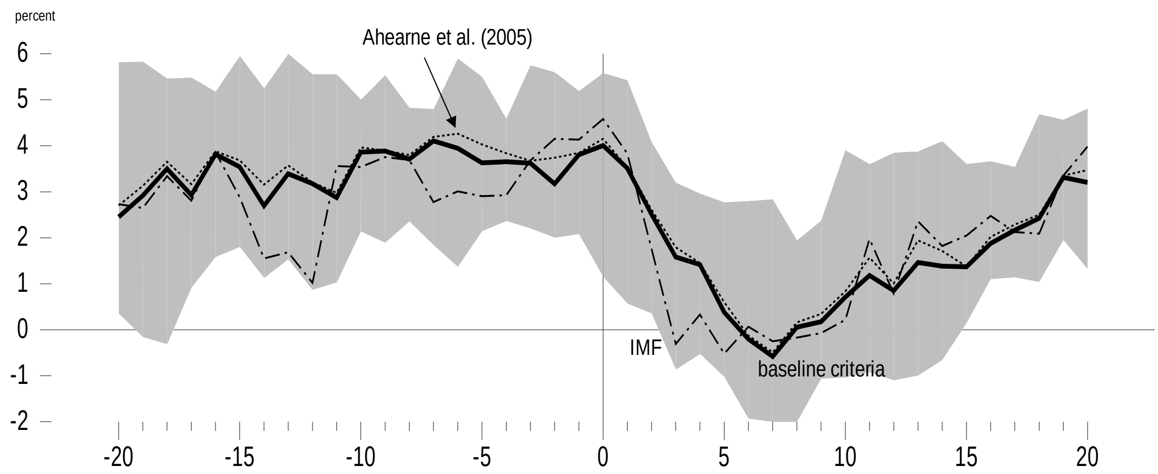
The baseline criteria chosen for identifying housing crises were, even though based on criteria already applied in the literature, rather ad hoc. They identify housing crises when real house prices reach a price peak within a period of eight years and decline in the following four years by at least 7.5 percent. In the following, we compare the results based on these criteria with those based on the criteria of Ahearne et al. (2005) on the one hand and those based on the criteria of the IMF on the other hand. These two alternative identification methods can be interpreted as extreme cases. While Ahearne et al. (2005) base their results on every price peak within a certain time period, the identification method of the IMF is much tighter and only identifies the 25 percent most severe price declines following price peaks as housing crises. Applying these identification methods to our sample, we identify 30 housing crises if we only take every price peak within a period of eight years into account and 8 housing crises if we apply the identification method of the IMF (2003), compared to the 27 crises that we identify with our baseline method. Therefore, our identification method seems

[19] Detailed sources of the current data are available upon request.

to be much more closely related to that of Ahearne et al. (2005). The baseline method would lead to similar results as the IMF method if we tightened the necessary price decline following a price peak to roughly 40 percent. Therefore, the comparison between the baseline results and those based on the IMF method displays a large range of criteria that could possibly be chosen with respect to the minimum price decline.

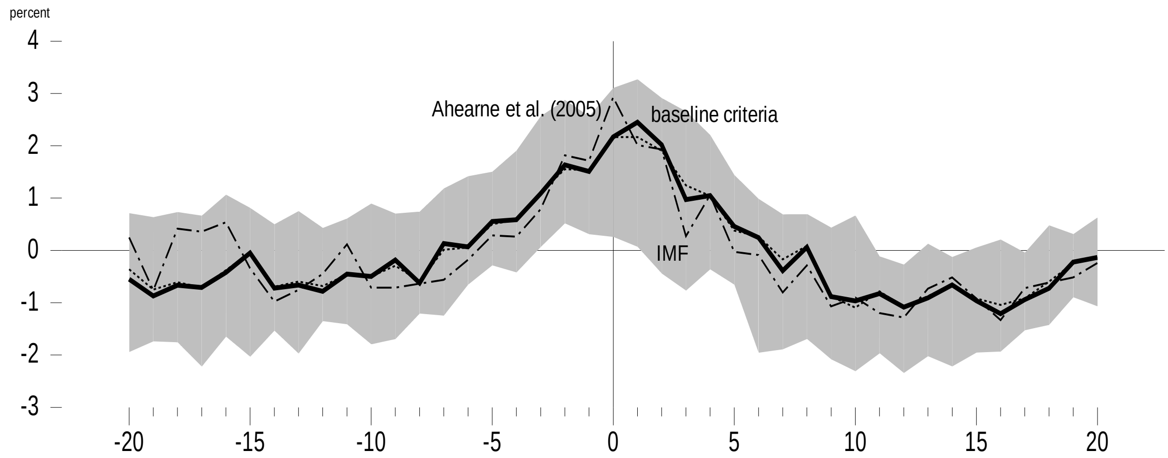
A comparison of the typical GDP growth during housing crises shows that the three different identification methods yield similar results (Figure 2.B.1). The baseline method and the method used in Ahearne et al. (2005) lead to nearly exactly the same results. The method used in IMF (2003) assesses GDP growth during housing crises to be considerably weaker only between the third and the fourth quarter following the price peak. For the rest of the observed period, the IMF method yields, despite there being some quarters before the onset of a housing crisis, roughly the same results as the other two methods.

Figure 2.B.1:
Comparison between Different Identification Methods for Housing Crises Based on GDP Growth



A comparison of the results for the output gap shows that the development of the output gap is nearly identical with all three identification methods (Figure 2.B.2). The IMF (2003) estimates the output gap to be persistently lower than the other two methods. However, with respect to overall uncertainty, the deviation is very small. Overall, we conclude that our results are absolutely robust to modifications of our housing crisis identification criteria.

Figure 2.B.2:
Comparison between Different Identification Methods for Housing Crises Based on the Output Gap

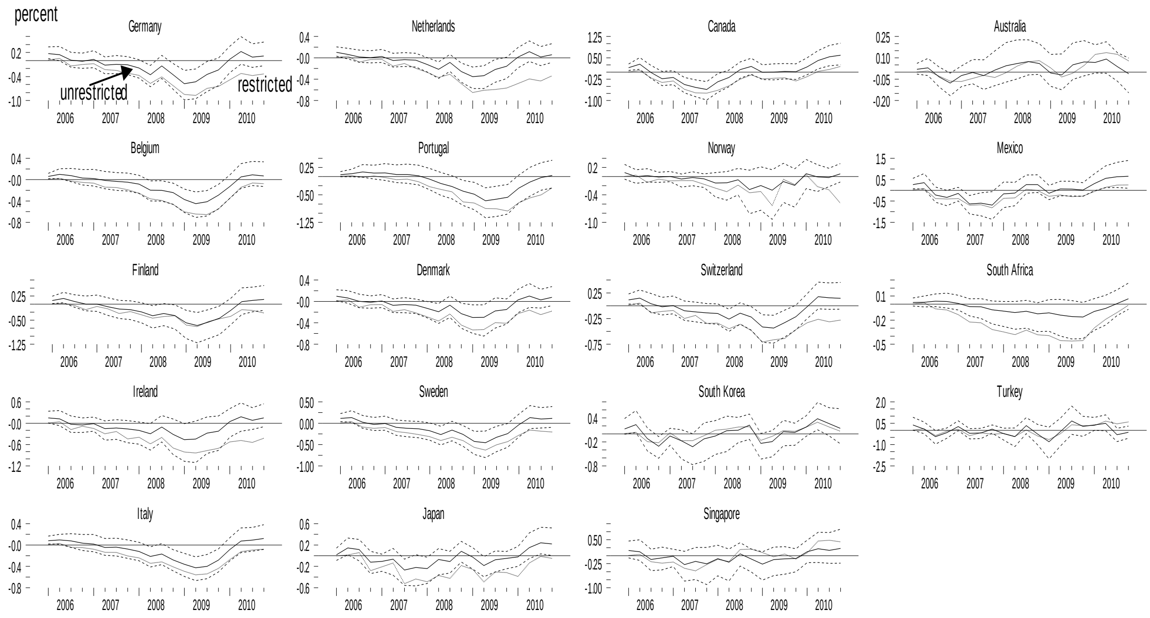


2.8 Appendix C: Comparison of the Results of the Restricted and the Unrestricted Model

The results presented for the international business cycle effects of housing crises are based on a restricted model in which regressors that are not significant according to a certain threshold are set to zero. Brüggemannn and Lütkepohl (2001) claim that this method might fail to appropriately represent the data generating process. Therefore, we compare the results based on the restricted model with the results of the unrestricted model to ensure that the dynamics of the impulse response function are not driven by the model selection method applied.

We compare the results of both models for housing crises in the United States, the United Kingdom, Spain, and France. Figure 2.C.1 shows that the dynamics of the impulse response functions qualitatively for both models are nearly identical for all countries. However, for many countries, such as Germany, Italy, and Japan the restricted model assesses the negative impact of foreign housing crises to be much more severe than the unrestricted model. The confidence bands, which are computed based on the unrestricted model, illustrate that the results are usually not significantly different from each other at the five percent level. Most of the exceptions to this observation occur at the end of the simulation period from the end of 2009 until the end of 2010. Because the confidence bands, which are now considerably broader than with the restricted model, still points to a significant decline in GDP growth for the same set of countries as with the restricted model, we conclude that our results are qualitatively robust irrespective of whether we apply a model reduction method or not.

Figure 2.C.1:
International Impact of Housing Crises Based on the Restricted and the Unrestricted Model



Note: Dashed lines mark the 95 percent confidence bands calculated via bootstrap simulation with 1,000 replications based on the unrestricted model.

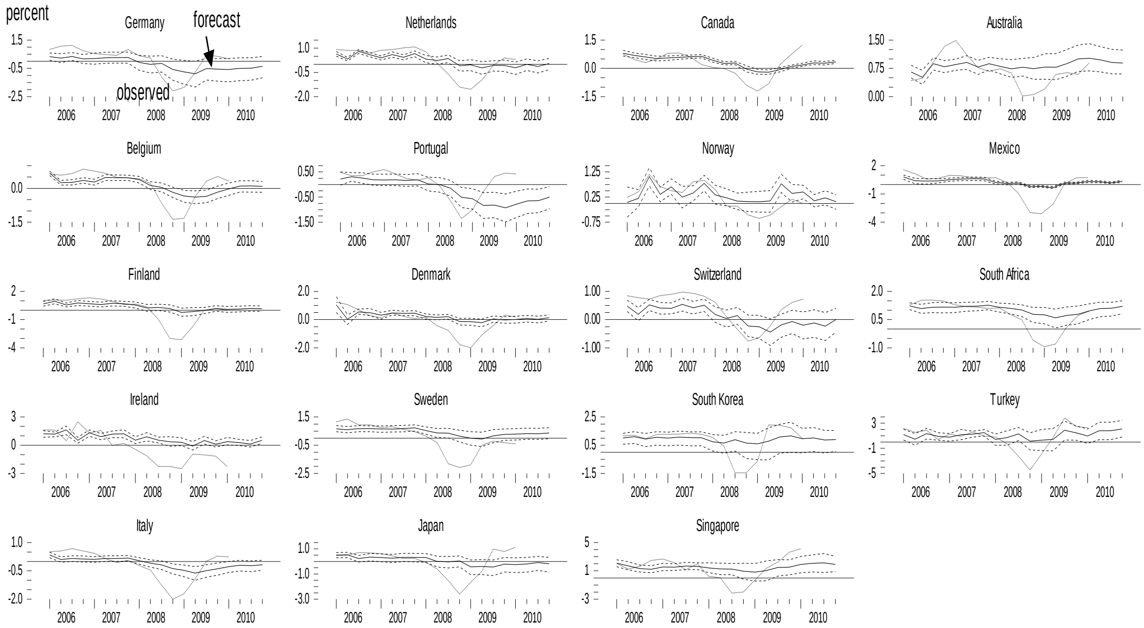
2.9 Appendix D: Additional Results

In Appendix D, we provide two additional results of forecasting exercises to test how well the international business cycle model in Section 2.3.2 can explain GDP growth during the Great Recession.

Section 2.2 shows that GDP growth in the United States during the housing crisis beginning in 2006 was subject to a delay of roughly six quarters when compared with historical housing crises. If we account for this observation in our simulation exercise, the housing crises in all four countries occurred nearly parallel to each other, reaching the trough of GDP growth between the fourth quarter 2008 and the third quarter 2009. However, while the forecast improves somewhat by accounting for this observation, the model still fails to explain the strong decline in GDP growth in the winter half year 2008/2009 (Figure 2.D.1).

During the Great Recession, international transmission mechanisms that work through the financial sector obviously played an important role. Therefore, the assumption that international transmission during housing crises works mainly through the trade channel might be too restrictive for this period. Consequently, we augment model (2.5) with a variable that aggregates foreign GDP growth with an indicator of financial openness and then re-estimate

Figure 2.D.1:
Forecast with Delayed Recession in the United States

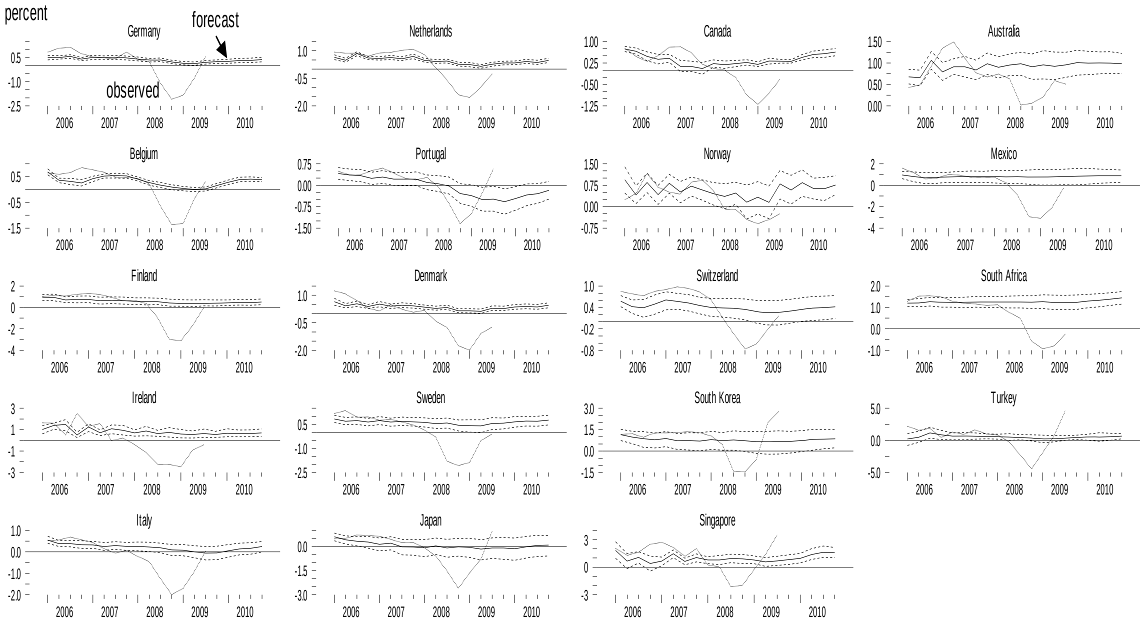


Note: Dashed lines mark the 95 percent confidence bands calculated via bootstrap simulation with 1,000 replications.

the model. To calculate the financial openness indicator, we use the data set described in Lane and Milesi-Ferretti (2007). We calculate the financial openness indicator as the ratio of the sum of total foreign assets and total foreign liabilities relative to GDP for all countries in our sample. These ratios are then used as weights for calculating foreign GDP growth in equation 2.6. To calculate foreign GDP growth for country *i*, we set the financial openness indicator of country *i* equal to zero and then rescale the other financial openness indicators to sum to zero. However, since we do not have bilateral financial openness indicators, the weights used to calculate foreign GDP growth are, in contrast to the export weights, basically the same for all countries, leading to nearly identical foreign GDP growth variables. We find that the predicted GDP growth rates of the model are higher for nearly all countries in our sample than with the baseline model (Figure 2.D.2). Hence, the augmented model fails to explain the downturn during the Great Recession.[20]

[20] These results remain valid when we do not augment the model with the financial openness indicator for aggregated foreign GDP growth, but rather use an indicator for the export-weighted foreign GDP growth.

Figure 2.D.2:
Forecast of a Model Including Foreign GDP Weighted with a Financial Openness Indicator



Note: Dashed lines mark the 95 percent confidence bands calculated via bootstrap simulation with 1,000 replications.

3 Estimating the Shape of Economic Crises under Heterogeneity[21]

3.1 Introduction

The Great Recession of 2008/2009 has increased the interest of economic researchers, forecasters, and policy makers in the analysis of severe economic crises and in particular in the analysis of financial crises. A series of studies has investigated the shape and the costs of financial crises and found, among other things, that such crises usually lead to severe recessions. However, the analysis of financial crises as of other severe economic crises, like housing crises, has to rely on large panel data sets, because such crises are rare events. This raises the problem of heterogeneity within the panel, which can occur in several dimensions: The overall macroeconomic conditions, institutions, and economic policy regimes can differ substantially across countries and over time. These heterogeneities potentially bias the estimates of the shape and the costs of severe economic crises considerably.

In the literature several methods have been applied to investigate the shape and the costs of severe economic crises. Since such crises are extraordinary events, during which the 'ordinary' interdependencies might not apply, researchers do not rely only on times series models, but frequently use event-study approaches.[22] Within these event-study approaches historical episodes of severe economic crises are identified and investigated separately. Two closely related approaches are (i) to estimate the shape of severe economic crises or (ii) to estimate the costs of severe economic crises. First, the shape of economic crises is estimated by calculating the average of the variables of interest before, during, and after a crisis over all crises in the sample. Well-known early examples are Eichengreen et al. (1995) and Kaminsky and Reinhart (1999). With the onset of the financial crisis of 2008/2009 a series of studies analyzed the shape of financial crises, housing crises, and credit crunches. Reinhart and Rogoff used this approach in a number of papers to illustrate that financial crises usually have a dramatic negative impact on output (Reinhart and Rogoff 2008a, 2008b, 2008c, 2009). A series of other studies relies on this method to establish stylized facts of financial crises or other severe economic crises and to draw conclusions for recent developments (Claessens et al. 2008 and 2010, IMF 2009a and 2009b, Jannsen 2010). Second, a closely

[21] This Chapter is based on the paper: J. Dovern and N. Jannsen (2009). Estimating the Shape of Economic Crises Under Heterogeneity. Kiel Working Papers 1520, Kiel Institute for the World Economy.

[22] Examples for studies that rely on time-series models to investigate severe economic crises are Cerra and Saxena (2008) and Boysen-Hogrefe et al. (2010).

related approach used in the literature is to estimate the costs of severe economic crises—usually in terms of GDP—capturing the consequences of crises in a single scalar measure (Bordo et al. 2001, Cecchetti et al. 2009, Claessens et al. 2008, Hoggarth et al. 2002). The options to control for heterogeneity in the sample of severe economic crises within these approaches are limited. One well-known and frequently used option is to adjust the data by eliminating their trend. Furthermore, the problem of heterogeneity can be dampened to some extend by choosing a homogeneous panel. However, these options might be—in dependence on the specific research question—not appropriate, not feasible, or not sufficient to account for heterogeneity in a formal and consistent way.

In this paper, we suggest an alternative option to deal with heterogeneities in the panel. We propose that time dependent mean growth rates and volatilities of the variable of interest are reasonable measures to account for heterogeneity inherent in a panel of crises. In this paper, we focus on the effects of severe economic crises on real GDP. There is strong theoretical and empirical evidence that differences in macroeconomic conditions, institutions or economic policy regimes are reflected in the mean growth rate of GDP and its volatility. For example, it is well-established that better institutions lead on average to higher growth rates of GDP and that independent central banks with a strong focus on inflation stabilization usually dampen the volatility of GDP growth. Therefore, accounting for heterogeneity with these measures might lead to more reliable results for the shape and the costs of severe economic crises.

We illustrate the relevance of our approach by demonstrating that the estimated costs of crises—measured with several concepts based on GDP—crucially depend on time dependent mean growth rate and the time dependent volatility of GDP for a large panel of financial crises. Furthermore, we show that forecasts of the costs of crises are significantly improved by accounting for heterogeneity across countries and historical episodes. Then, we apply our approach to the analysis of the shape of severe economic crises. We show that our approach leads to results that are much less dependent on the available data panel used to estimate the shape. Thus, our approach provides more reliable information. Moreover, we show that accounting for heterogeneity considerably changes the assessment when comparing different types of severe economic crises. We conclude that accounting for the heterogeneity by time dependent means and volatilities of growth rates is a relevant issue when estimating the costs and the shape of severe economic crises.

The remainder of the paper is structured as follows. In Section 2, we describe the data set, the measures we use to account for heterogeneity, and the methods we use to estimate the shape and the costs of severe economic crises. In Section 3, we illustrate the relevance of accounting for heterogeneity when analyzing the costs of financial crises. In Section 4, we show that accounting for heterogeneity is relevant when we analyze the shape of severe economic crises. Finally, Section 5 summarizes our results.

3.2 Data Set and Measures of Heterogeneity

We use yearly data for GDP per capita for 40 countries between 1960 and 2006 provided by Barro and Usura (2008). The countries in the sample are: Argentina, Australia, Austria, Belgium, Brazil, Canada, Chile, Colombia, Denmark, Egypt, Finland, France, Germany, Greece, Iceland, India, Indonesia, Italy, Japan, Korea, Malaysia, Mexico, Netherlands, New Zealand, Norway, Peru, Philippines, Portugal, South Africa, Singapore, Spain, Sri Lanka, Sweden, Switzerland, Taiwan, Turkey, United Kingdom, United States, Uruguay, and Venezuela. Overall, our sample exhibits a considerable degree of heterogeneity, since industrial countries as well as emerging markets and developing countries are included.

Regarding the dating of financial crises, we rely on the dating scheme described in Reinhardt and Rogoff (2008b). Overall, we identify 58 financial crises in our data set. While most of our analysis is based on this sample of financial crises at a later stage we compare financial crises with housing crises. We identify housing crises based on a data set of real house prices provided from the Bank for international Settlements. This data set is available only for 16 industrial countries from 1970 to 2009.[23] We identify housing crises as price peak within a rolling window of nine years, when prices fall at least by 7.5 percent following the peak. These identification criteria have been used in the literature (see, e.g. Aßmann et al. 2010, Jannsen 2010) and are similar to alternative identification criteria used in the literature (see, e.g., IMF 2003, Ahearne et al. 2005). They have been proved to provide considerably stable results. Overall, we identify 29 housing crises in our sample.[24] We define that a housing crisis begins in the year house prices have peaked.

We propose to use two measures, namely the time dependent mean and the volatility of GDP growth, to account for heterogeneity in our panel of severe economic crises. Even though these measures are hardly sufficient to comprehensively control for all types of heterogeneity and other variables might be useful as well, they have the advantage that they are usually available and can be easily calculated. This is particular true when we estimate the typical shape of crises, where it is difficult to use other variables to control for heterogeneity.

[23] The countries are Australia, Belgium, Canada, Denmark, Finland, France, Germany, Great Britain, Italy, Japan, the Netherlands, Norway, Spain, Sweden, Switzerland, and the United States.

[24] For a more detailed description of the identified housing crises and robustness checks with respect to the identification criteria, see Boysen-Hogrefe et al. (2010).

However, other control variables are also frequently not available when the costs, of severe economic crises are calculated for panels that include, e.g., many developing or emerging economies or when they cover long time spans. We calculate the time dependent mean and the volatility of GDP growth before a severe economic crisis begins to guarantee that these two measures are not influenced by the crisis itself.

3.3 Heterogeneity and the Costs of Severe Economic Crises

We illustrate the relevance of accounting for heterogeneity when calculating the costs of crises threefold. First, we show that there is a significant relationship between the strength of a financial crisis and our measures of heterogeneity. Second, we demonstrate that the correlation of different measures for the strength of financial crises increases, once we account for heterogeneity. Finally, we perform an out-of-sample forecasting exercise and illustrate that using our measures of heterogeneity improves the forecasting accuracy. Before we illustrate the relevance of accounting for heterogeneity, we describe the methods we use to calculate the costs of financial crises.

3.3.1 Costs of Financial Crises

Several methods to calculate the costs of severe economic crises haven been used in the literature. Therefore, we do not exclusively focus on a single method, but calculate the costs of severe economic crises with six different measures. First, we calculate the sum of negative output gaps until the output gap becomes positive. The output gap is calculated as difference between GDP and trend GDP estimated with a Hodrick-Precott filter using a value of 100 for the smoothing parameter lambda (Costs I). Second, we calculate the sum of the differences between the former peak of GDP and GDP until it reaches its old peak again (Costs II, Cecchetti et al. 2009). Next, we calculate the sum of the differences between the pre-crisis trend growth of GDP and GDP growth until it reaches the first time its trend growth again. Trend growth is calculated for the three years preceding the financial crisis (Costs III, Bordo et al. 2001) and alternatively for the five years preceding the crisis (Costs IV, Hoggarth et al. 2002). Finally, we estimate the trend growth of GDP for the year *t-1* (when a financial crisis starts in year *t*) with a HP-Filter using a value of 100 for lambda. Then, we extrapolate trend GDP with the trend growth rate in *t-1* and calculate the sum of differences between trend GDP and GDP (Hoggarth et al. 2002). While Hoggarth et al. (2002) used a defined end of the financial crises to determine the period for which they calculate the costs, we use—because the end of the financial crises for our data set is not available—two different approaches to determine the period: We calculate the sum until GDP growth reaches the first time the trend growth of t-1 again (Costs V) and alternatively, we follow Laeven and Valencia (2008) and calculate the sum for the first four years of the crisis (Costs VI). The first year of the period for that we calculate the cost is the first year when output gap becomes negative, the first year when GDP is below its pre-crisis peak or the year a severe economic crisis begins. When a cost measure signals no costs, we delete the observation from our sample of crises.

3.3.2 Relevance of Accounting for Heterogeneity

We use a linear regression framework to illustrate the relevance of accounting for heterogeneity when estimating the costs of financial crises:

$$\mathrm{cost}_i^j = \mathrm{c} + mean_i^m + vol_i^n + \varepsilon_i \,, \tag{3.1}$$

where cost_i^j is cost measure *j* calculated for crisis *i*, $mean_i^m$ is the mean of GDP growth calculated for the period from t-m to t-1 before crisis *i*, and vol_i^n is the volatility calculated for the period from t-n to t-1 before crisis *i*. The fitted values of the linear regression (3.1) are the measures of the costs of financial crises that account for heterogeneity.

We start, by investigating whether our measures of heterogeneity have some explanatory power for the cost measure described above. Since there is no strong empirical or theoretical evidence which period should be used to calculate the mean growth rate or the volatility of GDP growth to account for heterogeneity, we use ad-hoc a period of 10 years preceding a crisis. Usually at least one of these two variables has some explanatory power for the costs of a financial crisis (Table 3.1). Moreover, likelihood ratio tests indicate that models that incorporate mean and volatility are in most cases superior in explaining the costs of a crisis compared to the commonly used models that incorporates only a constant. An exception is cost measure II, which calculates the cost by taking the sum of the difference between the former peak of GDP and GDP until it reaches its former peak again.

Table 3.1:
Dependence of Costs of Financial Crises on Mean and Volatility of GDP Growth

	Mean and volatility calculated for 10 years					
	I	II	III	IV	V	VI
Constant	2.9 (1.2)	57.0 (0.7)	0.4 (0.2)	−0.0 (0.0)	35.7 (0.6)	14.9 (1.3)
Mean	1.0 (1.1)	3.3 (0.2)	−0.1 (0.2)	0.3 (1.1)	24.3 (2.4)	5.2 (2.7)
Volatility	1.9 (1.7)	−1.1 (0.1)	1.7 (3.5)	1.3 (3.5)	−6.6 (0.5)	1.7 (0.7)
AIC	379.0	470.5	220.8	207.4	567.1	367.6
LR-test	0.22	0.95	0.00	0.00	0.01	0.02
Observations	50	37	40	40	46	41

Notes: t-values in parenthesis; LR-test indicates the p-value of the hypothesis that the model is better than a model that includes only a constant.

The period of 10 years for calculating mean and volatility preceding the crises is chosen rather ad-hoc. Therefore, we run a grid search over alternative periods. Within the grid search, we compare models over alternative periods for calculating mean and volatility up to 10 years preceding a crisis and chose the model with the best fit according to the Akaike Information Criterion (AIC). We calculate the p-values of the estimated parameter values with a bootstrap simulation over 1,000 draws. The results that we received with our ad-hoc measures are largely affirmed. Usually at least one of our two measures of heterogeneity turns out to have a significant explanatory power for the costs of a crisis and for five of six cost measures the model is significantly better compared to the standard model according to likelihood ratio tests (Table 3.2). Again only the cost measure based on GDP compared to its former peak (costs II) is an exception. Overall, the grid search chooses periods for calculating mean and volatility of GDP growth preceding a crisis that are somewhat shorter than our ad-hoc choice.

The different measures, we use to calculate the costs of financial crises are positively correlated, but are not unique, e.g. when we calculate the rank of the crises in terms of their costs. However, when our hypothesis that macroeconomic conditions are at least to some extent relevant for the measured costs of financial crises is true, the correlation of the different cost measures should in tendency increase, once we account for these conditions. Therefore, we compare the correlation between the different cost measures based on Spearman' rank correlation when we do not account for heterogeneity with the correlation when we account for heterogeneity. Spearman' rank correlation is based on the rank that is appointed by the cost measures to the crises. It has the advantage that it is more robust to outliers than simple correlation measures of the costs. We find that the correlation increases in 11 out of 15 cases, once we account for heterogeneity (Table 3.3). However, the increase in correlation is usually not significantly different from zero according to conventional significance levels; only in one case the correlation is significantly lower.

Table 3.2:
Dependence of Costs of Financial Crises on Mean and Volatility of GDP Growth: Grid Search

	I	II	III	IV	V	VI
Constant	2.5 (0.5)	18.9 (0.4)	−1.2 (0.9)	−0.2 (0.2)	63.7 (1,7)	7.7 (0.8)
Mean	1.5 [0.13]	11.4 [0.41]	0.6 [0.57]	0.4 [0.18]	23.2 [0.07]	7.1 [0.01]
Volatility	2.8 [0.11]	4.7 [0.53]	1.6 [0.00]	1.2 [0.00]	−21.0 [0.69]	2.7 [0.27]
Best mean	5	1	3	3	2	7
Best lag	8	3	4	6	6	3
AIC	375.6	468.7	209.4	215.4	561.8	361.8
LR-test	0.04	0.40	0.00	0.00	0.00	0.00

Notes: t-values in parenthesis; p-values in square parenthesis; p-values were calculated by simulations with 1,000 draws; LR-test indicates the p-value of the hypothesis that the model is better than a model that includes only a constant.

Table 3.3:
Difference between Spearman's Rank Correlation when Cost Measures are adjusted for Mean and Volatility and Original Cost Measures

	I	II	III	IV	V	VI
I						
II	0.12 (0.5)					
III	0.30 (1.2)	−0.22 (0.9)				
IV	0.36 (1.5)	−0.04 (0.1)	0.02 (0.1)			
V	−0.24 (1.1)	0.29 (1.2)	0.08 (0.4)	0.17 (0.7)		
VI	0.14 (0.6)	0.15 (0.6)	0.21 (0.9)	0.17 (0.7)	−0.44 (1.9)	

Notes: Positive value indicates that the correlation coefficient is higher for the adjusted data; z-values in parenthesis; z-values were calculated based on a Fisher transformation of the calculated correlation coefficients.

The relevance of accounting for heterogeneity can be proved further with a forecast comparison. When accounting for heterogeneity is relevant it should improve the forecasting performance of a model that includes our measures of heterogeneity. We showed already that models that include these measures are in most cases significantly better than models that do not according to a likelihood ratio test and therefore exhibit a better in-sample forecasting performance. However, this does imply that the out-of-sample forecasting performance is better as well. To test the (quasi) out-of-sample forecasting performance, we chose randomly a subsample of financial crises, estimate models that include our measures of heterogeneity and models that include only a constant and compare the forecasting performance of both models for the remaining crises.[25] We randomly draw 2/3 of the crises in our sample to estimate the models and compare the forecasting performance for the remaining 1/3 of the crises. This procedure is repeated 1,000 times. We find that the forecasting performance improves significantly when we account for heterogeneity (Table 3.4). For all cost measures the models that account for heterogeneity provide a better forecasting performance for more than 95 percent of all draws than the models based on the (unadjusted) average cost measure.

Table 3.4:
Forecasting Costs of Financial Crises with Mean and Volatility

	I	II	III	IV	V	VI
Relative RMSE	0.91	0.91	0.70	0.75	0.82	0.82
p-value	0.97	0.99	0.97	0.97	1.00	0.99

Notes: Relative RMSE denotes the RMSE of the models including mean and volatility relative to the RMSE with the models that only include a constant; p-values indicate the likelihood that the RMSE for the model that includes mean and volatility is lower; p-values were calculated by simulations with 1,000 draws.

3.4 Accounting for Heterogeneity When Estimating the Shape of Severe Economic Crises

For estimating the typical shape of severe economic crises, we follow the literature and take the average of the variable of interest over all crises in our sample (see, e.g., Reinhart and Rogoff 2008c, Claessens et al. 2008, or IMF 2009a). Consider a variable y_{it} that is observed for different countries i over different time periods t. Furthermore, assume that a number of C crises are identified. Denote as $i(c)$ and $t(c)$ the country and time at which crisis c occurred. The typical shape of y_{it} in a window of size $2S+1$ around a crisis is then estimated as

$$\hat{y}_s = \frac{1}{C}\sum_{c=1}^{C} y_{i(c),t(c)+s} \text{ , for } s = -S,...,S \text{ .[26]} \tag{3.2}$$

However, this approach disregards the fact that usually the identified historical episodes of severe economic crises exhibit fundamentally different overall macroeconomic conditions,

[25] When estimating the models, we use the periods for calculating mean and volatility of GDP growth the grid search proved to be optimal. This approach is equivalent to account for parameter uncertainty, but not for model uncertainty, what is standard in the literature that investigates the forecasting performance of models.

[26] We present our approach in terms of the mean but all results carry over to the case, where the median serves as the preferred measure.

institutions, or economic policy regimes. Consequently, the estimates of $\hat{y}_s$ in (3.2) might be sensitive to the composition of the sample used to identify severe economic crises.

To this end, we suggest to account for heterogeneity by standardizing the variable of interest $y_{i,t}$ with measures that account for the heterogeneity in the sample. We propose to subtract from $y_{i,t}$ the "local" mean of GDP growth $\bar{y}^{w}_{i(c),t(c)}$ and then divide by the "local" standard deviation $\sigma^{w}_{i(c),t(c)}$, each calculated over the w periods before the crisis c begins. The standardized typical shape of y can then be obtained by

$$\tilde{y}_s = \frac{1}{C}\sum_{c=1}^{C}\frac{\left(y_{i(c),t(c)+s} - \bar{y}^{w}_{i(c),t(c)+s}\right)}{\sigma^{w}_{i(c),t(c)+s}}, \text{ for } s = -S,\ldots,S. \tag{3.3}$$

The result can be calibrated to a crisis $C+1$, for which we want to estimate the path of $y_{i(C+1),t(C+1)}$ for $s = -S,\ldots,S$ that is in line with the average behaviour of this variable during other financial crises. The calibrated path $\tilde{y}_s$ for the crisis $C+1$ can be calculated with the "local" mean $\bar{y}^{w}_{i(C+1),t(C+1)}$ and standard deviation $\sigma^{w}_{i(C+1),t(C+1)}$ over the most recent w periods:

$$\hat{y}_{i(C+1),t(C+1)+s} = \tilde{y}_s \cdot \sigma^{w}_{i(C+1),t(C+1)} + \bar{y}^{w}_{i(C+1),t(C+1)}, \text{ for } s = -S,\ldots,S. \tag{3.4}$$

Local means and local standard deviations can be calculate for single countries or alternatively for particular country groups, e.g., for industrial countries, and for certain time periods, e.g., only taking periods after a particular year into account.

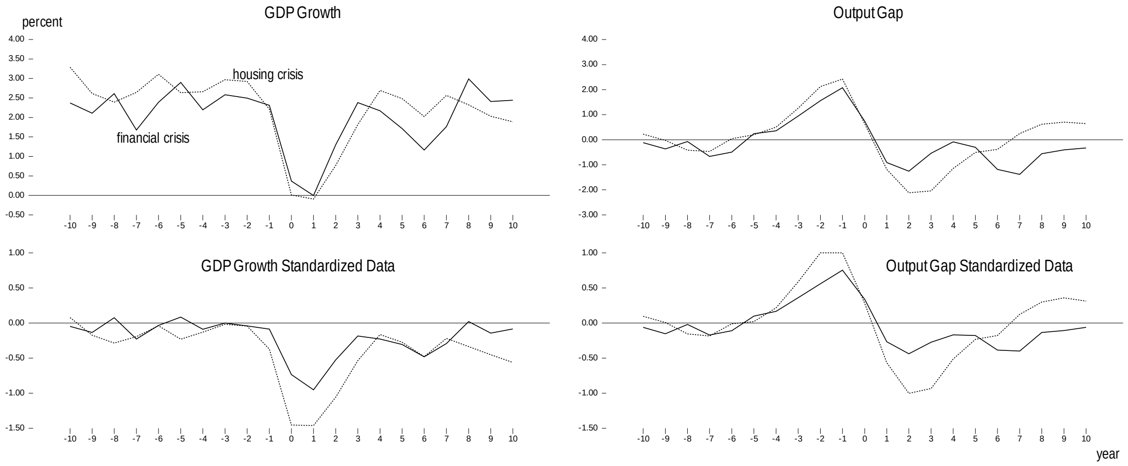
As an example for standardization, we compare the shape of financial crises with the shape of housing crises. For this comparison, the standardization could be particular useful, because due to data availability housing crises can be identified only for a subsample of our sample of financial crises. Furthermore, the subsample differs considerably from the overall sample, because it includes only industrial countries from 1970 to 2008. An alternative would be to scale the sample of financial crises down to the sample of housing crises. However, then we would end up with only 16 financial crises in our subsample, with only 8 of them associated with a downturn of economic activity.[27] Moreover, these 8 financial crises were associated with housing crises, so that one might not receive conclusive results when using only the subsample to estimate the shape of financial crises.[28]

[27] In this context we define a downturn as at least one year with negative GDP growth rate.

[28] Even if there would have been enough financial crises in the subsample to estimate the shape, the case of for standardization could arise again when financial crises occurred only in countries and during periods that were very different from those when housing crises occurred.

We calculate our two measures to standardize the data during the financial and housing crises for a period of 10 years before a crisis begins. When we compare GDP growth during financial crises and housing crises, it seems to evolve nearly similarly in the first years of a crises (Figure 3.1). A small difference is that GDP growth before and after the crisis seems to be somewhat higher in the case of housing crises. However, once we use the standardized results housing crises apparently are more severe than financial crises. When we compare the output gap during financial and housing crises, the differences between the original result and the standardized result is considerably smaller. This result illustrates that estimating the output gap is already some kind of standardization of the data, which might be appropriate for our sample. However, the standardized results show a somewhat more pronounced business cycle movement during housing crises, with a higher output gap before the crisis begins and a lower output gap during the crisis.

Figure 3.1:
GDP Growth and the Output Gap during Financial Crises and Housing Crises

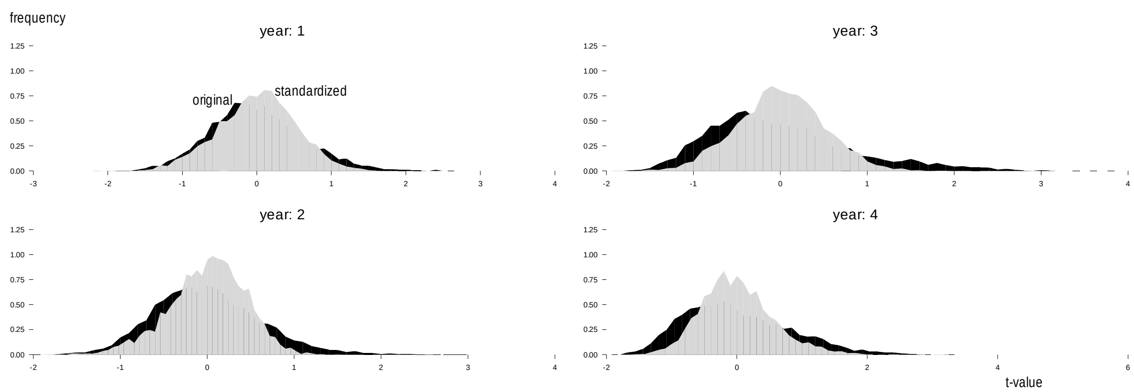


Notes: Year 0 indicates the first year of a financial or a housing crisis.

Even though the results revealed that our approach can lead to different conclusions this does not mean necessarily that it is useful concept. In the following, we illustrate the usefulness by demonstrating that the standardization of data leads to more homogeneous results when we estimate the shape of crises for different samples. Consequently the results are less dependent on the sample one has at hand to estimate the shape of severe economic crises. We draw randomly 75 percent of our financial crises and calculate the average of GDP growth during crises based on this subsample and compare the results for the original data and the standardized data. We repeat this procedure 1,000 times and check whether the standard deviation of the 1,000 results is lower for the standardized data. However, the standardized data should exhibit a lower standard deviation by construction. Therefore, in our 1,000 draws we do not collect mean growth rates for a particular year, but calculate the t-value as ratio of the mean growth rate and the standard deviation of the 75 percent of crises, which are in its size not systematically dependent on differences in the standard deviations in different data sets.

When we compare the distribution of t-values obtained in 1,000 random draws of financial crises, we find that the distribution for the standardized data is closer centered around its mean (Figure 3.2).[29] Moreover, based on the original data we receive more extreme results when we change the sample used to estimate the shape of financial crises.

Figure 3.2:
Distribution of *t*-values for the Deviation of GDP Growth Based on Original Data and on Standardized Data



Notes: Distribution based on *t*-values of the men growth rate of GDP for particular years of subsamples of financial crises; Distributions were calculated by simulations with 1,000 draws.

These findings are supported by formal tests. An F-test reveals that the variance of the results based on the original data is significantly higher compared to the variance of the results of the standardized data (Table 3.5). Moreover, the (excess) kurtosis is considerably higher and significantly different from zero for the results based on the original data, while the results based on the standardized data in several cases do not exhibit significant excess kurtosis at conventional significance levels.[30] When we adjust our rather ad-hoc chosen period of 10 years to calculate the two measures to standardize the data to 15, 10, and 5 years our results remain valid.

[29] We report the mean-adjusted t-values.

[30] Tests on skewness of the distribution and on Normal-distribution show for both cases that the distributions are skewed and not normal distributed.

Table 3.5:
Variance and Kurtosis of Distributions Based on Original Data and Standardized Data

Year		Financial Crises				Housing Crises	Output Gap
		5	10	15	20	10	10
1	Variance	0.00	0.00	0.00	0.00	0.03	0.00
	Kurtosis	0.00/0.80	0.00/0.89	0.00/0.42	0.00/0.68	0.00/0.00	0.02/0.24
2	Variance	1.00	0.00	0.00	0.00	0.59	1.00
	Kurtosis	0.00/0.00	0.00/0.00	0.00/0.00	0.00/0.78	0.00/0.00	0.02/0.00
3	Variance	0.00	0.00	0.00	0.00	1.00	0.19
	Kurtosis	0.00/0.61	0.00/0.34	0.00/0.73	0.00/0.10	0.00/0.00	0.02/0.10
4	Variance	0.00	0.00	0.00	0.00	0.00	0.00
	Kurtosis	0.00/0.00	0.00/0.00	0.00/0.00	0.00/0.00	0.00/0.20	0.00/0.00

Notes: Variance denotes the p-value of an F-test on equal variance of the results based on the original data compared to the standardized data; first value of kurtosis denotes the p-value of an F-test on (excess) kurtosis for the original data, second value refers to the standardized data.

The relevance of accounting for heterogeneity diminishes when we investigate housing crises. The variance of the results is significantly lower only for two of the four years. To some extend this result is not surprising. It supports our hypothesis that accounting for heterogeneity is particular useful for samples that exhibit a considerably degree of heterogeneity. Since our sample of housing crises is much more homogeneous than our sample of financial crises the gains from standardization are lower. The relevance of accounting for heterogeneity also diminishes when we investigate the impact of financial crises on the output gap. Since estimating an output gap is already some form of accounting for heterogeneity, this supports our hypothesis, too. However, it depends strongly on the specific research question whether to use trend-adjusted data is appropriate. Moreover, when using trend-adjusted data the results considerably depend on the method applied for the trend-adjustment.

Overall, we find that accounting for heterogeneity in the panel by standardizing the data can change the results dramatically when we compare the shape of different types of severe economic crises, which are only available for different panels. Moreover, the estimated shapes of severe economic crises could be considerably more dependent on the underlying sample for original data than for standardized data. The result that the relevance of accounting for heterogeneity diminishes, when we use a more homogeneous panel of severe economic crises, i.e. as in the case of housing crises, or when we use an alternative method of accounting for heterogeneity, i.e. as in the case of the output gap, supports our hypothesis that accounting for heterogeneity is particular useful when the panel of severe economic crises exhibits a considerable degree of heterogeneity. However, in dependence on the specific research question in several cases it might not be feasible or appropriate to use a homogeneous sample or alternatively to use trend-adjusted data.

3.5 Conclusion

The analysis of severe economic crises, like financial crises or housing crises, often relies on large panel data sets, as these events are rarely observed. This raises the problem of heterogeneity in the panel, e.g., when very different countries are included or very long time periods are used. This, in turn, can lead to biased or imprecise estimates. In some cases, the problem of heterogeneity might be dampened by restricting the data set to a homogeneous group of countries or by using some kind of standardization of the variables of interest. However, the feasibility and appropriateness of these strategies strongly depend on the research question and on the available number of observations of severe economic crises.

In this context, we propose a standardization approach that can considerably reduce the problem of heterogeneity. When the panel data set is highly heterogeneous with respect to the overall macroeconomic conditions, the institutions, or the economic policy regimes across different countries and over time periods this should show up in the average GDP growth rate and the volatility of GDP. Therefore, we suggest using time dependent mean growth rates and volatilities of GDP to account for heterogeneity when estimating the costs of severe economic crises and when estimating the shape of severe economic crises.

In this paper, we have shown that these two measures have explanatory power for the estimated costs of financial crises, that they increase the forecasting power for costs of crises significantly, and that accounting for heterogeneity usually increases the correlation between different costs measures—even though not significantly at conventional significance levels. Moreover, we illustrate that it can make a huge difference to standardize the data before estimating the shape of severe economic crises, e.g. when we compare the shape of different types of crises. We illustrate, that the estimated shape of financial crises is significantly more robust to the composition of the sample of crises and produces considerably less extreme results when we account for heterogeneity and use standardized data. However, our results show also that the gains of our approach are lower in particular circumstances. Overall, it depends strongly on the specific research question and the available data set, whether our approach is a useful tool for analyzing severe economic crises.

3.6 References

Ahearne, A.G., J. Ammer, B.M. Doyle, L.S. Kole and R.F. Martin (2005). House Prices and Monetary Policy: A Cross-Country Study. International Finance Discussion Papers 841. Board of Governors of the Federal Reserve System, Washington, D.C.

Aßmann, C., J. Boysen-Hogrefe and N. Jannsen (2010). Costs of Housing Crises: International Evidence. Bulletin of Economic Research, forthcoming.

Barro, R.J., and J.F. Ursua (2008). Macroeconomic Crises Since 1870. NBER Working Paper Series 13940. National Bureau of Economic Research, Cambridge, MA.

Bordo, M., B. Eichengreen, D. Klingebiel and M.S. Martinez-Peria (2001). Is the Crises Problem Growing More Severe? *Ecocomic Policy* 16 (32): 53–82.

Boysen-Hogrefe, J., N. Jannsen and C.-P. Meier (2010). The Ugly and the Bad: Banking and Housing Crises Strangle Output Permanently, Ordinary Recessions Do Not. Kiel Working Papers 1586. Institute for the World Economy, Kiel.

Cerra, V., and S.C. Saxena (2008). Growth Dynamics: The Myth of Economic Recovery. *American Economic Review* 98 (1): 439–457.

Cecchetti, S.G., M. Kohler and C. Upper (2009). Financial Crises and Economic Activity. NBER Working Paper 15379. National Bureau of Economic Research, Cambridge, MA.

Claessens, S., M.A. Kose, and M.E. Terrones (2008). What Happens During Recessions, Crunches and Busts? IMF Working Paper 08/274. International Monetary Fund, Washigton, D.C.

Eichengreen, B., A.K. Rose, C. Wyplosz, B. Dumas and A. Weber (1995). Exchange Market Mayhem: The Antecedents and Aftermath of Speculative Attacks. *Economic Policy* 10 (21): 249–312.

Hoggart, G., R. Reis and V. Saporta (2002). Cost of Banking System Instability: Some Empirical Evidence. *Journal of Banking & Finance* 26: 825–855.

IMF (International Monetary Fund) (2003). When Bubbles Burst. *World Economic Outlook*. April. Washington, D.C.

IMF (International Monetary Fund) (2008). Financial Stress and Economic Downturns. *World Economic Outlook*. October, Chapter 4. Washington, D.C.

IMF (International Monetary Fund) (2009a). From Recession to Recovery: How Soon and How Strong? World Economic Outlook. April, Chapter 3. Washington D.C.

IMF (International Monetary Fund) (2009b). What's The Damage? Medium-Term Output Dynamics After Financial Crises. World Economic Outlook. October. Washington D.C.

Jannsen, N. (2010). National and International Business Cycle Effects of Housing Crises. *Applied Economics Quarterly* 56 (2): 175–206.

Kaminski, G.L., and C.M. Reinhart (1999). The Twin Crises: The Causes of Banking and Balance-of-Payments Problems. *American Economic Review* 89 (3): 473–500.

Laeven, L., and F. Valencia (2002). Systemic Banking Crises: A New Database. IMF Working Paper 08/224. International Monetary Fund, Washington, D.C.

Milesi-Ferretti, G.M., and A. Razin (1998). Sharp Reductions in Current Account Deficits – An Empirical Analysis. *European Economic Review* 42: 897–908.

Reinhart, C.M., and K.S. Rogoff (2008a). Banking Crises: An Equal Opportunity Menace. NBER Working Paper Series 14587. National Bureau of Economic Research, Cambridge, Mass.

Reinhart, C.M., and K.S. Rogoff (2008b). Is the 2007 U.S. Sub-Prime Crisis So Different? An International Historical Comparison. NBER Working Paper Series 13761. National Bureau of Economic Research, Cambridge, MA.

Reinhart, C.M., and K.S. Rogoff (2008c). This Time is Different: A Panoramic View of Eight Centuries of Financial Crises. NBER Working Paper Series 13882. National Bureau of Economic Research, Cambridge, MA.

Reinhart, C.M., and K.S. Rogoff (2009). The Aftermath of Financial Crises. NBER Working Paper Series 14656. National Bureau of Economic Research, Cambridge, MA.

4 Costs of Housing Crises: International Evidence[31]

4.1 Introduction

The severe recessions of 2008/2009 in almost all industrialized countries renewed interest in the analysis of economic crises. Since these recessions were mainly perceived to be triggered by a financial crisis, the literature initiated by the work of Reinhart and Rogoff (2008) usually focuses on the consequences of financial crises.[32] However, the recession in the United States was preceded by a boom and bust cycle in the housing market. Other countries, such as the United Kingdom or Spain, also experienced a boom and bust cycle in their housing markets. Therefore, it is necessary to build not only on the experience of historical financial crises but also on the experience of historical housing crises to gain further insights into the behavior of an economy during and after the time of severe economic decline. Claessens et al. (2008) and Jannsen (2010) analyze the consequences of housing crises on the economy and document that housing crises usually lead to long-lasting and deep recessions (see also IMF 2003). However, these studies conduct non-parametric analysis and do not deal with the links between the housing market and overall economic activity, through which a housing crisis leads to recessions, or with what economic conditions cause a housing crises to have higher costs.

Several links between the housing market and general economic activity exist. Wealth effect's that describe a positive relationship between the wealth of private households and their consumption activity constitute a first possible. Since housing wealth usually accounts for the bulk of the overall wealth of private households, fluctuations in house prices should influence private consumption. Case et al. (2005) find for the United States and a set of industrialized countries that housing wealth, of all the classes of household wealth, is the most important determinant of private consumption. Using micro data, the studies of Bostic et al. (2009) and of Gan (2010) also find a close link between housing wealth and consumption in the United States and Hong Kong. Accordingly, the negative impact of a housing crisis which is usually defined as an exceptional strong decline of house prices might relate to a negative wealth effect. However, the link between consumption and housing is not confirmed by all

[31] This Chapter is based on the paper: C. Aßmann, J. Boysen-Hogrefe, and N. Jannsen (2011). Costs of Housing Crises: International Evidence. Bulletin of Economic Research, forthcoming.

[32] Overall, these papers conclude that financial crises lead to particularly long-lasting and deep recessions (Reinhart and Rogoff 2009a and 2009b, IMF 2009a, Cecchetti et al. 2009) and to permanent output losses (Cerra and Saxena 2008, IMF 2009b, Furceri and Mourougane 2009).

studies. The relation between housing wealth and private consumption seems to be less pronounced especially in most European countries (see, e.g., European Commission 2008).[33]

A second possible link between the housing market and economic activity discussed in the literature is a direct link via the construction sector. In general, according to Tobin's q, residential investment should decrease when the worth of the housing stock decreases relative to its construction costs. Therefore, housing crises should be accompanied by a considerable decrease in residential investment as construction costs presumably do not decline as strong as house prices. Leamer (2007) stresses the close relation between residential investment and overall economic activity for the United States, where residential investment typically leads the business cycle. Further, he observes that sales of new homes are much more volatile than real house prices and he argues that the housing sector follows a volume cycle rather than a price cycle.[34] When house prices start to fall, large volume adjustments might be necessary to stop prices from falling further. Therefore, during housing crises, economic activity should be damped considerably by depressed construction activity. Ghent and Owyang (2010) challenge the link between residential investment and the business cycle by investigating regional data for the United States spanning from 1984 to 2008. On a regional basis, they find no close link between housing permits—as a measure of construction activity—and GDP, but on a nationwide level they do find such a link. The authors conclude that other links between housing and economic activity should exist and argue that their findings might point to the importance of wealth effects. Girouard and Böndal (2001) analyze the importance of both of the described links between housing and economic activity for a panel of OECD countries. They find strong evidence for the importance of wealth effects and somewhat weaker evidence for the importance of construction activity. Note that the two described links between the housing market and economic activity so far have been investigated only in general, but not during housing crises.

Additionally, there is at least one further possible link that might be of *particular* importance during housing crises, namely a link via the banking sector. Activity in the housing market, i.e., construction or purchases of houses, usually goes hand in hand with a high degree of leverage financed by the banking sector. Since houses usually serve as collateral for this leverage, a sharp decrease in house prices occurring during housing crises deteriorates collateral considerably, which could mark the beginning of a banking crisis, as noted by

33 While the empirical evidence for a general link between housing wealth and consumption is mixed, Buiter (2010) generally denies the existence of housing wealth effects, based on theoretical arguments, since home buyers are negatively affected by increases in house prices.

34 Even though large price adjustments in houses during housing crises are observed, there is a priori no reason that this relationship should not hold during such crises.

Kaminsky and Reinhart (1999). Related to this, Reinhart and Rogoff (2008) show that exceptional severe banking crises have been accompanied by a boom-and-bust cycle in the housing market (see also Leaven and Valencia 2008). Banking crises have been proved to have severe consequences for overall economic activity. Therefore, it seems reasonable that housing crises that spread over to the banking sector are more severe than housing crises that do not.

In order to investigate the circumstances making housing crises particularly costly, we assess in our model cross terms between the housing crisis indicator and proxies capturing the relevance of the three described links between the housing market and economic activity. To estimate the relevance of the link via the construction sector, we consider a cross term of the housing crisis indicator and the change of residential investment relative to GDP in the year of the peak at the housing market.[35] If the boom-bust of housing investment would be the main driver we argue that a high acceleration during the boom should be an indicator for the resulting costs of the bust. Thus, one underlying assumption is that housing crises are particularly costly when an oversized construction sector needs rescaling. To assess the relevance of the wealth effect, we use a cross term of the housing crisis indicator and the share of homeowners. Thereby, we assume that the more people in a country own housing wealth, the more house price declines dampen private consumption. In contrast, in countries where housing wealth is more concentrated to relatively few people or houses are more often owned by firms or communities, the wealth effect should be less important during housing crises. An implicit assumption behind this is that the housing wealth elasticity of private consumption diminishes with increasing wealth. Therefore, a higher homeownership rate might translate into a stronger aggregate wealth effect. For a robustness check of the importance of the wealth effect, we also use the change of private consumption relative to GDP in the cross term, which is more symmetric to our proxy for measuring the relevance of the construction sector. We test for the relevance of the link via the banking sector by using an indicator taking value one when a housing crisis was accompanied by a banking crisis and zero otherwise. Thereby, we are able to test directly whether stress at the banking sector worsens the effect of a housing crisis.[36]

To measure the costs of housing crises, we deviate from the existing literature in using a parametric framework rather than a nonparametric framework. We apply a *differences-in-*

[35] Besides the specification with the year-to-year change in the year of the peak we also consider specifications that monitor the change of housing for three years before the peak. Further, we also considered levels as well as Hodrick-Prescott filtered gaps. All specifications reveal similar results.

[36] Measuring the costs of housing crises in terms of loss in GDP growth is a common approach in the literature (see, e.g., Claessens et al. 2008), but not the only one. Other approaches include adding up the difference between the hypothetical potential output path and observed GDP as long as observed GDP is below the hypothetical potential output (Boyd et al. 2005).

differences specification incorporating structures for latent heterogeneity and serial correlation. The robustness of results is checked against potential endogeneity of crises via an extended panel treatment model with random coefficients. Also alternative crisis definitions are assessed yielding similar results. By including control variables into our model that capture influences on GDP growth other than the crises, we are able to provide parameter estimates capturing the direct impact of defined crisis events on economic growth. Since growth persistence in terms of positive first-order autocorrelation is identified, the parameter estimates do not reflect costs in terms of cumulated output losses to the full extent.[37]

We find that the costs of housing crises on average amount to roughly 2 percent of GDP in the first year after crisis occurrence and an additional 1.5 percent in the second year after the crisis. A housing crisis that is accompanied by a banking crisis leads to a loss of GDP that is 1.4 percent higher in the first year after crisis and for which an extensive prolongation of reduced growth can be observed even in the second year after crisis. We find limited evidence for the importance of wealth effects. While countries with a higher homeownership rate suffer, on average, a higher loss of GDP during a housing crisis, specifications that control for the effect of the homeownership rate do not explain the variation in observed growth significantly better than models that include only the crisis dummies. Our results are robust against alternative crisis definitions and no evidence for selection bias is found. However, the only weak evidence in favor of housing wealth effects does not deny their importance. As Aron et al. (2006) and Aron et al. (2010) argue, financial institutions play an important role for wealth effects. Such institutions have been developed mainly in recent years, see IMF (2008). The sample data used for the empirical analysis mainly covers housing crises from periods where less developed financial institutions prevailed. Thus, during the current housing crises in the US or the UK, wealth effects may have played an important role. Finally, we find no evidence for a special role of the construction sector.

The paper proceeds as follows. Section 4.2 describes the data set applied in this analysis as well as the methodology used to define a housing crisis. Section 4.3 reassesses the relationship between housing crises and recessions. Section 4.4 presents the panel model and our results, while robustness checks are presented in Section 4.5. Section 4.6 summarizes our results and concludes.

[37] An assessment of overall cumulated output losses could be based on a simulation study involving assumptions concerning dynamic interactions between all of the (presumably weak) exogenous regressors. See Aßmann (2008) for an application in the context of current account reversals and currency crises.

4.2 Data Description

Our data set includes data for 15 industrial countries.[38] In addition to real house prices taken from a database of the Bank of International Settlements, house prices for France (Existing Houses & Apartments, I.N.S.E.E.), the United States (House Price Index - All Transactions, Office of Federal Housing Enterprise), as well as land prices for Japan (Nationwide Land Price Index, Japan Real Estate Institute) deflated by consumer prices, were taken from the national statistical agencies. Data for GDP, residential investment, private consumption, short- and long-run interest rates, and the inflation rate based on consumer prices from 1970 to 2007 were taken, when available, from the OECD Economic Outlook Database. Residential investment for Spain and Switzerland was taken from Quarterly National Accounts from the OECD. The homeownership rates were collected from several national and international sources: mainly from the United Nations Economic Commission for Europe, the European Mortgage Federation, and national statistical offices.[39]

Following Ahearne et al. (2005) and IMF (2003), we identify housing crises as turning points in real house prices followed by large price declines, i.e., a housing crisis is defined as a peak in house prices within a rolling window of eight years, followed by a price decline of at least 7.5 percent *(baseline definition)*.[40] Using quarterly data for real house prices between 1970 and 2004, we can identify 23 housing crises in our data set.[41] The starting year of a housing crisis is defined as the year that includes the quarter of the price peak. Besides for France and for Belgium, we identify for each country in our sample at least one housing crisis (Table 4.1). Most of the housing crises cluster within certain time periods, namely between 1973 and 1976, between 1979 and 1981, and between 1989 and 1991. When considering further explaining variables, which are not all available for all countries and the whole time span under consideration in the regression analysis, only 18 of the identified housing crises can be used

[38] These are: Australia, Belgium, Canada, Denmark, Finland, France, Great Britain, Ireland, Japan, The Netherlands, Norway, Spain, Sweden, Switzerland, and The United States. For Germany house prices are not available on a quarterly basis. Thus, Germany is only considered when using a annual timing methodology for housing crisis as a robustness check.

[39] The homeownership rate was not available for several countries for each single year between 1970 and 2004. In these cases, the time series were interpolated, which is a straightforward approach, given that the homeownership rate usually changes very smoothly over time.

[40] In doing so, we deviate slightly from the approach used in Ahearne et al. (2005), which identifies the beginning of housing crises as price peaks within a rolling window of six years. However, since we are more interested in housing crises than in cyclical house price movements, we impose a restriction on the minimum size of the following price decline.

[41] While in general, it is not obvious whether the identification of housing crises on a quarterly or an annual basis is more appropriate, for our baseline results we use the identification on a quarterly basis, because it allows a more timely identification of the crises and we use the quarterly for the empirical investigation in section 3. For a robustness check we also use a corresponding identification method based on annual data, see Appendix for the results. Due to the identification with annual data Germany can be included into the analysis. The main results stay the same.

for inference on the (unbalanced) panel model. The starting year of a housing crisis is defined as the year that includes the quarter of the price peak. Nevertheless, since our identification method is rather ad hoc, we provide robustness checks of our results using the identification method from Ahearne et al. (2005) *(loose definition)* which yield similar findings.[42]

Table 4.1:
Timing of Housing Crises and Recessions

	Housing crises	Recessions
JP	1973, 1991	1973, 1993, 1997, 2001
FR		1974, 1992
US	1979	1973, 1980, 1981, 1990
UK	1973, 1980, 1989	1973, 1974, 1979, 1990
CN	1976, 1981, 1989	1981, 1990
ES	1991	1978, 1980, 1992
AU	1974, 1981, 1989	1974, 1981, 1990
NL	1978	1974, 1979, 2003
BG		1974, 1980, 1992
SD	1979, 1990	1970, 1976, 1980, 1990
SW	1973, 1989	1974, 1981, 1990, 1991, 2002
DK	1979, 1986	1973, 1979, 1986, 1992, 2003
NW	1987	1988
FN	1989	1975, 1990
IR	1979	1982, 1985

Notes: The figures denoted the year a housing crisis or a recession started in according to the timing methods described in the text.

Banking crises are usually identified as historical episodes with bank runs or closures of relevant financial institutions. We rely on the chronology of banking crises published in Reinhard and Rogoff (2009a), and thus have 15 banking crises in our sample. We define a housing crisis as being accompanied by a banking crisis if the banking crisis starts at least two years before the housing crisis and at most two years after the housing crisis. According to this definition, 8 out of 23 housing crisis were accompanied by a banking crisis. While it is not straightforward and beyond the scope of this paper to reveal the causality between these housing crises and banking crises, it turns out that none of these 8 housing crises started after the respective banking crises. Specifically, two housing crises started in the same year as the banking crisis, 3 housing crises started one year before the banking crisis, and three housing crises started two years before the banking crisis. Therefore, for most of the housing

[42] A tight crisis definition as applied by IMF (2003) reduces the number of housing crises such that a econometric analysis, especially regarding the cross terms, is rarely meaningful anymore. However, concerning the crisis dummies results are in line with the other crisis definitions.

crises accompanied by a banking crisis, house prices already started to fall before the banking crisis began. This is at least descriptive evidence that it is not likely that the housing crises in our sample are systematically triggered by banking crises.

4.3 Housing Crises and Recessions

There is broad evidence in the literature that a housing crisis usually goes hand in hand with a slowdown of economic activity (see, e.g., IMF 2003). In particular, Leamer (2007) points at the close link between housing crises and the business cycle in the US, and Jannsen (2010) shows the impact of housing crises on the business cycle on an international level. We broaden this evidence by analyzing the link between housing crises and recessions. In 15 out of the 23 cases a recession started within one year after the start of the housing crises.[43] Recessions are defined according to the Bry-Boschan algorithm for quarterly GDP data. The Bry-Boschan algorithm identifies peaks and troughs via analyzing several moving averages of the log level series. The algorithm identifies a peak (trough) when the moving averages of the following period are lower (higher) and the corresponding business cycle phases comply with some conditions concerning the minimum duration of business cycles.[44] Overall, the data set contains 45 recessions. To check whether this seemingly connection is not just a random phenomenon, we perform a simulation exercise to derive a distribution for the number of recessions that are connected to housing crises. In the simulation, we assume that the occurrence of the 23 housing crises is random and not correlated to the recessions. We generate 10,000 random draws. In each draw, 23 housing crises are distributed on a sample of the same size as the original one. The drawn set of housing crises thereby has to fulfill some conditions to be accepted as a draw for the distribution: a minimum distance between two crises is assumed for example. Otherwise, an unrealistic case can occur in which housing crises start in consecutive years, which is not observed in the data.[45] The random draws of the housing crises are then connected with the observed recessions and the number of joint housing crises and recessions is calculated as for the original sample. In the 10,000 random draws, the event that 15 housing crises or more are followed by a recession virtually never occurred, which thus provides evidence for a clear relation between housing crises and recessions.

[43] The dates of housing crises and recessions respectively are given in Table 4.1.

[44] For further details, see Bry and Boschan (1971), and for the quarterly version, Watson (1994).

[45] Note that due to these restrictions (dependency structure) a typical x^2-test is not applicable.

We further assess this relation by comparing the properties of a recession following a housing crises and those without a housing crisis, see Table 4.2. We do not find differences between both types of recessions according to the mean growth rate of GDP during a recession. The mean growth rate is slightly higher in recessions with a housing crisis but the differences are not significant according to the common levels. However, we do find evidence that recessions with housing crises last longer, namely 5.5 quarters on average, compared to 4 quarters in a recession without housing crisis, see Table 4.2. We conclude that recessions are often preceded by housing crises and that recessions preceded by housing crises lead to longer lasting output reductions than other recessions.

In the following section we discuss a parametric approach to grasp the costs of housing crises and to ask which circumstances might be particularly adverse.

Table 4.2:
Mean Growth Rates and duration in Recessions

	With housing crisis	Without housing crisis	*t*-value of difference	*p*-value
Mean quarterly growth rate	−0.689	−0.631	−1.569	0.124
Duration in quarters	5.467	4.000	5.159	0.000

4.4 Costs of Housing Crises

To assess the costs of a housing crisis in terms of output growth, we set up a *differences-in-differences* specification (see Bertrand et al. 2007). The model for GDP growth takes the form

$$y_{i,t} = \alpha_1^{(i)} y_{i,t-1} + \beta^{(i)} X_{i,t-1} + \sum_{j=1}^{2} y_j \, I_{i,t-j} + \sum_{j=1}^{2} \delta_j \, I_{i,t-j} \times Z_{i,t-j} + u_{i,t} \qquad (4.1)$$

where $y_{i,t}$ represents the GDP growth of country i in year t. The variable $I_{i,t-j}$ indicates whether a housing crisis started in the year before or two years before. In a second term, the crisis indicator is multiplied by the variable $Z_{i,t-j}$ assess what economic conditions increase the costs of housing crises. To assess such conditions, we use a proxy measure of the impact of housing prices on consumption, namely the homeownership rate, a measure for the impact on construction, namely the change of the share of housing investment in real GDP, *and a measure for the impact of stress in the banking sector, namely a banking crisis dummy variable.* Furthermore, lagged GDP growth and additional standard control variables, namely short and long term interest rates and inflation rates, represented by $X_{i,t-1}$ are included to capture other influences on GDP growth. We specify the error term $u_{i,t}$ as an moving average process of order one,

$$u_{i,t} = \rho e_{i,t-1} + e_{i,t} \qquad \text{with } e_{i,t} \sim \mathcal{N}(0,\sigma^2) \tag{4.2}$$

allowing for serial dependence within the unobserved component. To take possible heteroscedasticity in the panel into account, a random coefficient approach is specified. Analysis reveals that the consideration of a random coefficient for the persistence term α_1 and the coefficient for the long term interest rates is sufficient to control for heteroscedasticity in the panel. Thus, we assume that $\alpha_1^{(i)}$ is a random variable following a normal distribution with parameters $\mu_{\alpha 1}$ and $\sigma_{\alpha 1,}$ and for one of the β, we assume that it follows a normal distribution with parameters $\mu_{\beta 3}$ and $\sigma_{\beta 3,}$ while all other parameters are constant in i. Estimation of this basic *differences-in-differences* specification is done via the maximum likelihood method (Beck and Katz 2007).

The estimated effects of specified crisis events using the *differences-in-differences* specification are given in Table 4.3. Robustness checks concerning possible endogeneity and definition and timing methodology of the crises are provided in Section 4.5. We estimate the (unbalanced) panel model in equation 4.1 in several specifications with respect to the crisis dummies and cross terms, thus conditioning on a given set of control variables. Note, that all models with contemporaneous impacts of housing crises and cross terms were not preferred according to likelihood ratio tests and are thus not reported. Specification *I* takes into account the crisis indicators only and no cross terms. A housing crisis has a significant impact on growth in both years after its occurrence. In the first year, the growth rate is dampened by 2.0 percentage points and in the second year by an additional negative impact of 1.5 percentage points. Specifications *II* through *V* all control for a single additional cross term. In specification *II,* the cross term of the change in the share of housing investment and the crisis indicator is added, but no significant impact is revealed. Thus, we find no evidence that a boom-bust cycle in the construction sector is the main driver of costs induced by housing crises. In specification *III,* the homeownership rate cross term is included and turns to be highly significant. However, it does not improve the model fit according to Akaike's

Table 4.3:
Costs of Housing Crises: Baseline Crisis Definition and Quarterly Timing Methodology

		I	II	III	IV	V	VI	VII
α_0	Constant	2.5743	2.5362	2.5513	2.5726	2.4930	2.4239	2.4245
		5.6217	5.5942	5.7721	5.6131	5.5387	5.3942	6.2077
μ_{α_1}	Δ GDP (t-1)	0.1699	0.1745	0.1686	0.1692	0.1849	0.1914	0.1866
		1.7829	1.7835	1.7887	1.8770	1.7543	1.8319	2.0296
σ_{α_1}		0.1390	0.1387	0.1391	0.1401	0.1366	0.1333	0.1365
		3.3824	3.3168	3.2335	3.3250	3.1622	2.4915	2.8739
β_1	short interests (t-1)	−0.2970	−0.3028	−0.2976	−0.2939	−0.2888	−0.2872	−0.2899
		−5.6735	−5.7657	−5.5674	−5.6513	−5.2760	−5.2646	−5.3057
β_2	inflation (t-1)	−0.0171	−0.0181	−0.0165	−0.0158	−0.0180	−0.0320	−0.0303
		−0.4763	−0.5271	−0.4857	−0.4374	−0.4865	−0.9190	−0.8771
μ_{β_3}	long interests (t-1)	0.2645	0.2730	0.2673	0.2612	0.2619	0.2738	0.2779
		3.8032	4.2965	3.9958	3.7781	3.9251	3.8211	4.1387
σ_{β_3}		0.0395	0.0384	0.0437	0.0383	0.0390	0.0428	0.0460
		1.4220	1.4696	1.6543	1.1262	1.5169	1.4503	1.5845
γ_1	crisis (t-1)	−2.0353	−1.9748	0.0026	−1.9794	−1.6955	−1.5486	
		−5.0922	−4.9753	0.0039	−4.9923	−3.2568	−3.1623	
$\delta_1^{(1)}$	crisis x Δ shi (t-1)		−0.5293					
			−0.9931					
$\delta_1^{(2)}$	crisis x hor (t-1)			−3.4631				−2.7665
				−3.3676				−3.2061
$\delta_1^{(3)}$	crisis x Δ cr (t-1)				0.4821			
					0.7577			
$\delta_1^{(4)}$	crisis x bc (t-1)					−0.9667	−1.3674	−0.7914
						−1.1333	−1.7526	−1.6328
γ_2	crisis (t-2)	−1.4714	−1.4519	−1.4849	−1.4711	−1.4640	−0.7712	−1.1907
		−3.7458	−3.6728	−3.4162	−3.5443	−3.5862	−1.4795	−1.6080
$\delta_2^{(1)}$	crisis x bc (t-2)						−1.8274	−1.8370
							−2.2960	−2.1096
ρ		0.2303	0.2238	0.2241	0.2317	0.2101	0.1889	0.1890
		2.6885	2.4994	2.6430	2.8093	2.2429	1.8666	2.2206
σ		1.6368	1.6361	1.6323	1.6362	1.6344	1.6215	1.6194
		34.2816	32.4375	32.9248	33.2248	33.3580	33.0352	34.3187
Log likelihood		−968.5	−968.0	−967.8	−968.1	−967.6	−964.7	−964.4
AIC		1.9809	1.9840	1.9836	1.9843	1.9833	1.9807	1.9807
LR-test Treatment[a]		0.96	1.05	0.99	1.11	0.89	0.32	0.23

Notes: Δ shi: change in share of housing investment; hor: rate of homeownership; Δ cr: change in consumption ratio; bc: banking crisis. [a]The probit part of the treatment model yields a log likelihood of −76.2 if estimated separately. The probit model contains the following list of regressors: lagged growth, short interest rates, long interest rates, inflation, and consumption ratio.

information criteria (AIC).[46] The cross term including the change in the share of consumption (specification *IV)* does not provide any improvement of the model fit. In specification *V*, we include an additional dummy that identifies housing crises accompanied by banking crises. Again the overall fit is not improved by this specification, compared to specification *I*. However, the additional inclusion of a two period lagged banking crisis cross term in specification *VI* provides a significantly better model fit compared to specification *V*. According to this specification, a housing crisis depresses growth by 1.5 percentage points in the first year after its occurrence and has an additional impact of –0.8 percentage points in the second year after. If a banking crisis accompanies the housing crisis, the first year effect amounts to –2.9 percentage points and the recession is substantially prolonged with an additional dampening effect of –2.6 percentage points. The best of all considered specifications is specification *VII*, where compared to specification *VI*, the first year dummy for the housing crisis is replaced by the cross term with the homeownership rate. The impact of the homeownership rate is lower when controlling for banking crises than in specification *III*, which might indicate that the homeownership rate is not a pure proxy for wealth effects. Collateral effects may interact. Our model specifications provide evidence that certain economic conditions potentially worsen the effect of a housing crisis on economic growth.

Overall, given that banking crises induce a substantial additional reduction of GDP growth and the disability of all other cross terms to provide additional explanatory power, we conclude that the banking sector is a channel that is important in transmitting the housing crisis to overall economic activity. Non-performing loans and loss in value of collaterals as a consequence of falling house prices seem to loop back to the economy with the banks' balance sheets. A connection between housing wealth and output via consumption seems comparably less important. However, this study mainly captures housing crises in the 1970s and 1980s. Financial tools that enable house owners to transmit wealth increases into additional consumption were less developed than they are today.[47] No special impact of the size of the construction sector could be found.

[46] *t*-values might be misleading, as the joint inclusion of cross terms and dummies induces the problem of multicollinearity.

[47] Aron et al. (2006) and Aron et al. (2010) point at the importance of the development status of the credit channel for the link between housing prices and consumption.

4.5 Robustness Checks

Empirical results given in Table 4.3 are conditional on the crisis definition, i.e., dating with quarterly data and assuming a minimum price decline of 7.5 percent *(baseline crisis definition).* Three kinds of robustness checks are considered. Results on the robustness checks are presented, see Tables 4.4, 4.5 and 4.6. The first robustness check considers a dating of housing crisis based on annual price data, which allows also to include Germany, see Table 4.4. As a next robustness check, we apply the definition of Ahearne et al. (2005) *(loose crisis definition)* thereby varying the minimum price decline needed to identify a housing crisis. This leads to 26 identified housing crises. Results for both quarterly and annual timing methodology are given in Table 4.5 and Table 4.6 respectively. The main results are merely unchanged when applying the loose crisis definition or the dating based on annual data. The effect of banking crises are even a bit more pronounced in the latter case.

Finally, all specifications including those considered as robustness checks are checked against the possible endogeneity or selection bias. Factors causing the occurrence of a housing crisis may be correlated with unobserved factors influencing growth. This correlation leads when ignored to biased parameter estimates. Although we find no contemporaneous effect of the crisis, endogeneity of the crisis indicators may be problematic due to autocorrelated errors. Thus, the model in equation 4.1 is enhanced with a second equation,

$$\delta^*_{i,t} = \xi^{(i)} Q_{i,t} + \epsilon_{i,t} \tag{4.3}$$

where $\xi^{(i)}$ comprise individual specific random coefficients. In addition to lagged growth, short interest rates, long interest rates, inflation and the consumption ratio are included in $Q_{i,t}$. The analysis suggests that this variable is connected to a random coefficient. $\epsilon_{i,t}$ denotes an autoregressive process of order one, i.e., $\epsilon_{i,t} = \varphi\epsilon_{i,t-1} + \nu_{i,t}$. Further, $\nu_{i,t}$ and e_{it} (error in equation 4.1) are modeled as bivariate normal with contemporaneous correlation ψ. This serial correlation structure in the errors implies a possible dependence of growth on all past shocks in the crisis equation, while the process for crises depends on past growth via the inclusion of lagged growth rates. Thus, even when no contemporaneous crisis dummy is included, a treatment model might be needed. For a more detailed description of the implied correlation structure and estimation thereof, see Aßmann (2008). Our model is closely related to treatment framework established in the seminal work of Heckman (1979). Estimation is performed using the maximum likelihood method, where the corresponding likelihood function

Table 4.4:
Costs of Housing Crises: Baseline Crisis Definition and Annual Timing Methodology

		I	II	III	IV	V	VI	VII
α_0	Constant	2.4202	2.3359	2.3820	2.3638	2.2791	2.3477	2.3306
		6.1725	6.0371	5.5823	5.8139	5.3292	5.8721	5.3832
μ_{α_1}	Δ GDP (t-1)	0.2012	0.2228	0.2095	0.2148	0.2351	0.2086	0.2108
		2.4924	2.6108	2.3781	2.6053	2.5304	2.3638	2.4626
σ_{α_1}		0.1256	0.1244	0.1251	0.1263	0.1214	0.1282	0.1277
		2.9005	3.2085	3.5513	3.7633	2.9770	2.8397	2.8090
β_1	short interests (t-1)	−0.2843	−0.2759	−0.2825	−0.2800	−0.2728	−0.2813	−0.2836
		−5.9152	−5.0125	−5.1675	−5.2646	−4.8855	−5.3968	−5.3226
β_2	inflation (t-1)	−0.0070	−0.0123	−0.0070	−0.0086	−0.0121	−0.0234	−0.0225
		−0.2073	−0.3494	−0.2207	−0.2587	−03467	−0.6723	−0.6315
μ_{β_3}	long interests (t-1)	0.2471	0.2463	0.2476	0.2466	0.2462	0.2599	0.2630
		3.4862	3.7694	3.7055	3.5380	3.4565	3.7163	3.5915
σ_{β_3}		0.0361	0.0328	0.0398	0.0348	0.0354	0.0444	0.0464
		1.1886	1.1535	1.5514	1.3411	1.3963	1.4847	1.8775
γ_1	crisis (t-1)	−1.7950	−1.9273	0.0778	−6.2939	−1.3934	−1.2495	
		−5.1107	−4.9811	0.1167	−1.5721	−2.7388	−2.4807	
$\delta_1^{(1)}$	crisis x Δ shi (t-1)		−0.7958					
			−1.7459					
$\delta_1^{(2)}$	crisis x hor (t-1)			−3.2493				−2.2453
				−2.9195				−2.8838
$\delta_1^{(3)}$	crisis x Δ cr (t-1)				0.0804			
					1.1253			
$\delta_1^{(4)}$	crisis x bc (t-1)					−1.3115	−1.6423	−0.8069
						−1.4699	−1.8701	−1.8793
γ_2	crisis (t-2)	−1.3441	−1.3436	−1.3642	−1.3504	−1.3596	−0.8055	−1.5143
		−3.9114	−3.4691	−3.8059	−3.5919	−3.6334	−1.7054	−2.0200
$\delta_2^{(1)}$	crisis x bc (t-2)						−1.7264	−1.7478
							−2.2367	−2.1406
ρ		0.2177	0.1937	0.2040	0.1998	0.1758	0.1940	0.1886
		2.9276	2.2645	2.1862	2.5467	1.8760	2.4781	2.1107
σ		1.6149	1.6122	1.6112	1.6132	1.6103	1.5956	1.5928
		29.7087	31.7383	31.3625	30.4562	30.2033	31.9179	33.3109
Log likelihood		−1012.3	−1010.8	−1011.6	−1012.2	−1010.6	−1007.7	−1007.4
AIC		1.9626	1.9635	1.9651	1.9662	1.9632	1.9615	1.9609
$\mathcal{LR}$-test Treatment[a]		0.63	0.65	0.60	0.78	0.42	0.67	0.60

Notes: Δ shi: change in share of housing investment; hor: rate of homeownership; Δ cr: change in consumption ratio; bc: banking crisis. [a]The probit part of the treatment model yields a log likelihood of −86.4 if estimated separately. The probit model contains the following list of regressors: lagged growth, short interest rates, long interest rates, inflation, and consumption ratio.

Table 4.5:
Costs of Housing Crises: Loose Crisis Definition and Quarterly Timing Methodology

		I	II	III	IV	V	VI	VII
α_0	Constant	2.5267	2.5262	2.5305	2.5178	2.4437	2.3823	2.3818
		5.4042	5.4023	5.9948	5.8240	5.5199	5.6204	4.9623
μ_{α_1}	Δ GDP (t-1)	0.1802	0.1802	0.1722	0.1823	0.1998	0.2007	0.1965
		1.8075	1.8081	1.6806	1.6806	1.9236	2.1835	1.9364
σ_{α_1}		0.1402	0.1402	0.1454	0.1410	0.1364	0.1373	0.1400
		3.4473	3.4479	3.2913	3.3673	2.8310	3.1109	3.3539
β_1	short interests (t-1)	−0.2848	−0.2848	−0.2864	−0.2815	−0.2757	−0.2759	−0.2768
		−5.5615	−5.5618	−4.9667	−5.4719	−4.7809	−4.9169	−5.2077
β_2	inflation (t-1)	−0.0200	−0.0200	−0.0209	−0.0202	−0.0217	−0.0321	−0.0325
		−0.5871	−0.5874	−0.5932	−0.5891	−0.6009	−0.9115	−0.9824
μ_{β_3}	long interests (t-1)	0.2592	0.2592	0.2633	0.2569	0.2556	0.2688	0.2715
		3.8031	3.8041	3.7992	3.6771	3.6029	3.8010	3.9724
σ_{β_3}		0.0410	0.0410	0.0478	0.0393	0.0395	0.0435	0.0462
		1.4459	1.4460	1.8420	1.2967	1.4272	1.6472	1.6442
γ_1	crisis (t-1)	−2.1289	−2.1286	1.0189	−2.0860	−1.8678	−1.7492	
		−5.6563	−5.6555	1.5697	−5.2568	−3.6487	−3.6554	
$\delta_1^{(1)}$	crisis x Δ shi (t-1)		−0.2283					
			−0.2267					
$\delta_1^{(2)}$	crisis x hor (t-1)			−5.2409				−3.0863
				−5.1185				−3.8677
$\delta_1^{(3)}$	crisis x Δ cr (t-1)				0.4647			
					0.7493			
$\delta_1^{(4)}$	crisis x bc (t-1)					0.8540	−1.2147	−1.0365
						−0.9302	−1.4716	−1.3779
γ_2	crisis (t-2)	−1.4773	−1.4770	−1.5043	−1.4743	−1.4608	−0.8645	−0.8986
		−3.6641	−3.66635	−3.7627	−3.7975	−3.8619	−1.7251	−1.8652
$\delta_2^{(1)}$	crisis x bc (t-2)						−1.7597	−1.7679
							−2.1549	−2.0498
ρ		0.2154	0.2153	0.2176	0.2167	0.1924	0.1767	0.1775
		2.2266	2.2252	2.2099	2.5125	1.8855	1.9327	1.7636
σ		1.6267	1.6267	1.6176	1.6257	1.6251	1.6138	1.6077
		31.8834	31.8836	29.1939	29.4515	31.7388	33.9514	34.2050
Log likelihood		−965.8	−965.8	−964.3	−965.5	−965.1	−962.3	−961.2
AIC		1.9757	1.9797	1.9766	1.9791	1.9783	1.9765	1.9744
LR-test Treatment[a]		1.86	2.60	1.96	2.08	1.90	1.97	1.99

Notes: Δ shi: change in share of housing investment; hor: rate of homeownership; Δ cr: change in consumption ratio; bc: banking crisis. [a]The probit part of the treatment model yields a log likelihood of −81.0 if estimated separately. The probit model contains the following list of regressors: lagged growth, short interest rates, long interest rates, inflation, and consumption ratio.

Table 4.6:
Costs of Housing Crises: Loose Crisis Definition and Annual Timing Methodology

		I	II	III	IV	V	VI	VII
α_0	Constant	2.3685	2.3679	2.3060	2.3618	2.2167	2.2167	2.2397
		6.0143	5.4680	5.0898	5.8792	5.1042	4.7873	5.4308
μ_{α_1}	Δ GDP (t−1)	0.2134	0.2132	0.2249	0.2147	0.2490	0.2304	0.2344
		2.4947	2.4963	2.5158	2.2616	2.5733	2.4526	2.4975
σ_{α_1}		0.1263	0.1262	0.1283	0.1260	0.1216	0.1258	0.1275
		3.3503	3.0536	3.4829	2.6998	3.0866	3.1050	3.3737
β_1	short interests (t−1)	−0.2702	−0.2702	−0.2655	−0.2696	−0.2581	−0.2630	−0.2615
		−5.1481	−4.9573	−4.6866	−5.2340	−4.6349	−4.8568	−4.8584
β_2	inflation (t−1)	−0.0122	−0.0121	−0.0133	−0.0116	−0.0161	−0.0241	−0.0249
		−0.3504	−0.3543	−0.4228	−0.3396	−0.4899	−0.6980	−0.7374
μ_{β_3}	long interests (t−1)	0.2440	0.2440	0.2446	0.2434	0.2428	0.2523	0.2541
		3.6704	3.3252	3.2915	3.7369	3.6066	3.4338	3.6508
σ_{β_3}		0.0429	0.0424	0.0477	0.0416	0.0405	0.0456	0.0480
		2.0361	1.4239	1.6794	1.5946	1.5420	1.6709	1.7301
γ_1	crisis (t−1)	−1.8273	−1.8289	0.9147	−1.8233	−1.5022	−1.4043	
		−5.6518	−6.1313	1.2187	−5.2691	−3.8252	−3.2270	
$\delta_1^{(1)}$	crisis x Δ shi (t−1)		−0.4893					
			−0.4839					
$\delta_1^{(2)}$	crisis x hor (t−1)			−4.7087				−2.5463
				−3.6871				−3.3345
$\delta_1^{(3)}$	crisis x Δ cr (t−1)				0.4821			
					0.7577			
$\delta_1^{(4)}$	crisis x bc (t−1)					−1.3165	−1.5870	−1.4383
						−1.6513	−1.8854	−1.8860
γ_2	crisis (t−2)	−1.4264	−1.4258	−1.4530	−1.4249	−1.4396	−1.0359	−1.0528
		−4.3439	−4.2743	−4.2724	−4.1418	−4.3679	−2.5227	−2.6777
$\delta_2^{(1)}$	crisis x bc (t−2)						−1.8274	−1.5574
							−2.2960	−1.8594
ρ		0.2018	0.2025	0.1814	0.1996	0.1534	0.1651	0.1606
		2.6006	2.2670	1.8172	1.9918	1.5478	1.6507	1.8872
σ		1.5994	1.6006	1.5920	1.5998	1.5953	1.5830	1.5792
		31.6827	30.8858	30.4045	30.1050	30.4184	32.7127	30.9168
Log likelihood		−1008.6	−1007.8	−1007.0	−1007.9	−1006.7	−1004.1	−1003.1
AIC		1.9556	1.9840	1.9564	1.9581	1.9558	1.9546	1.9528
LR–test Treatment[a]		1.63	1.54	2.52	2.47	2.44	2.56	2.62

Notes: Δ shi: change in share of housing investment; hor: rate of homeownership; Δ cr: change in consumption ratio; bc: banking crisis. [a]The probit part of the treatment model yields a log likelihood of −100.0 if estimated separately. The probit model contains the following list of regressors: lagged growth, short interest rates, long interest rates, inflation, and consumption ratio.

involves high dimensional integrals. Hence, a simulation-based estimator is used based on the GHK importance sampling proposed by Geweke (1989), Hajivassiliou (1990), and Keane (1992). To ensure numerical precision of the likelihood evaluations, a set of common random numbers with a size of 500 has been found sufficient. Overall, likelihood ratio test statistics given in the last column of Tables 4.3 and 4.4–4.6 suggest that no selection mechanism or endogeneity of crisis is present in the data set and different crisis definitions.

4.6 Conclusion

This paper provides evidence for a close link between housing crises and severe contractions of overall production at the level of industrialized countries. Housing crises are often followed by recessions that are longer than other recessions. Using a panel study, we assessed the costs of housing crises. They diminish GDP growth in the following year by about 2 percentage points on average and have an additional detrimental effect of roughly 1.5 percentage points in the second year after the outbreak of the housing crisis. We could not observe any significant contemporaneous effects of housing crises.

The economic conditions that may lead to particular costly housing crises are analyzed via several cross terms. We find no evidence that a high increase in the share of housing investment prior to a crisis has a particular impact. Thus, we conclude that a housing crisis does not simply indicate a boom-bust cycle in the construction sector. A detrimental wealth effect does not seem to be the driver of costs, since we find no evidence for a boom-bust in consumption either. However, there is some evidence that a higher rate of homeownership increases costs. This may indicate an asymmetric behavior. While homeowners might feel a loss in wealth due to decreasing house prices, potential home buyers do not translate decreased prices into a positive wealth effect in times of economic stress or even recessions. Due to multicollinearity, this result should be interpreted with care. Finally, we analyzed the growth effect of housing crises that are connected to banking crises. A joint occurrence of a banking and housing crisis increases costs. While the difference between housing crises with and without banking crises is rather moderate in the first year, banking crises play a major role in the second year after the house price peak. We conclude that the effect of housing crises on the banking sector seems to be an important channel on output.

4.7 References

Ahearne, A.G., J. Ammer, B.M. Doyle, L.S. Kole and R.F. Martin (2005). House Prices and Monetary Policy: A Cross-Country Study. International Finance Discussion Papers 841. Board of Governors of the Federal Reserve System, Washington, D.C.

Aron, J., JV. Duca, J. Muellbauer, K., Murata and A. Murphy (2010). Credit, Housing Collateral and Consumption: Evidence from the UK, Japan and the US. Working Paper 1002. Federal Reserve Bank of Dallas, TX.

Aron, J., J. Muellbauer and A. Murphy (2006). Housing wealth and UK consumption. *Economic Outlook* 30 (4): 11–20.

Aßmann, C. (2008). Assessing the Effect of Current Account and Currency Crises on Economic Growth. Economics Working Papers 2008-1. Christian-Albrechts-Universität, Kiel.

Beck, N., and J.N. Katz (2007).Random Coefficient Models for Time-Series-Cross-Section Data: MonteCarlo-Experiments. *Policy Analysis* 15: 182–195.

Bostic, R., G. Stuart, and G. Painter (2009). Housing wealth, financial wealth, and consumption: new evidence form micro data. *Regional Science and Urban Economics* 39 (1): 79–89.

Boyd, J.H., S. Kwak and B. Smith (2005). The Real Output Losses Associated with Modern Banking Crises. *Journal of Money, Credit, and Banking* 376: 977–999.

Bry, G., and C. Boschan (1971). Cyclical analysis of time series: selected procedures and computer programs. NBER Technical Paper 20, Columbia University Press. New York, NY.

Buiter, W.H. (2010). Housing Wealth Isn't Wealth. *Economics: The Open-Access. Open-Assessment E-Journal* 4: 2010–2022.

Case, K.E., J.M. Quigley and R.J. Shiller (2005). Comparing Wealth Effects: The Stock Market versus the Housing Market. *Advances in Macroeconomics* 5 (1): 1–34.

Cerra, V., and S.C. Saxena (2008). Growth Dynamics: The Myth of Economic Recovery. *American Economic Review* 98 (1): 439–457.

Cecchetti, S.G., M. Kohler and C. Upper (2009).Financial Crises and Economic Activity. NBER Working Paper 15379. National Bureau of Economic Research, Cambridge, MA.

Claessens, S., M.A. Kose and M.E. Terrones (2008). What Happens During Recessions, Crunches and Busts? IMF Working Paper 08/274. International Monetary Fund, Washigton, D.C.

European Commission (2008). Household consumption: what are the risks attached to falling house prices and high debt? *Quarterly Report on the Euro Area* 7 (3): 12–17.

Furceri, D., and A. Mourougane (2009). The Effect of Financial Crises on Potential Output. OECD Economics Department Working Papers 699. Paris.

Gan, J., 2010. Housing wealth and consumption growth: Evidence from alarge panel of households. *The Review of Financial Studies* 23 (6): 2229–2267.

Geweke, J. (1989). Bayesian inference in econometric models using monte carlo integration. *Econometrica* 57: 1317–1340.

Ghent, A.C., and M.T. Owyang (2010). Is housing the business cycle? Evidence from US cities. *Journal of Urban Economics* 67: 336–351.

Girouard, N., and S. Blöndal (2001). House Prices and Economic Activity. OECD Economic Department Working Papers 279. Paris.

Hajivassiliou, V. (1990). Smooth simulation estimation of panel data LDV models. Department of Economics, Yale University.

Heckman, J. (1979). Sample selection bias as a specification error. *Econometrica* 47: 153–161.

IMF (International Monetary Fund) (2003). When Bubbles Burst. *World Economic Outlook*. April. Washington, D.C.

IMF (International Monetary Fund) (2009a). From Recession to Recovery: How Soon and How Strong? *World Economic Outlook*. April. Washington, D.C.

IMF (International Monetary Fund) 2009b. What's The Damage? Medium-Term Output Dynamics After Financial Crises. *World Economic Outlook*. October. Washington, D.C.

Jannsen, N. (2009). National and International Business Cycle Effects of Housing Crises. *Applied Economics Quarterly* 56 (2): 175–206.

Kaminsky, G.L., and C.M.Reinhart (1999). The Twin Crises: The Causes of Banking and Balance-of-Payments Problems. *American Economic Review* 893: 473–500.

Keane, M. (1994). Computationally practical simulation estimator for panel data. *Econometrica* 62: 95–116.

Laeven, L., and F. Valencia (2008). Systemic Banking Crises: A New Database. IMF Working Paper 08/224. International Monetary Fund, Washington, D.C.

Leamer, E.E. (2007). Housing is the business cycle. NBER Working Paper Series 13428. National Bureau of Economic Research, Cambridge, MA.

Reinhart, C.M., and K.S. Rogoff (2008). Is the U.S. Sub-Prime Financial Crisis so Different? An International Historical Comparison. NBER Working Paper 13761. National Bureau of Economic Research, Cambridge, MA.

Reinhart, C.M., and K.S. Rogoff (2009a). *This Time is Different: Eight Centuries of Financial Folly*. Princeton, NJ.

Reinhart, C.M., and K.S. Rogoff (2009b). The Aftermath of Financial Crises. NBER Working Paper 14656. National Bureau of Economic Research, Cambridge, MA.

Watson, M.W. (1994). Business-Cycle Durations and Postwar Stabilization of the U.S. Economy. *The American Economic Review* 84 (1): 24–46.

5 The Ugly and the Bad: Banking and Housing Crises Strangle Output Permanently, Ordinary Recessions Do Not[48]

5.1 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

[48] This Chapter is based on the paper: J. Boysen-Hogrefe, N. Jannsen, and C.-P. Meier (2010). The Ugly and the Bad: Banking and Housing Crises Strangle Output Permanently, Ordinary Recessions Do Not. Kiel Working Papers 1586, Kiel Institute for the World Economy.

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 5.2 presents our estimation strategy. Section 5.3 describes the data set. Section 5.4 presents our estimation results and illustrates them graphically. Section 5.5 reports the results of several robustness checks and Section 5.6 summarizes the results and concludes.

5.2 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:

$$cdr_t = \max(y_{t-j})_{j\geq 0} - y_t , \tag{5.2}$$

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

$$\Phi(L)\Delta y_{t,i} = \alpha_i + [\Omega(L) - 1]cdr_{t,i} + \varepsilon_{t,i}, \tag{5.1}$$

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, $cdr^{bc}_{t,i}$, and, $cdr^{hc}_{t,i}$, in equation 5.2. The panel model then is given as

$$\Phi(L)\Delta y_{t,i} = \alpha_i + [\Omega(L) - 1]cdr_{t,i} + [\Theta(L) - 1]cdr^{bc}_{t,i} + [\Pi(L) - 1]cdr^{hc}_{t,i} + \varepsilon_{t,i}, \tag{5.3}$$

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.

5.3 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.[49] 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 5.1 and 5.2. For each country in our sample, we show log real GDP and the cdr term. Since we identify 41 recessions in the

[49] 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.

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.[50] 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.

5.4 Results

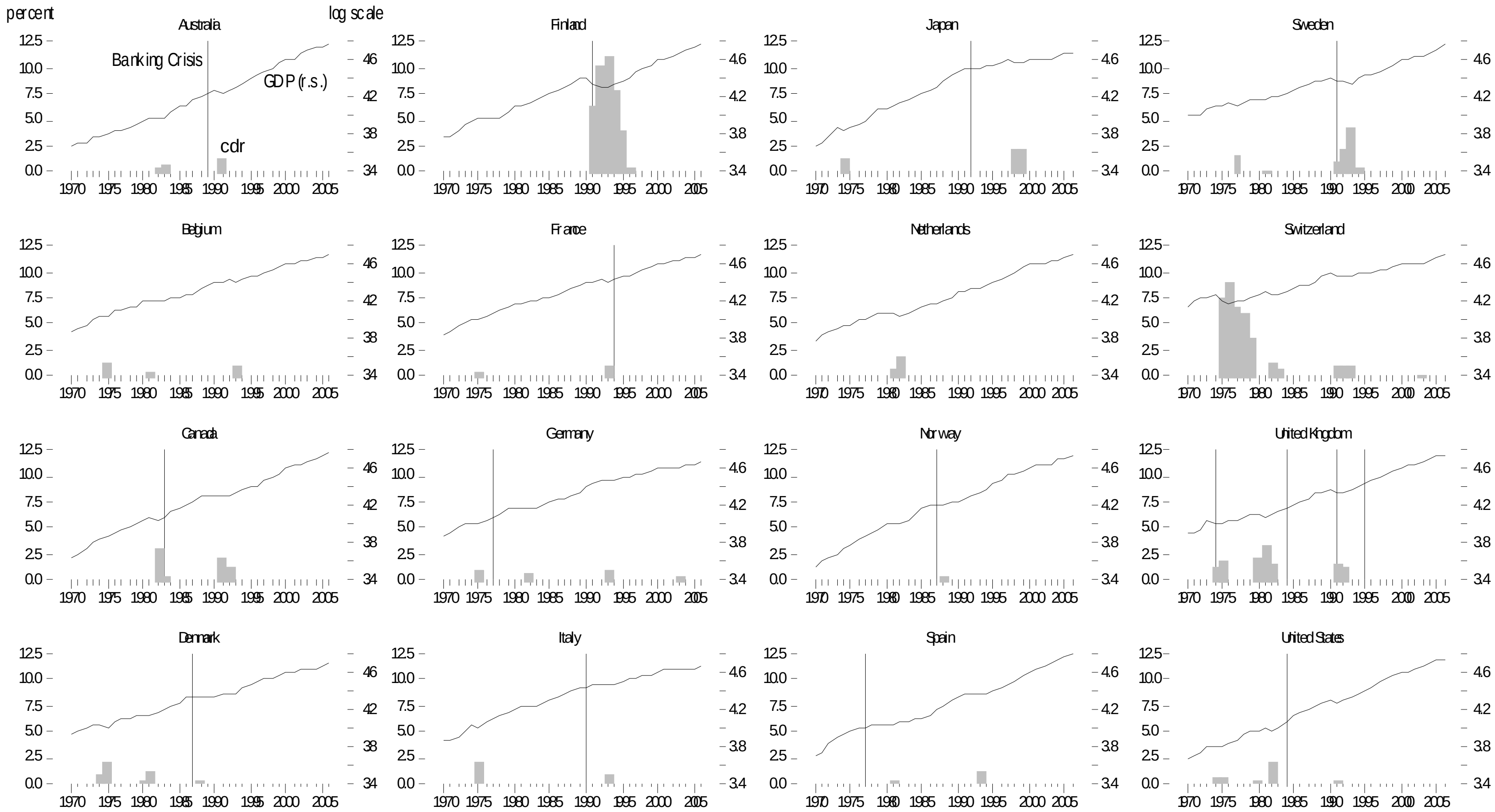
We first discuss the estimation results. After that we proceed by assessing the dynamic effects of recessions and severe crises graphically using impulse response functions.

5.4.1 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 5.1). 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).

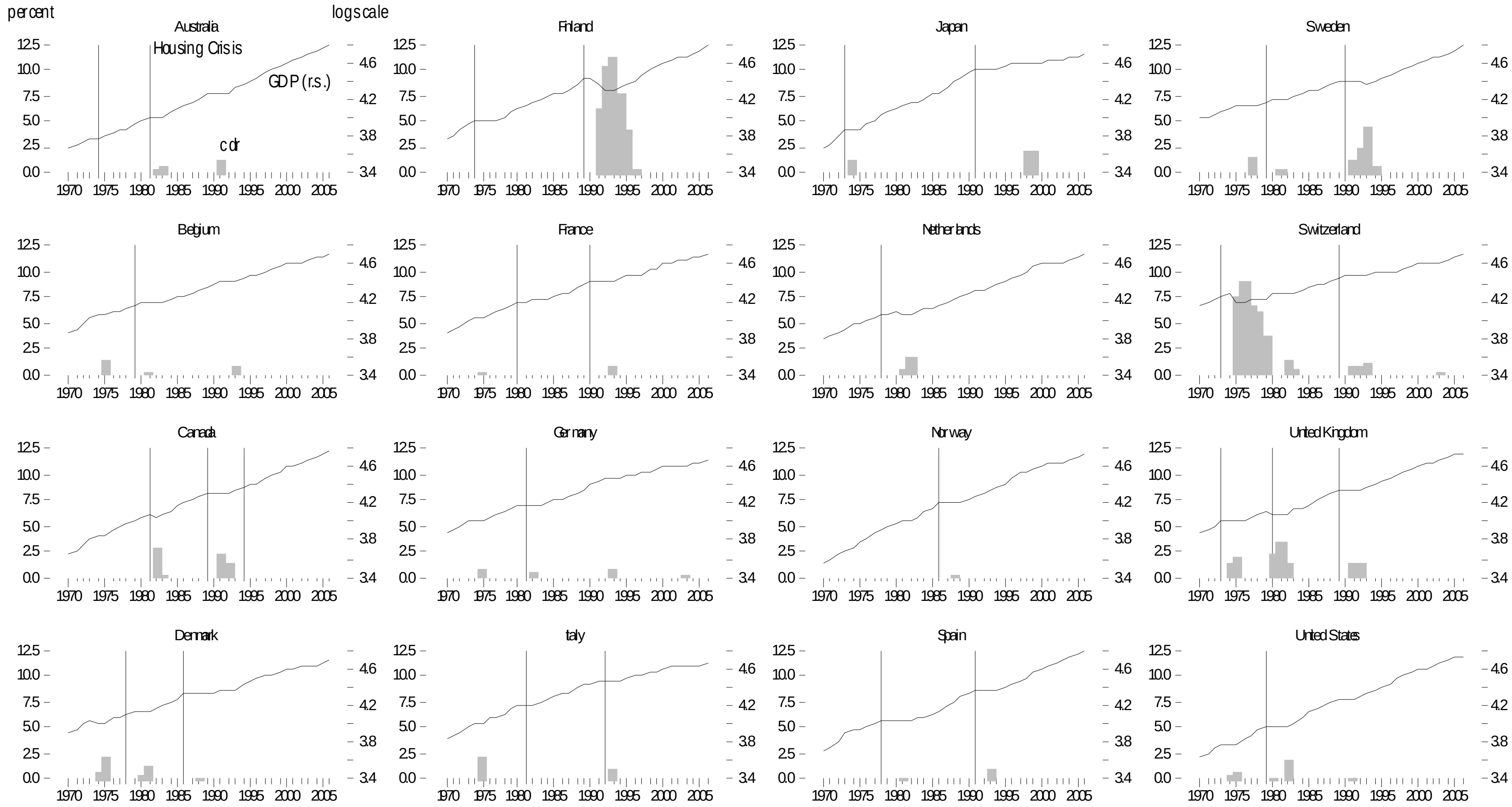
[50] We test the robustness of the results with regard to this definition in Section 5.

Figure 5.1:
GDP, Indicator of Current Depth of Recession and Banking Crises



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

Figure 5.2:
GDP, Indicator of Current Depth of Recession and Housing Crises



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

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.

Table 5.1:
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 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).

5.4.2 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

$$\Delta y_t = 1.7 + 0.50\Delta y_{t-1} - 0.21\Delta y_{t-2} + 1.48 cdr_{t-1} - 0.52 cdr_{t-2} + u_t \,, \tag{5.4}$$

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.[51] 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:

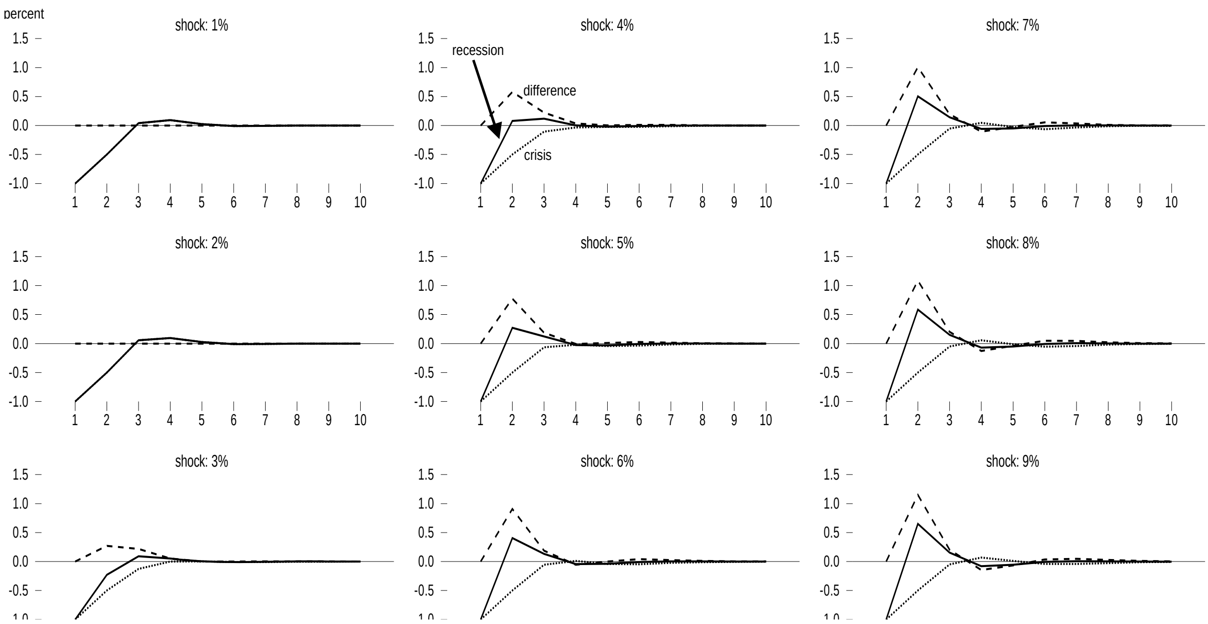
$$\Delta y_t = \begin{cases} 1.7 + 0.50\Delta y_{t-1} - 0.21\Delta y_{t-2} + u_t \text{, until } cdr_t \text{ becomes zero for the first time} \\ 1.7 + 0.50\Delta y_{t-1} - 0.21\Delta y_{t-2} + 1.48 cdr_{t-1} - 0.52 cdr_{t-2} + u_t \text{, else} \end{cases} \tag{5.5}$$

Figure 5.3 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 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 5.4). However, as the confidence interval indicates, GDP is still

[51] 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).

likely to remain permanently below the baseline for all considered shocks.[52] 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.

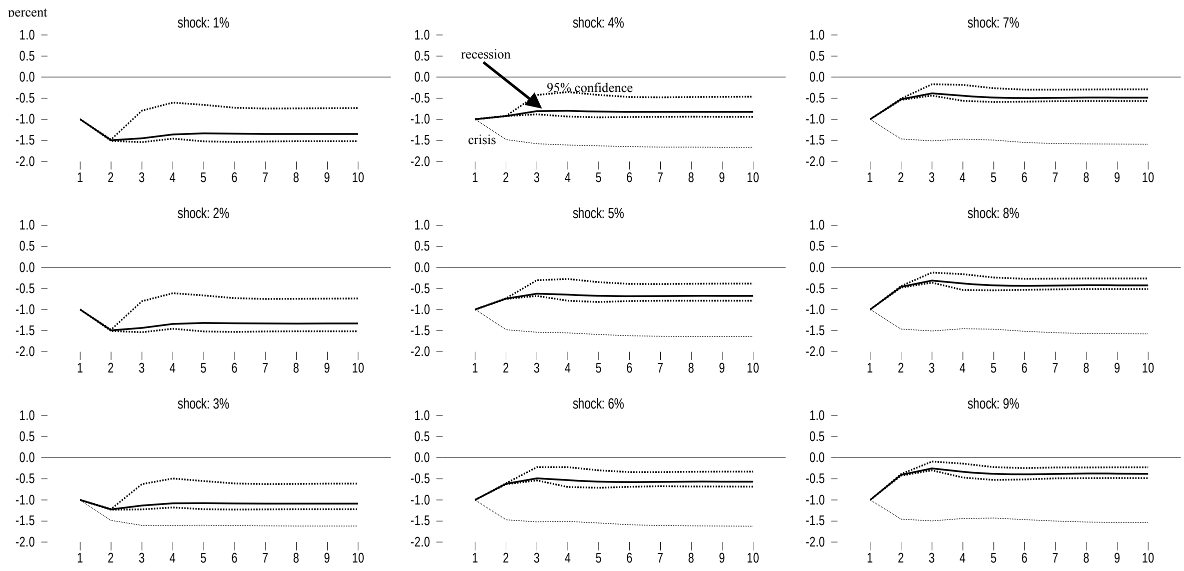
Figure 5.3:
GDP Growth: Deviation from Baseline



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.

52 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 5.4:
GDP Level: Deviation from Baseline

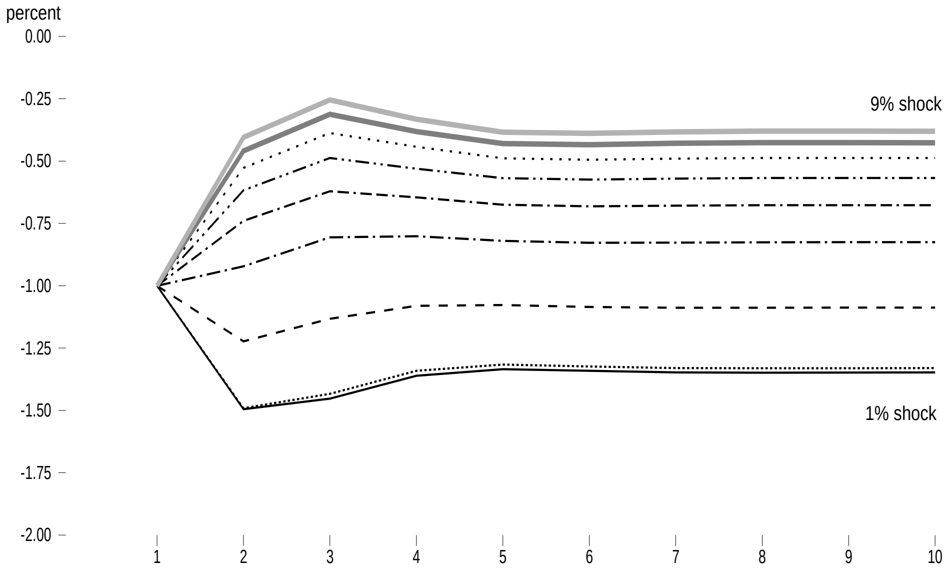


Notes: Impulse response functions are calculated as the difference to the baseline and are calculated as the mean over 1,000 bootstrap simulations. Impulse response functions are scaled by the absolute value of the respective shock.

Figure 5.5 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.

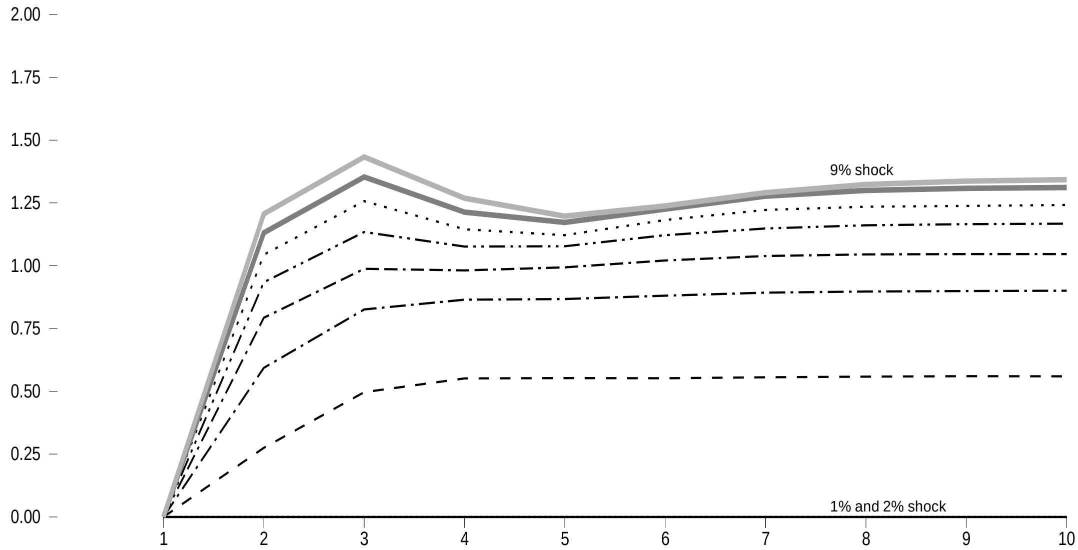
Similar patterns can be observed when comparing the recovery following an ordinary recession and a recession associated with a severe crisis (Figure 5.6). The recovery following an ordinary recession becomes relatively stronger with increasing size of the initial shock. Again, this effect diminishes with increasing size of the shock.

Figure 5.5:
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

Figure 5.6:
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.

5.5 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 5.2). 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.

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-

Table 5.2:
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)
$\Delta cdr^{bc}_{t-1,i}$			−1.18 (2.9)	−1.35 (3.1)
$\Delta cdr^{bc}_{t-2,i}$				0.66 (1.5)
$\Delta cdr^{hc}_{t-1,i}$			−0.81 (2.1)	−0.90 (2.2)
$\Delta cdr^{hc}_{t-2,i}$				0.46 (1.1)
dum^{FN1991}_{t-1}	−0.86 (4.1)	−1.3 (4.7)	−0.32 (1.0)	−0.56 (1.5)
dum^{FN1991}_{t-2}				0.24 (0.6)
dum^{SW1975}_{t-1}	−0.66 (3.0)	−0.62 (2.3)	−0.49 (1.5)	−0.37 (1.0)
dum^{SW1975}_{t-2}				−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^{FN}19 is a dummy variable for the starting year of the recession in Finland (1991). dum^{SW}1975 is a dummy variable for the starting year of the recession in Switzerland (1975).

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.[53]

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.[54]

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.[55] In a second step, we apply alternative identification

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

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

[55] 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., 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.

criteria that the 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.[56]

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.[57]

5.6 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

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

[57] 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.

5.7 References

Abeysinghe, T., and K. Forbes (2001). Trade-Linkages and Output-Multiplier Effects: A Structural VAR Approach with a Focus on Asia. NBER Working Paper 8600. National Bureau of Economic Research, Cambridge, MA.

Ahearne, A.G., J. Ammer, B.M. Doyle, L.S. Kole and R.F. Martin (2005). House Prices and Monetary Policy: A Cross-Country Study. International Finance Discussion Papers 841. Board of Governors of the Federal Reserve System, Washington, D.C.

Aßmann, C., J. Boysen-Hogrefe and N. Jannsen (2011). Costs of Housing Crises: International Evidence. Bulletin of Economic Research, forthcoming.

Balke, N.S., and M.A. Wynne (1996). Are Deep Recessions Followed by Strong Recoveries? Results for the G-7 Countries. *Applied Economics* 28: 889–897.

Beaudry, P., and G. Koop (1993). Do Recessions Permanently Change Output? *Journal of Monetary Economics* 31: 149–163.

Bordo, M.D., and O. Jeanne (2002). Boom-Busts in Asset Prices, Economic Instability, and Monetary Policy. NBER Working Paper 8966. National Bureau of Economic Research, Cambridge, MA.

Boyd, J.H., S. Kwak and B.D. Smith (2005). The Real Output Losses Associated with Modern Banking Crises. *Journal of Money, Credit, and Banking* 37 (6): 977–999.

Bradley, M.D., and D.W. Jansen (1997). Nonlinear Business Cycle Dynamics: Cross-Country Evidence on the Persistence of Aggregate Shocks. *Economic Inquiry* 35 (July): 495–509.

Campbell, J., and G. Mankiw (1987). Are Output Fluctuations Transitory? *Quarterly Journal of Economics* 102: 857–880.

Cerra, V., and S.C. Saxena (2005a). Did Output Recover from the Asian Crisis? *IMF Staff Papers* 52 (1): 1–23.

Cerra, V., and S.C. Saxena (2008). Growth Dynamics: The Myth of Economic Recovery. *American Economic Review* 98 (1): 439–457.

Cecchetti, S.G., M. Kohler and C. Upper (2009). Financial Crises and Economic Activity. NBER Working Paper 15379. National Bureau of Economic Research, Cambridge, MA.

Claessens, S., M.A. Kose, and M.E. Terrones (2009). What Happens During Recessions, Crunches and Busts? *Economic Policy* 24 (60): 653–700.

Detken, C., and F. Smets (2004). Asset Price Booms and Monetary Policy. ECB Working Paper 364. European Central Bank, Frankfurt/Main.

Furceri, D., and A. Mourougane (2009). The Effect of Financial Crises on Potential Output. OECD Economics Department Working Papers 699. Organization for Economic Cooperation and Development, Paris.

Hamilton, J.D. (1989). A New Approach to the Economic analysis of Nonstationary Time Series and the Business Cycle. *Econometrica* 57 (2): 357–384.

Haugh, D., P. Ollivaud and D. Turner (2009). The Macroeconomic Consequences of Banking Crises in OECD Countries. OECD Economics Department Working Paper 683. Organization for Economic Cooperation and Development, Paris.

IMF (International Monetary Fund) (2003). When Bubbles Burst. *World Economic Outlook*. April. Washington, D.C.

IMF (International Monetary Fund) (2009a). From Recession to Recovery: How Soon and How Strong? *World Economic Outlook*. April. Washington, D.C.

IMF (International Monetary Fund) (2009b). What's The Damage? Medium-Term Output Dynamics After Financial Crises. *World Economic Outlook*. October. Washington, D.C.

Jannsen, N. (2010). National and International Business Cycle Effects of Housing Crises. *Applied Economics Quarterly* 56 (2): 175–206.

Kaminski, G.L., and C.M. Reinhart (1999). The Twin Crises: The Causes of Banking and Balance-of-Payments Problems. *American Economic Review* 89 (3): 473–500.

Kim, C.-J., J. Morley and J. Piger (2005). Nonlinearity and the Permanent Effects of Recessions. *Journal of Applied Econometrics* 20 (2): 291–309.

Kose, M.A., C. Otrok and C.H. Whiteman (2003). International Business Cycles: World, Region, and Country-Specific Factors. *American Economic Review* 93 (4): 1216–1239.

Nelson, C., and C. Plosser (1982). Trends and Random Walks in Macro- economic Time Series: Some Evidence and Implications. *Journal of Monetary Economics* 10: 139–162.

OECD (Organization for Economic Cooperation and Development) (2009). *Economic Outlook*. June. Paris.

Pesaran, M.H., T. Schuermann and S.M. Weiner (2004). Modelling Regional Interdependencies Using a Global Error-Correcting Model. *Journal of Business & Economic Statistics* 22 (2) 129–181.

Potter, S.M. (2000). Nonlinear Impulse Response Functions. *Journal of Economic Dynamics & Control* 24: 1425–1446.

Reinhart, C.M., and K.S. Rogoff (2008). Is the 2007 US Subprime Crises so Different? An International Historical Comparison. *American Economic Review* 98 (2): 339–344.

Reinhart, C.M., and K.S. Rogoff (2009a). *This Time is Different: Eight Centuries of Financial Folly*. Princeton.

Reinhart, C.M., and K.S. Rogoff (2009b). The Aftermath of Financial Crises. NBER Working Paper 14656. National Bureau of Economic Research, Cambridge, MA.

Romer, C.D., D.H. Romer (1989). Does Monetary Policy Matter? A New Test in the Spirit of Friedman and Schwartz. *NBER Macroeconomics Annual* 4: 121–170.

Sichel, D.E. (1994). Inventories and the Three Phases of the Business Cycle. *Journal of Business and Economic Statistics* 12 (3): 269–278.

5.8 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.

5.8.1 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.

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.

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 5.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.

Table 5.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 1,000 draws.

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 5.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.[58] 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.[59] 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 5.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

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

[59] Furthermore, we consider only the model 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.

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

5.8.2 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.

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.

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 5.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.

Table 5.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.

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.[60] 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

$$\Phi(L)\Delta y_{t,i} = \alpha_i + [\Omega(L)-1]cdr_{t,i} + [\Theta(L)-1]cdr^{bc}_{t,i} + [\Pi(L)-1]cdr^{hc}_{t,i} + \Gamma(L)\Delta y^*_{t,i} + \varepsilon_{t,i} \quad (5.B5)$$

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.[61]

60 Export data were taken from the International Financial Statistics Database of the IMF.

61 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)).

The global GDP variable is highly significant and improves the fit of the model considerably (Table 5.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.

Table 5.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.

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.[62]

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 5.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).

Table 5.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.

5.8.3 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.

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 5.C1). The bounceback effect is nearly completely offset when a recession is

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

associated with a housing crisis.[63] 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.

Table 5.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)
$cdr_{t-1,i}^{\text{all } hc}$	−1.47 (4.8)	−1.21 (4.2)	−0.97 (4.0)

Note: t-values in parentheses.

In Section 5.2, 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 5.C2).

[63] 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.

Table 5.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.

5.8.4 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.

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 5.D1). However, our baseline results are qualitatively confirmed.

Table 5.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.

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 5.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 5.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.

6 International Recessions, Crises, and the Dynamics of Recoveries[64]

6.1 Introduction

The worldwide Great Recession of 2008/2009 is an outstanding example of an internationally synchronized recession. However, while the strength of the recession was already quite heterogeneous across the individual countries, the recoveries that followed apparently exhibited an even higher degree of heterogeneity. Some countries that were directly affected by a severe economic crisis, as a financial crisis or a housing crisis, such as the United States, Great Britain, or Spain, experienced a relatively sluggish recovery that was by far not strong enough to bring GDP back to its pre crisis growth path. Some countries that were apparently not directly affected by a severe economic crisis, like some East Asian emerging economies or Germany, experienced a strong recovery that brought GDP back relatively close or even completely to its pre crisis growth path. Other countries that were apparently not directly affected by a severe economic crisis, like Canada, nonetheless experienced a sluggish recovery. Given these heterogeneities, I analyze the extent to which the strength of recessions and the dynamics and the strength of recoveries are affected when recessions and severe economic crises are internationally synchronized.

While there is a rich literature that studies the international business cycle synchronization, the literature that studies particularly the relevance of international synchronization during recessions and recoveries for the strength of recessions and recoveries is scarce. Claessens et al. (2009) show that internationally synchronized recessions are considerably longer and deeper than recessions that are not internationally synchronized. The IMF (2009) shows, in a similar study, that recoveries following internationally synchronized recessions are particularly weak. Cerra et al. (2009) find no evidence that foreign GDP growth has a significant additional effect on the strength of domestic recoveries that goes beyond the normal transmission mechanism for industrial countries.[65] Jorda et al. (2011) show that internationally synchronized financial crises are deeper than not internationally synchronized financial crises or ordinary recessions.

However, from a theoretical point of view it is not obvious whether internationally synchronized recessions and recoveries are stronger or weaker than not internationally

64 This Chapter is based on the paper: N. Jannsen (2011). International Recessions, Crises, and the Dynamics of Recoveries. Mimeo.

65 They find a significant additional impact for developing countries and for a sample that comprises all countries.

synchronized recessions or recoveries. Increasing trade and financial linkages among countries could lead to the hypothesis that internationally synchronized recessions as well as recoveries are stronger. The empirical literature indeed provides some evidence that bilateral trade linkages and financial linkages lead to increasing business cycle co-movements across countries (compare, e.g., Baxter and Kouparitsas 2005, Imbs 2004). However, when a country experiences a recession and in particular when it experiences a severe economic crisis, the depreciation of the currency could stabilize the economy by stimulating exports and thus leading to stronger recoveries. When several countries experiencing recoveries at the same time, a considerable depreciation of the currency is much less likely and internationally synchronized recoveries therefore might be weaker. Moreover, when internationally synchronized recessions are caused by global shocks, as for example oil price shocks, the strength of the recession and the following recovery in a country might depend crucially on how vulnerable this country is to such shocks and how economic policy in this country reacts to them. In this context, several studies find evidence in favour of a world business cycle that affects national business cycles considerably, but also find country-specific factors still to be highly important for national business cycles (Kose et al. 2003, Canova et al. 2007, Kose et al. 2008).

Even though the results of Jorda et al. (2011) might be not easy to apply to the Great Recession, because they identified only phases of global financial crises before World War II, they bring up an important issue: the impact of international synchronization on the depth of recessions and the strength and dynamics of recoveries might depend on whether the recessions are associated with severe economic crises or not. This hypothesis is underpinned by the literature on national recessions and recoveries. For example, Beaudry and Koop (1993), show that recessions in the United States are usually followed by strong recoveries that bring GDP back close or even completely to its old growth path. In contrast, the literature on severe economic crises concludes that they lead to particularly deep and long-lasting recessions that have permanent effects on GDP (see, e.g., Reinhart and Rogoff 2008 or Cerra and Saxena 2008). Boysen-Hogrefe et al. (2010) reconcile these opposing results by differentiating between recessions that are associated with severe economic crises and recessions that are not (ordinary recessions). They show that ordinary recessions are usually followed by strong recoveries, while recessions associated with severe economic crises are not. Consequently, ordinary recessions exhibit much smaller or even no permanent effects on GDP.

This analysis contributes to the literature by providing stylized facts on whether internationally synchronized recessions and recoveries are different from not internationally synchronized recessions and recoveries. In particular, it differentiates between ordinary recessions and recessions associated with severe economic crises when analyzing the impact of international synchronization. Recessions and recoveries are investigated independently of each other. First, I analyze whether internationally synchronized recessions are deeper than other recessions. To do so, I build on the work of Claessens et al. (2009) and the IMF (2009) and use additional measures of international synchronization. Second, I investigate how the strength and the dynamics of recoveries are affected when they are internationally synchronized. Therefore, I augment the empirical model of Boysen-Hogrefe et al. (2010) to an open economy model. I estimate the strength of recoveries following ordinary recessions or severe economic crises in a panel framework for 16 industrial countries. The empirical results are used to run simulations to analyze the strength and the dynamics of recoveries in several scenarios. I analyze these scenarios using a stylized two-region model consisting of a (domestic) small open economy that is subject to international business cycle developments and a foreign 'rest-of-the-world' economy, which I model basically as a closed economy. The scenarios include cases in which the domestic and the foreign economy are hit by an ordinary recession or a severe economic crisis.

I find some evidence that internationally synchronized recessions are stronger than not internationally synchronized recessions. However, the results depend considerably on how the degree of international synchronization is measured and whether I control for outliers in the sample. Countries hit by severe economic crises tend to be more vulnerable to internationally synchronized recessions. Ordinary recessions seem to have larger international spillover effects. Moreover, I find that internationally synchronized recoveries tend to be stronger than not internationally synchronized recoveries. However, a country benefits only significantly from internationally synchronized recoveries when the foreign recoveries are following ordinary recessions, but not when they are following recessions associated with severe economic crises. The benefits are larger when the country itself was hit by a severe economic crisis.

The rest of this paper is structured as follows. Section 6.2 describes the data set used. Section 6.3 presents the results for internationally synchronized recessions. Section 6.4 presents the estimation and simulation results for internationally synchronized recoveries. Section 6.5 summarizes the results.

6.2 Data Set and Identification of Recessions and Severe Economic Crises

The empirical literature on the effects of severe economic crises relies on panel data sets, because such crises are rare events, what makes it difficult to estimate meaningful time series models for single countries. For our analysis I focus on a panel of 16 industrial countries, namely Australia, Belgium, Canada, Denmark, Finland, France, Germany, Great Britain, Italy, Japan, the Netherlands, Norway, Spain, Sweden, Switzerland, and the United States. The panel is restricted by the fact that I want to investigate besides recessions and financial crises also housing crises, but data for real house prices, which I use to identify housing crises, are only available for a limited number of countries. While data on financial crises are available for a lot of emerging economies or developing countries the restriction to industrial countries might have the advantage that countries with considerably different market structures, risk perceptions, institutions, etc are not mixed up. This dampens the risk that the results are biased by investigating a very heterogeneous set of countries.

I use real GDP data from the OECD's Economic Outlook (2011). Financial crises are usually identified as episodes of bank runs or closures of big financial institutions. I use the chronology of Reinhart and Rogoff (2009). Housing crises are identified based on real house price developments. Data on real house prices come from the Bank for International Settlements. Since financial crises and housing crises are usually identified on an annual basis and our data set for real house prices is on an annual basis as well, I use annual data throughout our analysis. The time span covered is 1970 to 2009, the longest possible time span for that all necessary data are available. Since the available times series data do not allow a conclusive assessment of the recessions and recoveries during the Great Recession, I do not include them in the analysis.

I follow the literature and identify housing crises as periods of sharp real house price declines (Ahearne et al. 2005, Jannsen 2010, or IMF 2003). In this literature a housing crisis is identified as real house price decline after prices have reached a peak within a rolling window of eight to ten years. The former literature differs in how much real house prices have to decline to be considered as a housing crisis. While sometimes only the most severe house price declines are considered to be housing crises (IMF 2003), sometimes all house price declines following a house price peak within a rolling window are considered to be housing crises (Ahearne 2005), and sometimes the house price decline has to pass a certain threshold to be considered housing crisis (Jannsen 2010). I follow the latter identification scheme and identify the beginning of a housing crisis as house price peak within a rolling window of nine years followed by a minimum house price decline of 7.5 percent within the next four years. A minimum price decline as identification criterion ensures that only exceptional developments at the housing market are identified as a housing crisis on the one hand and that a sufficient number of housing crises for our empirical investigation is identified on the other hand. Even though these identification criteria are rather ad-hoc, the former literature that uses these criteria has shown that their results are robust to modifications of these criteria, e.g. modifications in the minimum house price decline required (Jannsen 2010, Boysen-Hogrefe et al. 2010, and Aßmann et al. 2011).

I identify recessions as periods with negative GDP growth rates. This identification strategy is not unique in the literature, but frequently used. Compared to other frequently used identification strategies as strategies based on the output gap or the Bry-Boschan algorithm (adjusted to yearly data), the strategy used here usually identifies only recessions that would have been identified by the alternative strategies as well, but identifies fewer recessions. Overall, the strategy used here is relatively strict and identifies only relatively severe recessions. This identification strategy is convenient for the analysis, because the strength of recoveries following recessions is modeled by means of a current-depth of recession (*cdr*) term. The *cdr* term is defined as difference between current GDP and the historical maximum of GDP:

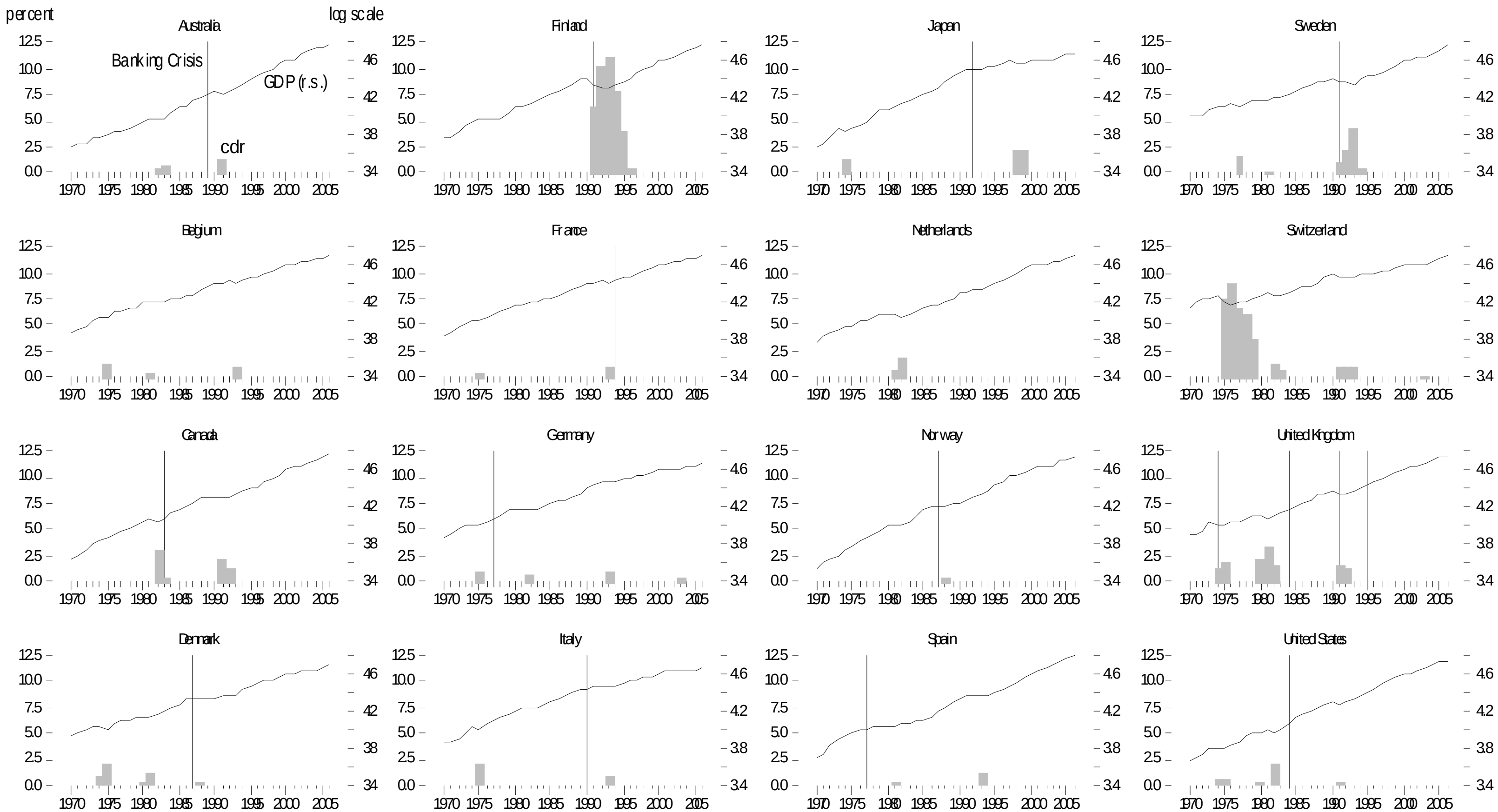
$$cdr_t = \max(y_{t-j})_{j \geq 0} - y_t . \tag{6.1}$$

As long as GDP does not decrease the *cdr* term is equal to zero. When an economy is in a recession and GDP growth is negative the *cdr* term becomes positive until GDP reaches its former maximum again. Beaudry and Koop (1993) showed that the *cdr* term has a singnificant positive impact on GDP growth in the United States and thus that recessions in the United states are followed by particular strong recoveries that are the stronger the deeper the preceding recession was. Boysen-Hogrefe et al. (2010) provide similar evidence on an international basis for ordinary recessions. Overall 41 recessions, i.e. 41 periods with positive *cdr* terms, 29 housing crises, and 16 financial crises are identified in the panel. The identified housing crises and banking crises, GDP, and the *cdr* term are presented in Figures 6.1 and 6.2.

I differentiate between ordinary recessions and recessions that are associated with severe economic crises. Therefore, a simple timing criterion is implemented that considers a recession to be associated with a housing crisis or a banking crisis when it begins in the same year or the two consecutive years after the crisis begins.[66] According to this criterion 21

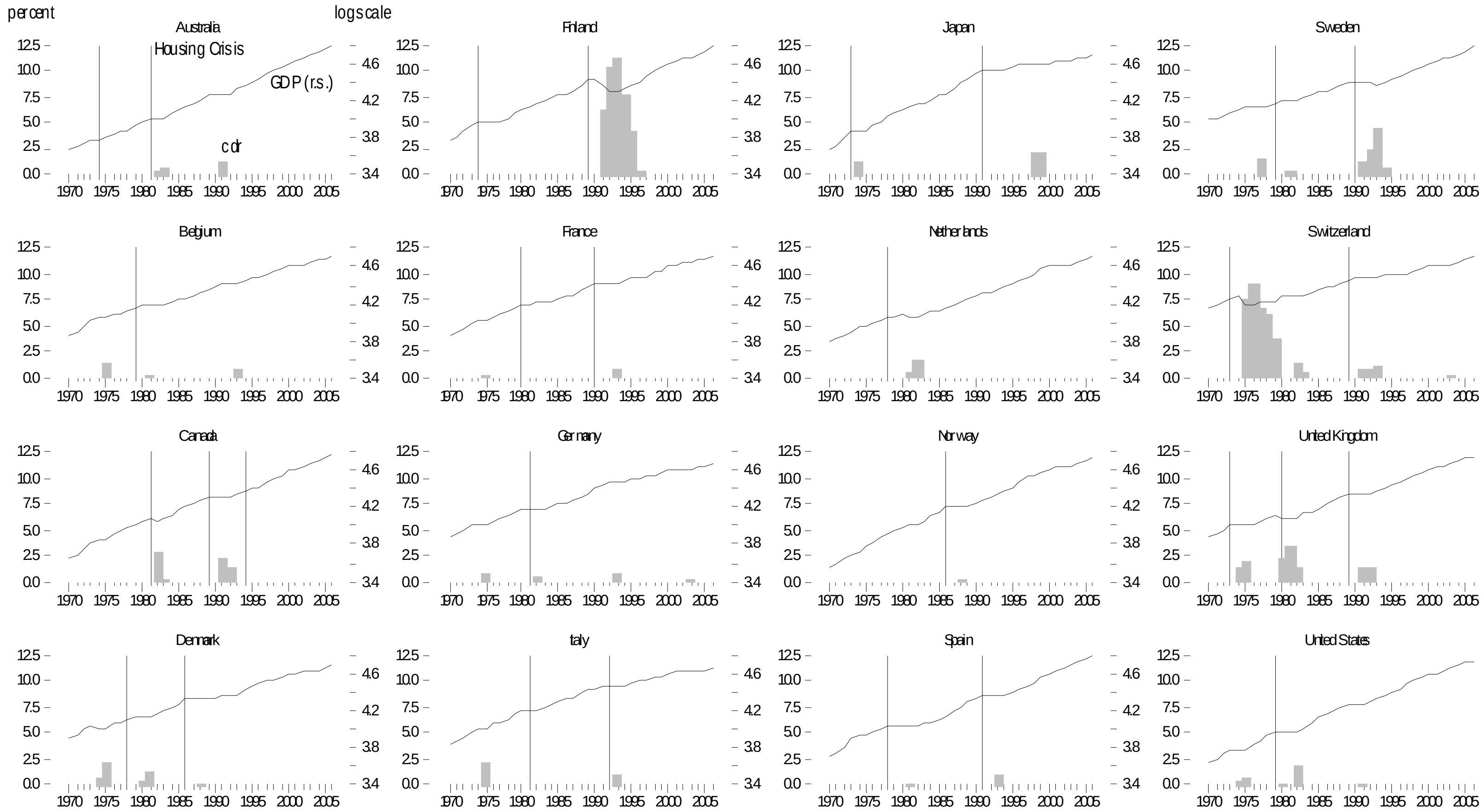
[66] Boysen-Hogrefe et al. (2010) demonstrate that their results are robust to modifications of this criterion.

Figure 6.1:
GDP, Indicator of Current Depth of Recession and Banking Crises



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

Figure 6.2:
GDP, Indicator of Current Depth of Recession and Housing Crises



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

housing crises and eight financial crises are associated with a recession. Moreover, seven out of the eight financial crises associated with a recession are associated with a housing crisis as well.

6.3 Internationally Synchronized Recessions

I investigate whether recessions that are highly internationally synchronized are more severe than recessions that are less internationally synchronized. Therefore, I extract recessionary years, i.e., years with negative GDP growth, from the panel data set and use several measures of the degree of international synchronization to estimate its impact on the strength of recessions. Finally, I differentiate between ordinary recessions and severe economic crises to analyze, on the one hand, whether they are differently vulnerable to foreign recession and, on the other hand, whether they have a different impact on the strength of foreign recessions. I begin by providing some basic descriptive statistics for ordinary recessions and severe economic crises that serve as useful background information for the following analysis.

6.3.1 Basic Descriptive Statistics

A recession is defined as a period of one year or several consecutive years with a negative GDP growth rate. Overall, there are 41 recessions and 55 recessionary years (years with negative GDP growth rates) in the sample.

On average, 1.2 recessions per year can be observed in the sample. In those years that exhibit at least one recession, on average 3.6 recessions can be observed. To check whether recessions are usually at least to some extent internationally synchronized or whether the cluster of recessions in certain years is just random, I perform a simulation exercise. In the simulation exercise, it is assumed that recessions are not internationally synchronized and 55 recessionary years are distributed on a sample with the same size as the original sample. For each draw the average number of recessions in one year is calculated for those years that exhibit at least one recession. When 10,000 draws are generated, I find for virtually no draw an average of 3.6 recessions per year. The average for all draws is 1.9 recessions. Therefore, the observation that recessions are at least to some extent internationally synchronized is not random, but a typical pattern.

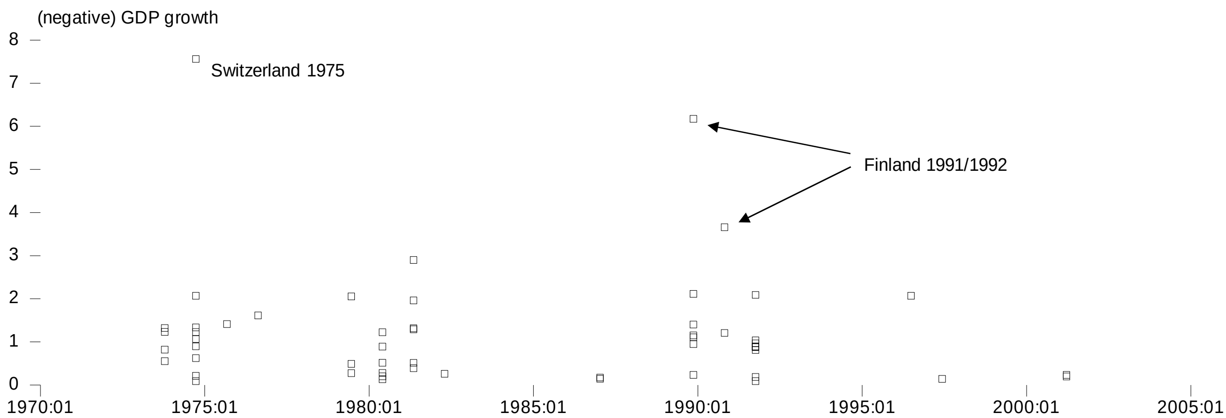
On average, a recessionary year exhibits a growth rate of GDP of -1.2 percent (Table 6.1, specification I). The growth rate does not depend systematically on the year when the recession occurred. When a variable that controls for the year of the recession is included in a regression analysis, the parameter is close to zero (II). Recessions that are associated with severe economic crises exhibit on average a—at the ten percent-level—significantly lower growth rate of GDP. While an ordinary recession usually exhibits a growth rate of -0.8 percent, in a recession that is associated with a severe economic crisis the growth rate is -0.7 percentage points lower (III).

Table 6.1:
Basic statistics for GDP Growth during Recessions

	I	II	III	IV	V	VI
Constant	1.2 (6.6)	1.5 (2.5)	0.8 (3.2)	0.9 (9.5)	1.1 (3.5)	0.8 (6.1)
dum FN/SW	no	no	no	yes	yes	yes
Year		-0.0 (0.5)			-0.0 (0.7)	
Crisis			0.7 (1.8)			0.2 (0.8)
AIC	189.9	191.6	188.6	119.3	120.8	120.5

Notes: t-values in brackets; dum FN/SW denotes dummy variables for Finland in the years 1991, 1992, and 1993 and for Switzerland in the years 1975 and 1976.

Figure 6.3:
GDP Growth during Recessions



However, the results are driven by two exceptional strong recessions that are associated with severe economic crises. When GDP growth during the recessions in the sample is plotted, it becomes obvious that the recessions in Finland beginning in 1991 and in Switzerland beginning in 1975 are by far stronger than the other recessions in our sample (Figure 6.3). Once, I control for these two recessions, recessions that are associated with severe economic crises exhibit no longer significantly lower growth rates than ordinary recessions (VI) and recessionary years exhibit on average a growth rate of -0.8 percent (IV).[67]

[67] The recession in Finland lasts three years and the recession in Switzerland last two years. To be consistent, I control for these recessions not only by building dummy variables for the years with exceptional low growth rates,

Besides the particularly strong recessions in Finland and Switzerland, recessions usually exhibit growth rates from -2.5 percent to close to zero.

Even though recessions associated with severe economic crises do not exhibit systematically lower growth rates when it is controlled for the recessions in Finland and Switzerland, it might be the case that they are usually longer and thereby deeper than ordinary recessions when the depth of a recession is measured as the maximal deviation from the former peak of GDP. On average the recessions in the sample exhibit a depth of 1.6 percent (Table 6.2, specification I). When I control for the recessions in Finland and Switzerland the average depth decreases to 1.2 percentage points (IV). The depth of a recession does not depend on the year when it occurs (II and V). Recessions associated with severe economic crises are significantly deeper by 1.1 percentage points (III). However, again this result is driven by the exceptional strong recessions in Finland and Switzerland. Once, I control for these two recession, there is no evidence that recessions associated with severe economic crises are significantly deeper (VI).

Table 6.2:
Basic Statistics for Depth of Recessions

	I	II	III	IV	V	VI
Constant	1.6 (4.8)	1.8 (1.7)	1.0 (2.1)	1.2 (7.6)	1.5 (2.9)	1.0 (4.5)
dum FN/SW				yes	yes	yes
Year		-0.0 (0.2)			-0.0 (0.6)	
Crisis			1.1 (1.7)			0.4 (1.2)
AIC	179.0	181.0	177.9	116.4	117.9	116.9

Notes: t-values in brackets; dum FN/SW denotes dummy variables for the depth of the recession in Finland beginning in 1991 and for the recession in Switzerland beginning in 1975.

6.3.2 Are Internationally Synchronized Recessions More Severe?

The question whether recessions that are highly internationally synchronized are more severe than recessions that are less internationally synchronized has attracted some attention during the Great Recession of 2008/2009, when most industrial countries fell into a recession. Claessens et al. (2009) and the IMF (2009) analyze this question and find that internationally synchronized recessions are more severe and that the following recoveries are sluggish. I re-examine their analysis for our data set and extend it by using alternative measures of internationally synchronized recessions. In doing so, I regress GDP growth in a recessionary year Δy_i on control variables that measure the degree of international

but for all years of the respective recessions. However, the results remain basically unchanged when I control only for the years with exceptional low growth rates.

synchronization of recessions x_i and on a set of deterministic terms c that can include dummy variables controlling for outliers, e.g. for the recessions in Finland in 1991 and in Switzerland in 1975:

$$\Delta y_i = \alpha \cdot \mathrm{c} + \beta \cdot x_i + \varepsilon_i \qquad (6.1)$$

I use three types of control variables to measure the degree of international synchronization. First, I follow Claessen et al. (2009) and the IMF (2009) and impose a threshold of 50 percent of all countries in the sample that have to be in recession at the same time to consider recessions to be internationally synchronized.[68] Second, I weight the countries in the panel based on their GDP denominated in dollars and identify a recession as internationally synchronized when the share in world GDP of the countries in a recession passes a certain threshold. Third, I take the perspective of a single country experiencing a recession and calculate the share of all other countries that experience a recession in the same year. In doing so the share is calculated, on the one hand, as share in world GDP and, on the other hand, as the share in exports of the country.

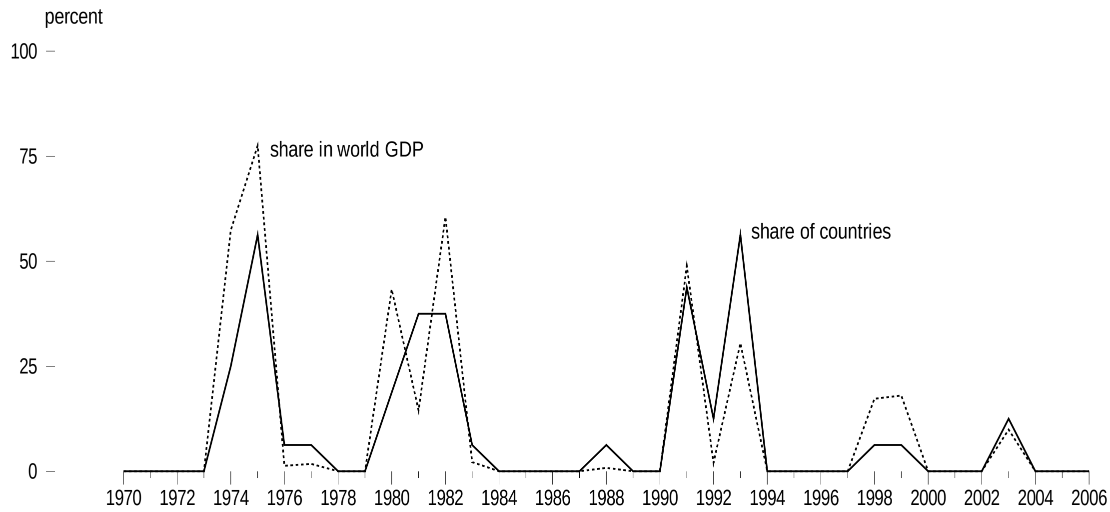
In a first steps, I follow Claessens et al. (2009) and the IMF (2009) and identify recession as internationally synchronized when at least 8 out of 16 countries in the sample are in a recession in the same year. In the sample, this is the case in two years, namely 1975 and 1993 (Figure 6.4). According to this identification criterion every third recession in the sample is internationally synchronized.

I construct a dummy variable that takes a value of 1 when a recession is internationally synchronized and 0 otherwise and use the dummy variable as regressor x_i in equation (6.1). The results show that internationally synchronized recessions are not significantly more severe than other recessions (Table 6.3, specification II). This result is robust when I control for the most severe recessions in Finland and in Switzerland (VII) or when I just use the share of countries in a recession as regressor instead of a threshold of at least 50 percent (I and VI). Similarly, when I use a grid search over all possible threshold values of the share of countries hit by a recession in the same year to identify internationally synchronized recessions, I do not find any evidence that such recessions are more severe (III and VII). [69]

[68] The IMF (2009) actually identifies an internationally synchronized recession when 10 out of 21 countries are at the same time in a recession.

[69] The grid search finds that a threshold value between 38 to 43 percent leads to the best model fit in our baseline model and a threshold value between 13 and 18 percent when I control for the recessions in Finland and Switzerland. However a bootstrap simulation with 1,000 draws shows that in both cases the parameter values are not significantly different from zero.

Figure 6.4:
Share of Countries Facing a Recession and Share of These Countries in World GDP



Second, I calculate what the share in world GDP is of the countries experiencing a recession. Therefore, I approximate world GDP as the sum of nominal GDP converted to dollars of the 16 countries in our panel and calculate the share in world GDP of the countries in the sample. In the year 1975 countries representing a share of more than 75 percent in world GDP were hit by a recession. Adjusting the definition of Claessen et al. (2009) and the IMF (2009) that a recession is internationally synchronized when at least half of the countries are in a recession leads to a definition that a recession is internationally synchronized when countries representing at least 50 percent of world GDP are in a recession. Besides 1975 this was the case in the years 1974 and 1982. I do not find evidence for internationally synchronized recessions being more severe when I use this threshold neither when I account for the recessions in Finland and in Switzerland as outlier (XI) nor when I do not (V). The result does not change, when I run a grid search over all possible threshold values (VI and XII).[70] However, when I use the share of countries in a recession as a regressor instead of a certain threshold, I find some evidence that internationally synchronized recessions are more severe. The parameter that captures the degree of international synchronization is close to conventional significance levels—even though with a p-value of 0.12 not significant at the 10 percent level—and the model fit improves compared to the models that use the measures of internationally synchronized recessions described

[70] The grid search finds that a threshold value between 44 to 48 percent leads to the best model fit in our baseline model and a threshold value between 15 and 17 percent when I control for the recessions in Finland and Switzerland. However a bootstrap simulation with 1,000 draws shows that in both cases the parameter values not significantly different from zero.

Table 6.3:
International Impact on Recessions Estimated With Shares in World GDP of Countries Facing a Recession

	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII
Constant	0.9 (2.1)	1.2 (5.1)	1.0 (3.9)	0.8 (2.4)	1.1 (4.6)	0.9 (3.5)	0.8 (3.4)	0.9 (7.6)	0.7 (3.0)	0.6 (3.7)	0.8 (6.6)	0.7 (5.1)
dum FN/SW							yes	yes	yes	yes	yes	yes
No.	0.0 (0.8)						0.0 (0.7)					
No. threshold (50%)		0.1 (0.3)						0.0 (0.1)				
No. threshold grid			0.5 [0.62]						0.3 [0.67]			
Share				1.1 (1.6)						0.7 (1.8)		
Share threshold (50%)					0.4 (1.0)						0.2 (0.9)	
Share threshold grid						0.7 [0.69]						0.4 [0.80]
AIC	191.3	189.3	*	186.9	188.5	*	-93.4	120.3	*	116.7	118.0	*

Notes: t-values in brackets; p-values in square bracket; p-values for the recession dummy defined by a grid search were calculated by simulations with 1000 draws; dum FN/SW denotes dummy variables for Finland in the years 1991,1992, and 1993 and for Switzerland in the years 1975 and 1976; No. denotes the share of countries in a recession; share denotes the share in world GDP of countries in a recession; threshold denotes a dummy variable that is equal to one when at least 50 percent of countries are in a recession; threshold grid denotes a dummy variable that is build for the threshold found by a grid search.

above (IV). When I control for the recessions in Finland and Switzerland as outliers the parameter value is significant at the 10 percent level (X). The growth rate of GDP in a recessionary year is 0.7 percentage points lower when all countries in the world are in a recession in the same year.

Third, I take the perspective of a single country experiencing a recession and calculate the share of all other countries that experience a recession in the same year. In doing so the share is calculated, on the one hand, as share in world GDP and, on the other hand, as the share in exports of the country. The variables that measure the international synchronization of recessions y^*_{jt} are calculated for each country *j* individually by using the export share or the share in world GDP w^*_{jkt} for a foreign country *k* in year *t*:

$$y^*_{jt} = \sum_{k=1}^{16} w_{jkt} x_{kt} \tag{6.2}$$

where x_{kt} denotes a dummy variable that takes a value of one when the foreign country *k* experiences a recession. In using this approach, I deviate from the approaches used in the first two steps, because I do not identify certain years of internationally synchronized recessions, but use a measure that is meant to capture the degree of international synchronization for each recession individually. However, those recessions that were identified as internationally synchronized before should be usually also those that are identified to be more synchronized by this approach.

When I measure the international synchronization of recessions by using the shares in world GDP of countries in a recession, I find evidence that highly internationally synchronized recessions are more severe than less internationally synchronized recessions (Table 6.4). GDP growth during a recession is lower by 1.5 percentage points when all other countries are in a recession as well (specification I). The result is robust when I control for the recessions in Finland and Switzerland (VII). However, the parameter estimate shows that the impact of internal synchronization is then estimated to be somewhat lower. The results do not suggest that there is any threshold of the share of countries in a recessions beyond that the international synchronization of recessions lead to more severe recessions. This is neither the case when I impose according to Cleassens et al. (2009) or IMF (2009) an ad-hoc

Table 6.4:
International Impact on Recessions Estimated With Export Share and Share in World GDP of Countries Facing a Recession

	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII
Constant	0.7 (2.3)	1.1 (5.0)	1.1 (5.5)	0.8 (2.3)	0.7 (4.9)	1.0 (5.4)	0.6 (4.0)	0.8 (7.4)	0.6 (3.6)	0.6 (3.6)	0.8 (8.6)	0.8 (8.6)
dum FN/SW							yes	yes	yes	yes	yes	yes
GDP share	1.5 (2.2)						0.9 (2.3)					
Threshold (50%)		0.5 (1.3)						0.3 (1.4)				
Threshold grid search			0.6 [0.59]						0.4 [0.79]			
Export share				1.0 (1.5)						0.7 (2.0)		
Threshold (50%)					0.5 (1.2)						0.4 (2.3)	
Threshold grid search						1.2 [0.66]						0.8 [086]
AIC	187.2	190.3	*	189.6	190.4	*	115.7	119.1	*	116.9	115.8	*

Notes: t-values in brackets; p-values in square bracket; p-values for the recession dummy defined by a grid search were calculated by simulations with 1000 draws; dum FN/SW denotes dummy variables for Finland in the years 1991,1992, and 1993 and for Switzerland in the years 1975 and 1976; GDP share denotes share in world GDP of countries in a recession; export share denotes the share in exports of countries in a recession; threshold denotes a dummy variable that is equal to one when at least 50 percent of foreign countries are in a recession; threshold grid denotes a dummy variable that is build for the threshold found by a grid search.

threshold of 50 percent nor when I run a grid search over all possible threshold values (II, III, VIII, and IX).

When I measure the international synchronization of recessions by using export shares of countries in a recession, the results differ somewhat from the results described above. I do only find evidence for a significant impact of the international synchronization of recessions, once I control for the recessions in Finland and Switzerland (X). Moreover, there is some evidence that using an ad-hoc threshold value of 50 percent for the export share of countries in a recession improves the model fit according to the Akaike Information Criterion (AIC) (XI). However, when I run a grid search over all possible threshold values the evidence that internationally synchronized recessions are more severe when the export share of countries in a recession passes a certain threshold becomes somewhat weaker (XII). [71]

Finally, I differentiate between ordinary recession and recessions associated with severe economic crises and analyze on the one hand whether they are differently vulnerable to internationally synchronized recessions and on the other hand whether they are differently strong affect recessions in other countries. Therefore, I build export-weighted foreign GDP growth rates either when foreign economies are in an ordinary recession (foreign ordinary recession GDP) or in a severe economic crisis (foreign crisis GDP).

I find that foreign ordinary recessions have a higher impact on GDP growth in a country that is in a recession than foreign severe economic crises. When I control for the recessions in Finland and Switzerland, foreign ordinary recessions have a highly significant impact, while this is not true for foreign severe economic crises (Table 6.5, specification II).

GDP growth during ordinary recessions does not seem to be particularly vulnerable to internationally synchronized recessions (III). This result is confirmed when I differentiate between foreign ordinary recessions and foreign severe economic crises (IV).

GDP growth during severe economic crises is apparently more vulnerable to internationally synchronized recessions. The parameter value for the impact of foreign recessions is with a t-value of 1.6 at least close to conventional significance levels (V). However, once I control for the recessions in Finland and Switzerland, the parameter value is highly significant (VI). When I differentiate between foreign ordinary recessions and foreign severe economic crises, I find evidence that foreign ordinary recessions have a higher impact on domestic GDP growth when the domestic economy is in a severe economic crisis than foreign severe economic crises. While the parameter value for the impact of foreign

[71] The grid search finds that a threshold value between 72 to 78 percent leads to the best model fit in our baseline model and a threshold value between 84 and 85 percent when I control for the recessions in Finland and Switzerland. However a bootstrap simulation with 1,000 draws shows that in both cases the parameter are not significantly different from zero for conventional significance levels.

recessions with a t-value of 1.6 is close to conventional significance levels (VII), it becomes highly significant once I control for the recessions in Finland and Switzerland (VIII).

Table 6.5:
International Impact on Ordinary Recessions and Housing Crises

	Recessions		Ordinary Recessions		Crises			
	I	II	III	IV	V	VI	VII	VIII
Constant	1.0 (3.4)	0.8 (5.1)	0.7 (3.1)	0.7 (3.0)	1.0 (2.1)	0.7 (3.5)	1.0 (2.0)	0.8 (3.9)
dum FN/SW		yes				yes		yes
R-foreign GDP			0.3 (0.9)		1.4 (1.6)	0.8 (2.2)		
Foreign ordinary recessions GDP	0.9 (1.5)	0.7 (2.3)		0.1 (0.3)			1.5 (1.6)	1.0 (2.6)
Foreign Crises GDP	0.0 (0.1)	0.0 (0.1)		0.5 (0.8)			0.8 (0.4)	-0.3 (0.4)
Likelihood	191.7	117.5	51.3	55.1	116.9	66.8	118.8	65.6

Notes: t-values in brackets; dum FN/SW denotes dummy variables for Finland in the years 1991,1992, and 1993 and for Switzerland in the years 1975 and 1976; R-foreign GDP denotes foreign GDP growth for those foreign economies that are in a recession weighted with export shares.

Overall, the results pertaining to whether recessions that are highly internationally synchronized are more severe than recessions that are less internationally synchronized are sensitive to the measure I use to estimate the degree of international synchronization of recessions and to outliers in the sample. When I follow the literature and use measures that calculate the share of countries in a recession at the same time, I find only limited evidence that internationally synchronized recessions are more severe than not internationally synchronized recessions. Only when I use the weight in world GDP of countries in a recession as measure of international synchronization and when I control for the recessions in Finland and Switzerland as outliers, I find some evidence that highly internationally synchronized recessions are more severe than less internationally synchronized recessions.

When I deviate somewhat from the literature and estimate whether a recession in a particular country is the more severe the more other countries are in a recession as well—weighted by their share in world GDP or by their export share—the evidence that highly internationally synchronized recessions are more severe than less internationally synchronized recessions is stronger. This is particularly true when I use the weight in world GDP to measure the degree of international synchronization. Usually, I do not find evidence that internationally synchronized recessions are more severe only when the degree of international synchronization passes a certain threshold.

When I differentiate between ordinary recessions and recessions associated with severe economic crises I find that countries facing a recession associated with a severe economic crisis are more vulnerable to internationally synchronized recessions than countries facing ordinary recessions. GDP growth in a country facing a recession associated with a severe economic crisis is the lower the more foreign countries are in a recession as well. Moreover, the effects of internationally synchronized recessions seem to be stronger when the foreign countries facing ordinary recessions than when they are facing recessions associated with severe economic crises.

6.4 Internationally Synchronized Recoveries

In this section, I analyze the relevance of international synchronization for the strength and the dynamics of recoveries. Boysen-Hogrefe et al. (2010) show that ordinary recessions and recessions associated with severe economic crises differ notably in the following recovery: while an ordinary recession is usually followed by a particularly strong recovery that is stronger the deeper the preceding recession was, such a recovery is absent when a recession is associated with a severe economic crisis. Consequently, the strength of recoveries might depend not only on the degree of international synchronization, but also on the type of recessions that occurred before the recoveries. In this context, I analyze three cases. First, I analyze the strength and the dynamics of recoveries in an open economy when foreign economies are not in a recovery. Second, I analyze the strength and the dynamics of recoveries when they are internationally synchronized. Finally, I analyze whether internationally synchronized recoveries differ significantly from not internationally synchronized recoveries. I begin by re-examining the results of Boysen-Hogrefe et al. (2010) in an open economy context.

6.4.1 Estimation Results

I follow Boysen-Hogrefe et al (2010) and estimate the strength of a recovery by augmenting an otherwise standard autoregressive panel model with a *cdr* term:

$$\Phi(L)\Delta y_{t,i} = \alpha_i + [\Omega(L) - 1]cdr_{t,i} + \varepsilon_{t,i}, \qquad (6.4)$$

where GDP growth Δy_t is regressed on its own lags, country specific fixed effects α_i, and the *cdr* term. A positive sum of all coefficients Ω indicates that GDP growth during recoveries is on average higher than during expansions. Consequently, a recession that is followed by a recovery that exhibits this so called bounceback effect has much lower (or even no) permanent effects on GDP compared to recessions followed by recoveries that do not exhibit such an effect. The bounceback effect is the stronger the deeper the preceding recession is. I differentiate between ordinary recessions and recessions associated with severe economic crises by building an interaction term $cdr^{c}_{t,i}$ that takes the value of the *cdr* term when a recession is associated with a severe economic crises and zero otherwise:[72]

$$\Phi(L)\Delta y_{t,i} = \alpha_i + [\Omega(L)-1]cdr_{t,i} + [\Pi(L)-1]cdr^{c}_{t,i} + \varepsilon_{t,i}\,. \tag{6.5}$$

Without loss of generality I simplify the model of Boysen-Hogrefe et al. (2010) somewhat and do not differentiate between housing crises associated with banking crises and 'pure' housing crises, but consider only housing crises in general.[73] I extend model (6.5) with a variable that captures the influence of the global business cycle on a country. The influence is modeled by means of a the global business cycle variable Δy^{*}_{t} that is calculated individually for each country as exported weighted GDP growth in the other 15 countries in our panel:[74]

$$\Phi(L)\Delta y_{t,i} = \alpha_i + [\Omega(L)-1]cdr_{t,i} + [\Pi(L)-1]cdr^{c}_{t,i} + \Gamma(L)\Delta y^{*}_{t,i} + \varepsilon_{t,i}\,. \tag{6.6}$$

I interpret the domestic economy as small open economy and therefore allow foreign GDP growth to influence domestic GDP growth contemporaneously without taking any feedback effects into account.

The results for the model (6.4) that does not differentiate between ordinary recessions and recessions associated with severe economic crises show only little evidence for a bounceback effect. After a recession with a negative GDP growth rate of 1 percent, GDP growth in the following year is only 0.13 percentage points higher than it would have been without the recession (Table 6.6, specification I).[75] Moreover, with a t-value of 1.6 the parameter value is

---

[72] I consider a recession to be associated with a severe economic crisis when it starts in the same year as the housing crisis or within the following two years. Boysen-Hogrefe et al. (2010) show that their results are robust when they consider a time span from three years between the beginning of a housing crisis and a recession. Considering a shorter time span, i.e. 1 year, would be not in line with the results of the literature on the effects of housing crises, which finds that housing crises usually dampen economic activity for several years, compare, e.g., Jannsen (2010).

[73] The results of Boysen-Hogrefe et al. (2010) illustrate that housing crises associated with banking crises in this set up only slightly deviate from 'pure' housing crises.

[74] This approach to model the influence of global business cycle developments is well-established in the literature, compare, e.g., Abeysinghe and Forbes (2001) or Pesaran et al. (2004).

[75] This result differs slightly from the result in Boysen-Hogrefe et al. (2010) due to data revisions.

hardly significantly different from zero. The results change dramatically when I differentiate between the two types of recessions. An ordinary recession is now followed by a recovery with GDP growth being 1.5 times the former loss in GDP higher than otherwise (II). Consequently the output loss is usually offset already in the first year after a recession.[76] In contrast, when a recession is associated with a severe economic crisis the parameter value of the interaction term shows that the bounceback effect is nearly completely offset. An F-Test indicates that the parameter values of the *cdr* term and the interaction term are not significantly different from each other, with a p-value of 0.24.

Table 6.6:
Estimation Results

	I	II	III	IV
$\Delta y_{t-1,i}$	0.43 (9.6)	0.48 (10.6)	0.48 (10.9)	0.50 (11.3)
$\Delta y_{t-2,i}$	−0,14 (3.3)	−0.15 (3.6)	−0.07 (2.0)	−0.08 (2.2)
$cdr_{t-1,i}$	0.13 (1.6)	1.52 (4.7)	0.13 (2.0)	0.88 (3.3)
$cdr^c_{t-1,i}$		-1.42 (4.4)		−0.76 (2.9)
$\Delta y^*_{t,i}$			0.84 (17.6)	0.82 (17.1)
$\Delta y^*_{t-1,i}$			−0.36 (6.4)	−0.36 (6.3)
AIC	2174.0	2155.9	1921.8	1915.1
F-Test		0.24		0.09

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

When I include foreign GDP growth in the model (6.6), the results remain qualitatively the same. The estimated parameter value for the *cdr* term is the same when I do not differentiate between types of recessions, even though it is now significantly different from zero according to conventional significance levels (III). When I differentiate between types of recessions, the results show that ordinary recessions are followed by strong recoveries, even though the parameter value of the *cdr* term is with 0.88 considerably smaller than in the model that does not include foreign GDP growth. The bounceback effect is again nearly completely offset when a recession is associated with a severe economic crisis (IV). An F-Test with a p-value of 0.09 does not definitely indicate whether the parameter values of the *cdr* term and the interaction term are significantly different from each other. The Akaike Information Criterion

[76] This does not lead to the result that recessions cannot have permanent effects on GDP or even are beneficial, given a positive trend growth rate of GDP.

(AIC) illustrates that the models that differentiate between the two types of recessions fit the data considerably better than the models that do not.

Given, that recessions are to some degree internationally synchronized and consequently recoveries are as well, the result that the bounceback effect is considerably smaller when I control for foreign GDP growth compared to the results for the closed economy model leads to the hypothesis that some of the bounceback effect that can be observed in the data is caused by foreign developments. Indeed, the result that ordinary recessions are followed by particularly strong recoveries and that foreign GDP growth has a strong contemporaneous impact on domestic GDP growth indicates that international synchronized recoveries are stronger—at least when they follow ordinary recessions.

6.4.2 Impulse Response Analysis

I illustrate our results by several impulse response analyses. In particular, I investigate the short-run dynamics of recoveries and the resulting long-run effects of recessions on GDP for the three scenarios described above. I begin, by introducing the methodology how to compute the impulse response functions.

6.4.3 Methodology

The impulse response functions are computed for an open economy model as it is given by equation (6). Because I am not only interested in the recoveries following domestic recessions, but also in domestic recoveries following foreign recessions, I model a foreign ‘rest-of-the-world’ economy as well. The domestic economy is assumed to be a small open economy and the foreign economy to be a large economy. This implies that the foreign economy can influence the domestic economy contemporaneously while the domestic economy has no influence on the foreign economy. Consequently, I model the foreign “rest-of-the-world” economy as closed economy as it is given by equation (5).

When the impulse response functions are computed, it has to be taken into account that the model is nonlinear in the cdr terms so that the shape of the impulse response functions depends on the sign and the size of the shock. Therefore, the impulse response functions are computed for shocks of various sizes. Since I am interested in the dynamics of recoveries following recessions, I focus exclusively on negative shocks. Because the model is nonlinear in the *cdr* term, the impulse response functions are sensitive to shocks that may hit the economy after the initial period.

To account for shocks that hit the economy after the initial period, I employ impulse response functions in line with Potter (2000). I assume that the economy is in its steady state before it is hit by the initial shock. The steady growth rate for the domestic and the foreign economy is roughly 2.3 percent. Consequently only shocks larger than 2.3 percent lead to negative growth rates or as in our definition to recessions. I compute a baseline forecast for the domestic economy when neither the domestic economy nor the foreign economy is hit by a shock in the initial period. Then a forecast for domestic economy is made when either the domestic economy or both the domestic and the foreign economy is hit by a shock in the initial period. After the initial period, I allow in both forecast both economies to be hit by further shocks, which I draw randomly from a Gaussian distribution with zero mean and a standard deviation calculated over all residuals of the respective model. Finally, I compute the impulse response functions by taking the difference between both forecasts. This process is repeated 1,000 times. I account not only for the uncertainty caused by the nonlinearity of the model, but also for the uncertainty given by the parameter estimates. Therefore, I draw in every repetition parameter estimates from a multivariate normal distribution, with the mean given by the point estimates and the variance covariance matrix given by the variance covariance matrix of regression coefficients.

I run forecasts for the domestic economy based on the results of specification IV in Table 6.4.1. The model is augmented by a constant term calculated as average over the estimated fixed effects terms. When simulations are computed for ordinary recessions, I set the interaction term between the *cdr* term and the dummy variable for severe economic crises equal to zero and remain with the model

$$\Delta y_t = 0.2 + 0.5\Delta y_{t-1} - 0.1\Delta y_{t-2} + 0.8\Delta y_t^* - 0.4\Delta y_{t-1}^* + 0.9cdr_{t-1} + u_t \,. \quad (6.7)$$

When simulations are computed for recessions associated with severe economic crises the interaction term is relevant. Even though, the result of the F-test on whether the parameter values of the *cdr* term and the interaction term are equal is not unique, I assume that they are equal. In doing so, I keep the model as simple as possible without a loss of generality of the results, because even if both terms would be included in the model the remaining bounceback effect would be considerably small. When computing the impulse response functions, I have to take into account that after the initial shock, the domestic economy might be hit by further recessionary shocks. I interpret these recessionary shocks as ordinary recessions once GDP in the domestic economy has reached its former maximum so that the bounceback effect is at work again. Therefore, I switch to model (6.7) when the *cdr* term becomes zero again after the initial shock:

$$\Delta y_t = \begin{cases} 0.2 + 0.5\Delta y_{t-1} - 0.1\Delta y_{t-2} + 0.8\Delta y_t^* - 0.4\Delta y_{t-1}^* + u_t, \text{until } cdr_t \text{ becomes zero for the first time} \\ 0.2 + 0.5\Delta y_{t-1} - 0.1\Delta y_{t-2} + 0.8\Delta y_t^* - 0.4\Delta y_{t-1}^* + 0.9cdr_{t-1} + u_t \text{ else} \end{cases} \tag{6.8}$$

I model the foreign economy accordingly to the domestic economy. When impulse response functions are computed for an ordinary recession, I use the estimation results for the closed economy with the *cdr* term, given by specification II in Table 4.1:

$$\Delta y_t^* = 1.6 + 0.5\Delta y_{t-1}^* - 0.2\Delta y_{t-2}^* + 1.5cdr_{t-1}^* + u_t, \tag{6.9}$$

where the constant term is calculated as the average of the estimated fixed effects terms. In case of a recession associated with a severe economic crisis, I use the model without the *cdr* term, since an F-test indicates that the parameter values of the *cdr* term and the interaction term are not significantly different from each other, and switch to model (6.9) once the *cdr* term has become zero for the first time:

$$\Delta y_t^* = \begin{cases} 1.6 + 0.5\Delta y_{t-1}^* - 0.2\Delta y_{t-2}^* + u_t, \text{until } cdr_t \text{ becomes zero for the first time} \\ 1.6 + 0.5\Delta y_{t-1}^* - 0.2\Delta y_{t-2}^* + 1.5cdr_{t-1}^* + u_t, \text{else} \end{cases} \tag{6.10}$$

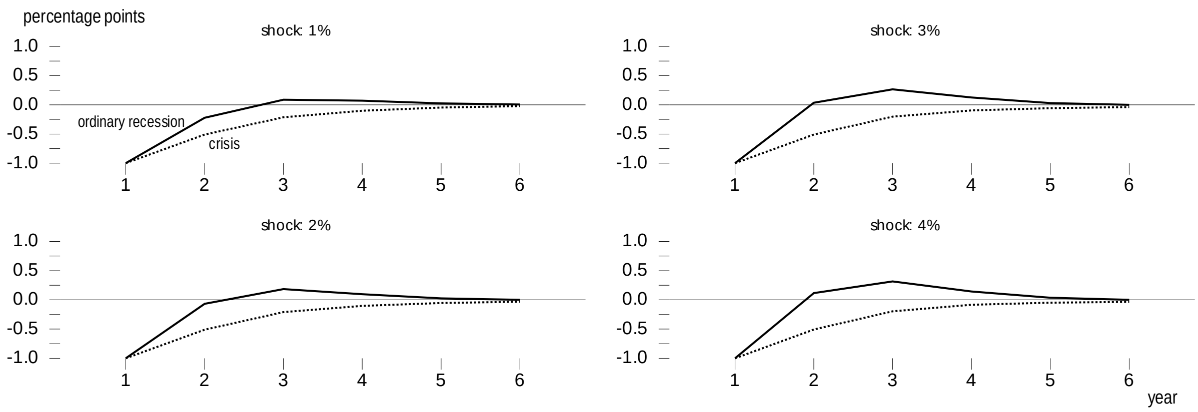
Domestic Recoveries

I begin by modeling the dynamics of a recovery following a domestic recession. Therefore, I combine the model of the foreign economy (6.9) with model (6.7) when I want to analyze the effects of an ordinary recession or with model (6.8) when I want to analyze the effects of a recession associated with an economic crisis. While the foreign economy is not hit by a shock in the initial period, in the following periods it is hit by randomly drawn shocks, as is the domestic economy. I calculate impulse response functions relative to the baseline of no initial shock and scale them by the absolute value of the initial size of the shock, so that in the first period the impulse response takes always a value of -1 for GDP and for GDP growth. In the following, I define a shock of, e.g., -1 percent to be a shock that leads to a GDP growth rate of -1 percent. Given that the trend growth rate of GDP in our sample is higher than 2 percent on average, a shock actually has to be larger to lead to the designated GDP growth rate.

However, since I am interested in recessions and the following recoveries, the results are easier to interpret when I use this definition.

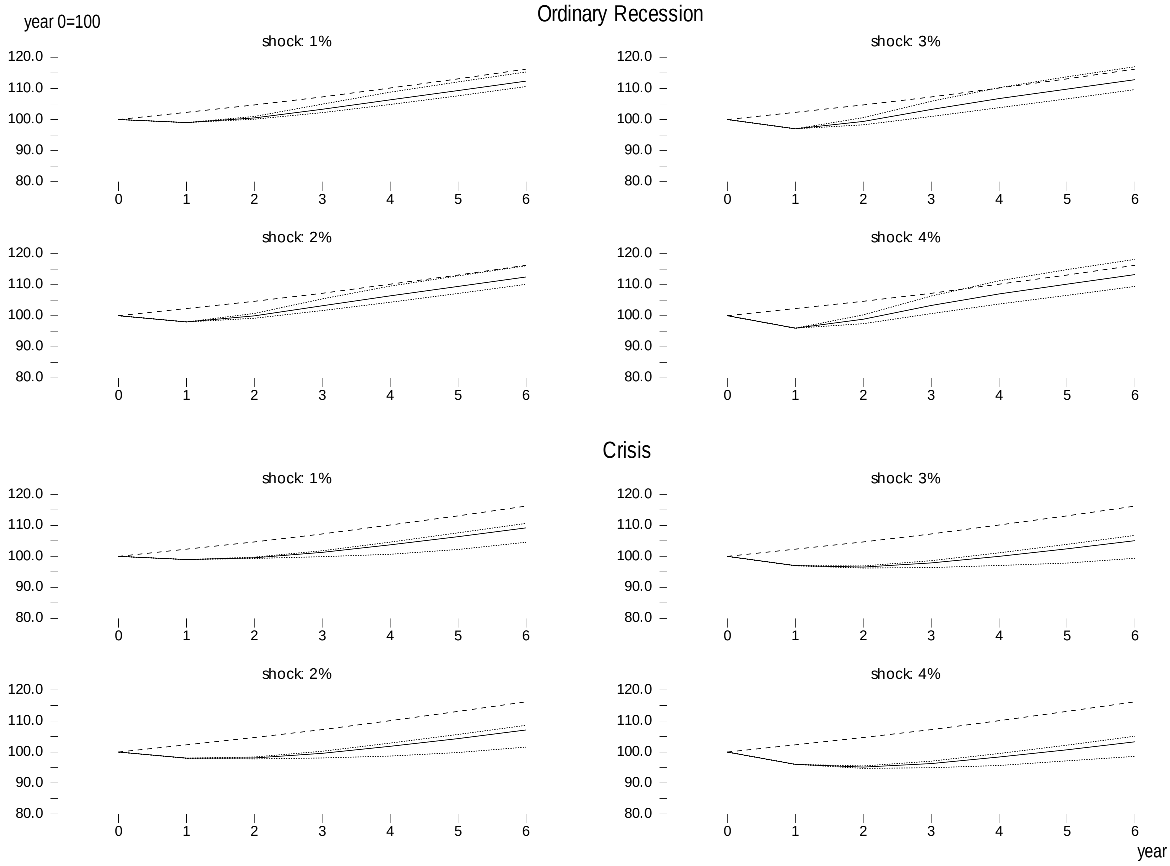
The estimation results show that the recovery following an ordinary recession is considerably stronger than following a severe economic crisis. A recovery following an ordinary recession is characterized by a bounceback effect that leads to GDP growth that is higher than it would have been without the recession (Figure 6.5). While the bounceback effect for a shock of -1 percent is relatively modest, it increases with the size of the initial shock, and beginning with -3 percent, it leads to a GDP growth rate above the baseline for a period of three to four years. In contrast, following a severe economic crisis, the recovery is sluggish and GDP growth stays below baseline for at least four years.

Figure 6.5:
GDP Growth Following a Domestic Shock: Deviation from Baseline



A severe economic crisis causes a significant reduction in the level of GDP (Figure 6.6). The reduction in GDP is permanent and is larger than the initial shock itself. An ordinary recession initially causes a significant reduction in the level of GDP as well. However, depending on the size of the initial shock, the reduction in GDP lasts for only some years. Following a shock of -1 percent, GDP is still significantly below the baseline six years after the initial shock, whereas following a shock of three percent, GDP is not significantly lower than the baseline four years after the initial shock.

Figure 6.6:
GDP Following a Domestic Shock

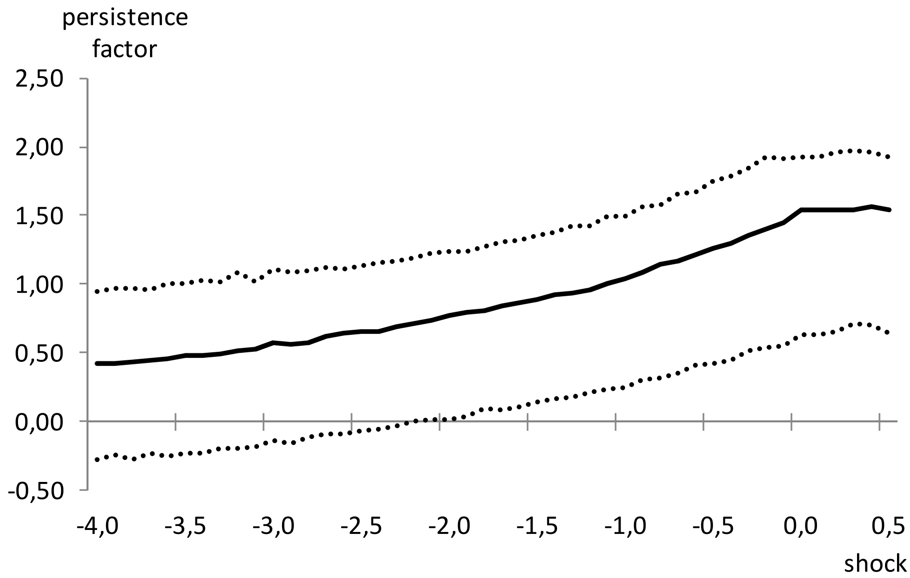


Notes: Baseline calculated via steady sate growth rate. Impulse response functions are calculated over 1,000 simulations. Dotted lines indicate 95 % confidence interval.

The long-run effects of an ordinary recession can be illustrated by means of the persistence factor of a shock that is calculated as the difference between GDP in the baseline (of no shock) and GDP in an ordinary recession calculated 10 years after the initial shock. As in Figure 6.5, the results are scaled again by the initial size of the shock.

Because the strength of the bounceback effect increases in the size of the initial shock, the long-run effect of an ordinary recession on GDP decreases with increasing size of the shock. Beginning with a shock with a size of -2 percent the long-run effect of an ordinary recession on GDP is not significantly different from zero (Figure 6.7). When the shock reaches a size of -8 percent the point estimate of the persistence indicates no significant effect on GDP. However, shocks of such size are very rare in industrialized countries and occurred not even one time in our sample.[77] For positive shocks, our model is linear in the size of the shock and therefore the persistence factor is constant with a value of roughly 1.6.

Figure 6.7:
Persistence Factor Following an Domestic Ordinary Recession



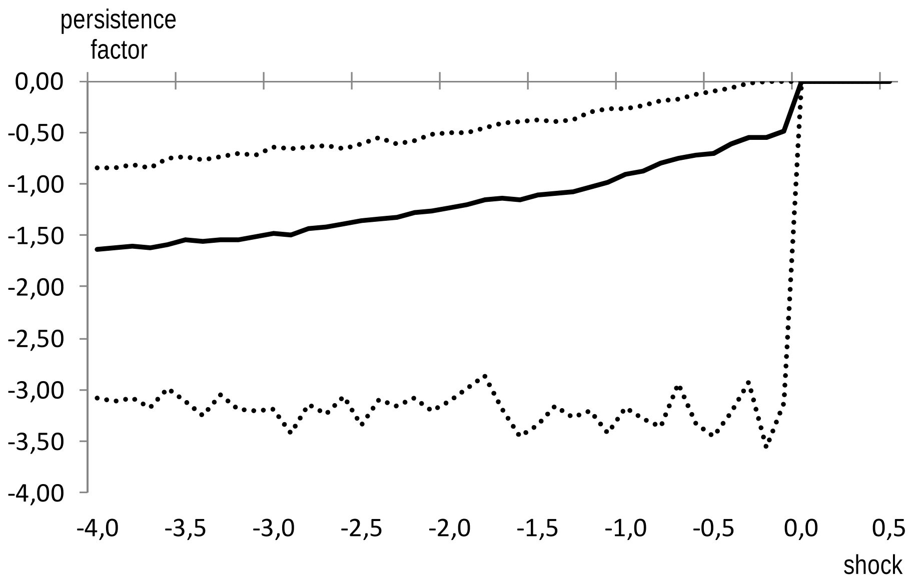
Notes: Persistence factor calculated as difference between baseline and ordinary recession ten years after the initial shock scaled by the size of the initial shock calculated over 1,000 simulations. Dotted lines indicate 95 % confidence interval. Value for the persistence factor for a shock of size zero was set equal to the value for a shock of size 0.1.

When I calculate in accordance to the persistence factor the long-run effects of a severe economic crises compared to an ordinary recession as the difference in GDP 10 years after the initial shock, I find that GDP in case of a severe economic crisis is significantly lower than in case of an ordinary recession independently of the size of the shock (Figure 6.8). The difference between the long-run effects in GDP increases with the size of the shock.[78]

[77] The lower bound of a 95 percent interval for the size of negative GDP growth rates during recessions in the sample is roughly -3.9 percent.

[78] The unusual shape of the lower confidence interval is a consequence of the simulation strategy used to compute the impulse response functions. When an economy is hit by a severe economic crisis, once the *cdr* term is zero again, any further recessionary shock later on in the simulation period are interpreted as ordinary recession with the consequence that the *cdr* dynamics are at work again. However, when a recessionary shock hits the economy before the *cdr* term is zero again, it is assumed that the reasons that hinder the economy to recover strongly are still at work and the shock is interpreted as part of the crisis. Consequently the long-run impact of a randomly drawn negative shock at the beginning of the simulation period is much more severe in case of a severe economic crisis compared to an ordinary recession, when a negative shock can even strengthen the recovery due to the non-linearity of the bounceback effect. Because the randomly drawn shocks are the more important for the long-run effect the smaller the shock in the initial period is, the lower confidence band plunge for shocks of small magnitude while this effect looses impact with the increasing size of the shocks.

Figure 6.8:
Long-run Effects on GDP after a Domestic Shock: Severe Economic Crisis Compared to Ordinary Recession



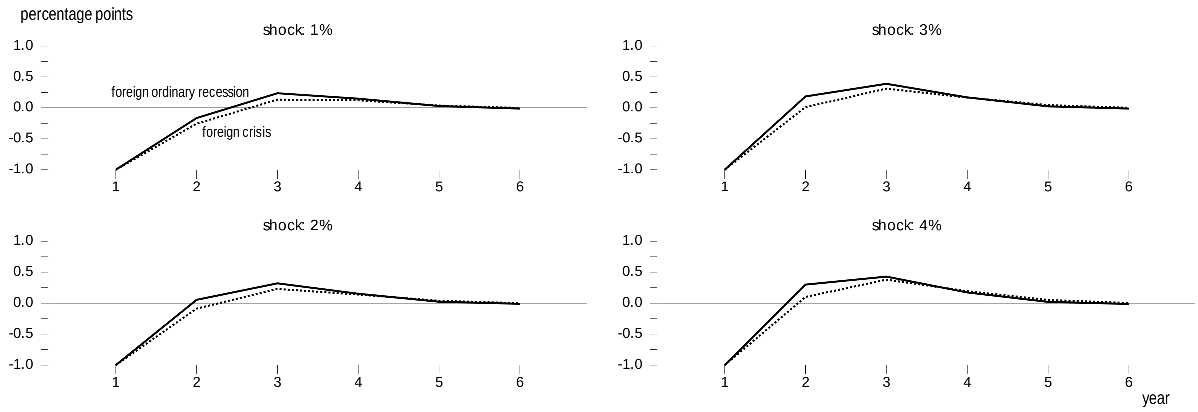
Notes: Calculated as difference in GDP after a severe economic crisis and an ordinary recession ten years after the initial shock scaled by the size of the initial shock calculated over 1,000 simulations. Dotted lines indicate 95 % confidence interval.

Internationally Synchronized Recoveries

In this section, I simulate the dynamics of a domestic recovery when the domestic economy and the foreign economy are in a recovery at the same time. In particular, I investigate how the domestic recovery is affected when the foreign economy was hit by an ordinary recession compared to the case when the foreign economy was hit by a severe economic crisis. Even though, recessions occurred to some extend internationally synchronized, usually domestic GDP growth was hit by a larger shock than the aggregated foreign GDP growth. In the following I assume in general that the foreign economy is hit by a recessionary shock with a quarter of the size of the domestic shock, which corresponds to the ratio between the domestic and the foreign *cdr* terms in the sample.

First, I simulate a domestic recovery following an ordinary recession when the foreign economy is either hit by an ordinary recession or a severe economic crisis. Overall, I can observe a bounceback effect independently of the size of the shock (Figure 6.9). The strength of the bounceback effect in the second and the third year is dampened somewhat when the foreign economy is hit by a severe economic crisis.

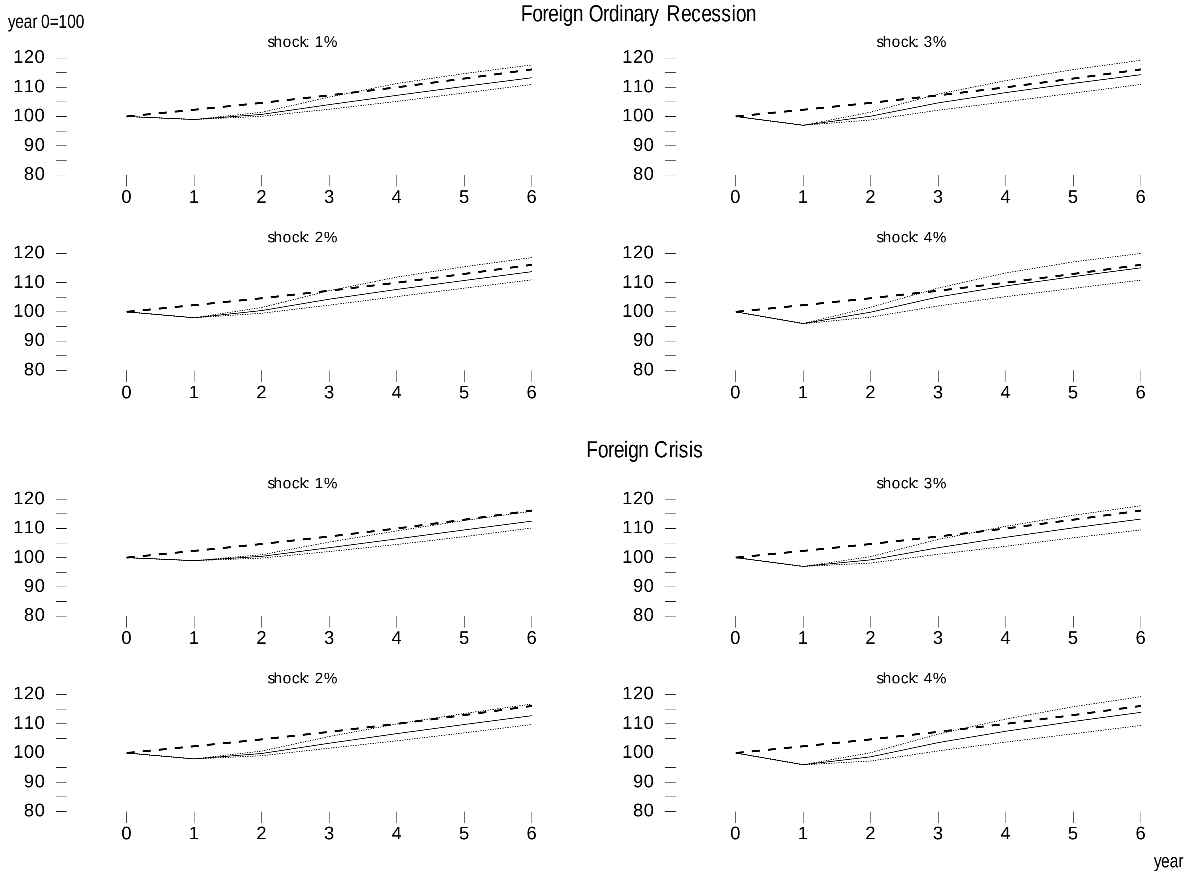
Figure 6.9:
GDP Growth Following a Domestic Ordinary Recession



GDP is usually significantly below the baseline of no shock for two or three years (Figure 6.10). An exception is when the foreign economy is hit by a severe economic crisis and the initial shock is relatively small, e.g. 1 percent, and thus the bounceback effect is relatively weak. In this case GDP stays significantly below the baseline for at least six years. The point estimates indicate that GDP stays at least six years below the baseline when the foreign economy is hit by a severe economic crisis, but reaches roughly its old level again beginning with shocks of -4 percent when the foreign economy is hit by an ordinary recession.

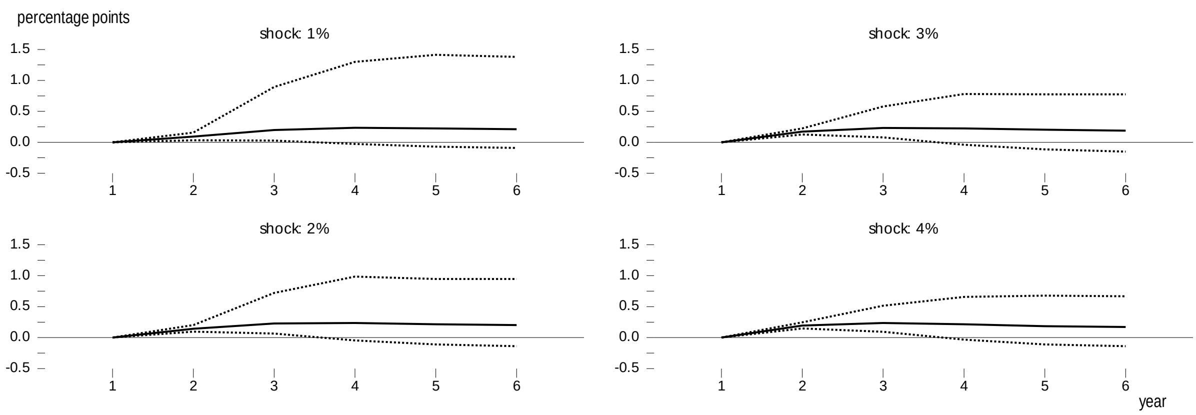
The difference in GDP when the foreign economy is hit by an ordinary recession and when it is hit by a severe economic crisis is significant for two to three years (Figure 6.11). While the point estimates indicate that GDP is always higher in case of a foreign ordinary recession, after at most four years the difference is not significantly different from zero.

Figure 6.10:
GDP Level Following a Domestic Ordinary Recession



Notes: Baseline calculated via steady sate growth rate. Impulse response functions are calculated over 1,000 simulations. Dotted lines indicate 95 % confidence interval.

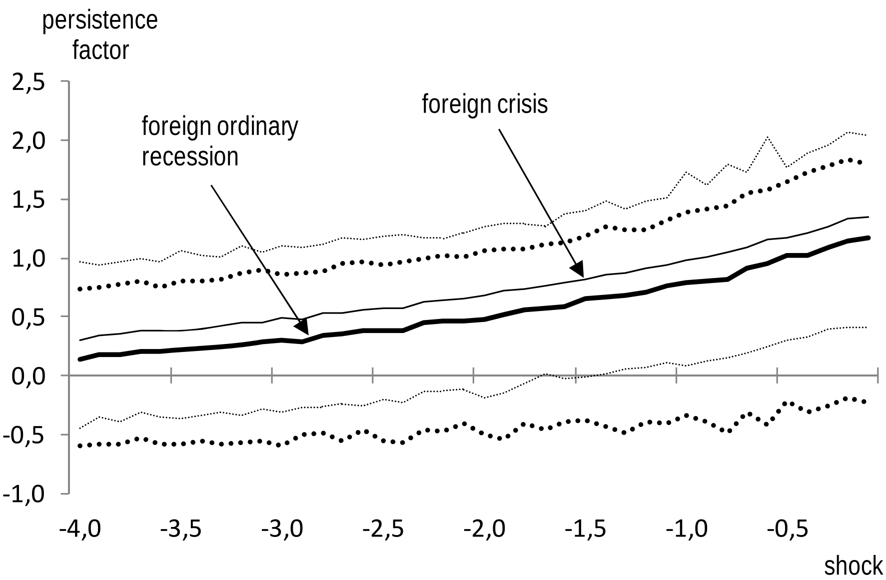
Figure 6.11:
Domestic Ordinary Recession: Difference between Foreign Ordinary Recession and Foreign Severe Economic Crisis in GDP Level



Notes: Dotted lines indicate 95 % confidence interval. Calculated over 1,000 simulations.

The long-run effects on GDP depend considerably on whether the foreign economy is hit by an ordinary recession or whether it is hit by a severe economic crisis. The persistence factor indicates that in case of a foreign ordinary recession, independently of the size of the initial shock no significant long-run effects on GDP can be observed (Figure 6.12). When the foreign economy is hit by a severe economic crisis, the persistence factor shows that no significant long-run effects on GDP can be observed beginning with shocks of a size of -1.5 percent. Given, that the recessionary shocks in our sample are usually smaller than -1.5 percent the likelihood that the domestic economy suffers a long-run loss in GDP when the foreign economy is hit by a severe economic crisis is considerably high.

Figure 6.12:
Domestic Ordinary Recession: Persistence Factor for Foreign Ordinary Recession and Foreign Severe Economic Crisis



Notes: Persistence factor calculated as difference between baseline and recession ten years after the initial shock scaled by the size of the initial shock calculated over 1,000 simulations. Dotted lines indicate 95 % confidence interval.

Second, I simulate a domestic recovery following a severe economic crisis when the foreign economy is either hit by an ordinary recession or a severe economic crisis. When comparing GDP growth during the recovery in both cases, the differences in the magnitudes are relatively small (Figure 6.13). However, when the foreign economy is hit by a severe economic crisis, GDP growth is usually below baseline for two years longer.

Figure 6.13:
GDP Growth Following a Domestic Severe Economic Crisis

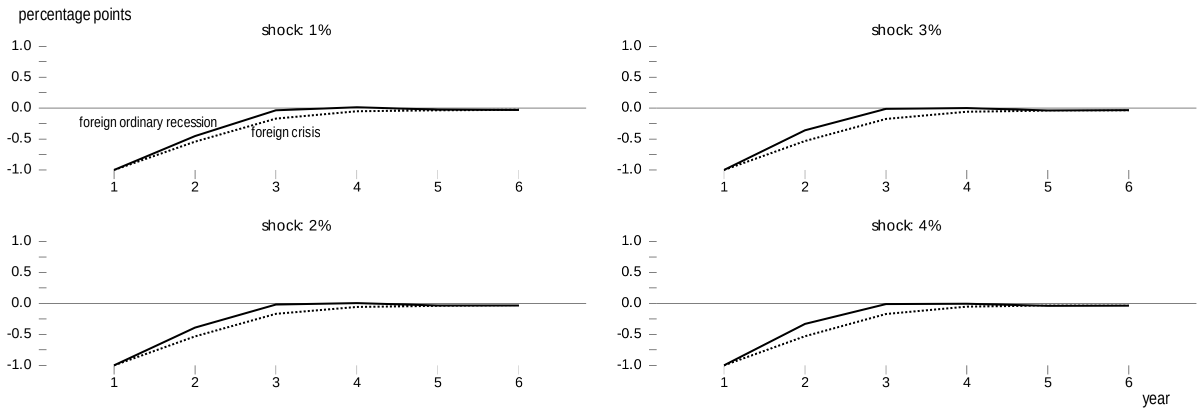
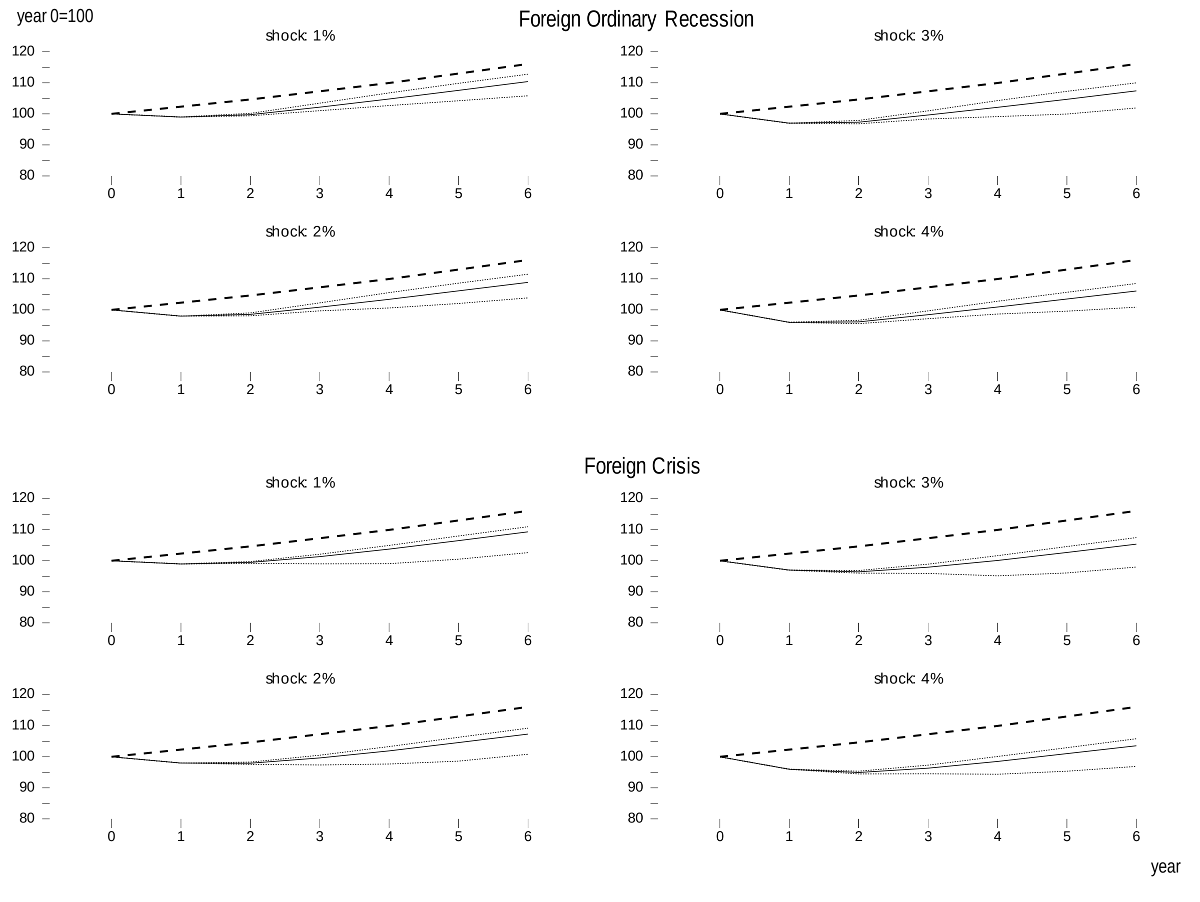


Figure 6.14:
GDP Level Following a Domestic Severe Economic Crisis

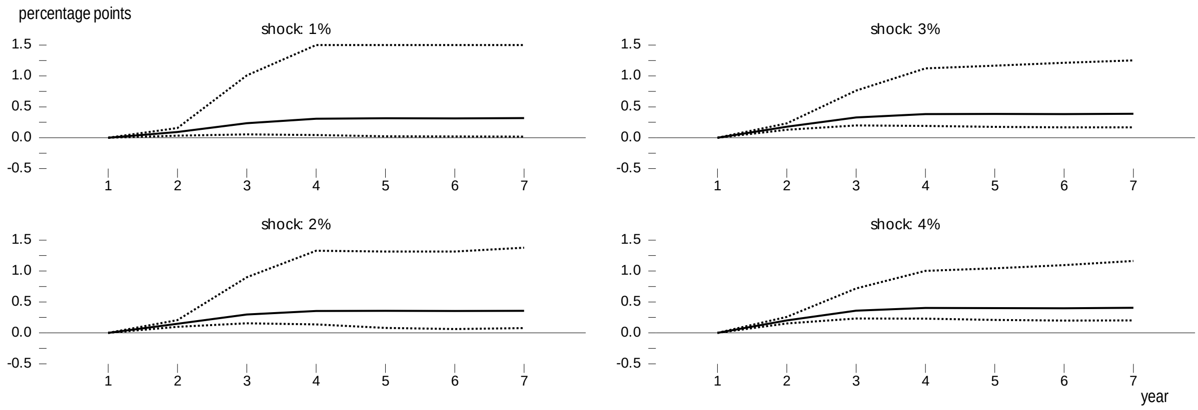


Notes: Baseline calculated via steady sate growth rate. Impulse response functions are calculated over 1,000 simulations. Dotted lines indicate 95 % confidence interval.

GDP is significantly below baseline for at least six years independently whether the foreign economy is hit by an ordinary recession or a severe economic crisis (Figure 6.14). However, in case of a foreign ordinary recession the loss in GDP is smaller.

A comparison between GDP in case of a foreign ordinary recession and in case of a foreign severe economic crisis shows that for shocks with a size from -1 percent to -4 percent GDP is always significantly higher when the foreign economy is hit by an ordinary recessions than when it is hit by a severe economic crisis (Figure 6.15). After the first two or three years of the recovery the difference between the levels of GDP does not increase any more.

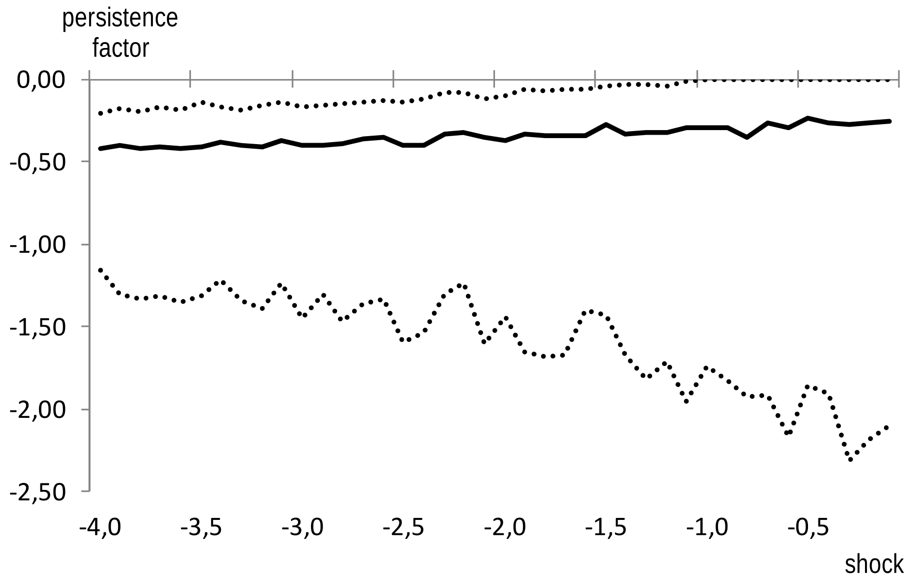
Figure 6.15:
Domestic Severe Economic Crisis: Difference between Foreign Ordinary Recession and Foreign Severe Economic Crisis in GDP Level



Notes: Dotted lines indicate 95 % confidence interval. Calculated over 1,000 simulations.

The difference between both types of recessions in the foreign economy in the persistence factor illustrates that also the long-run effect on GDP is always lower when the foreign economy is hit by an ordinary recession (Figure 6.16). The difference increases only slightly with increasing size of the shock in the initial period. For shocks with a size that can be observed in the sample, the difference is roughly 0.3 percentage points.

Figure 6.16:
Long-run Effects on GDP after a Domestic Severe Economic Crisis: Foreign Severe Economic Crisis Compared to Foreign Ordinary Recession



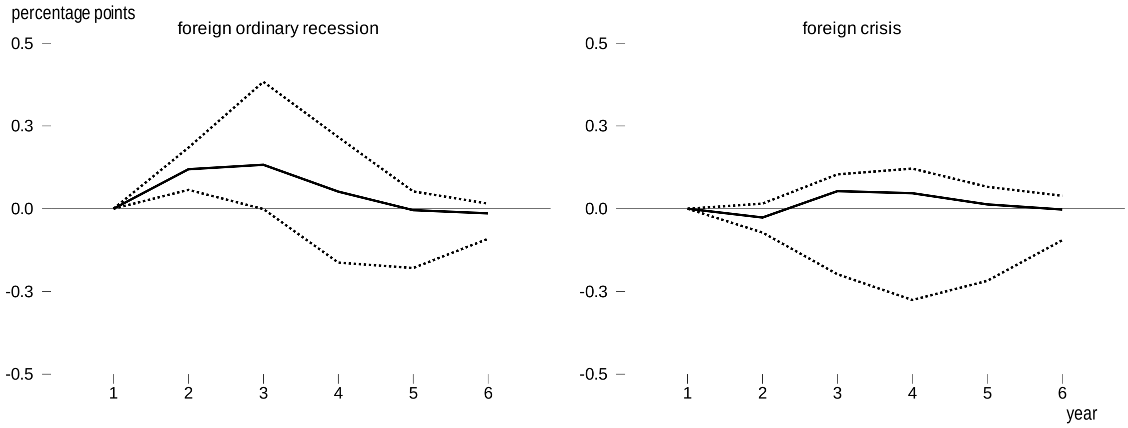
Notes: Calculated as difference in GDP after a severe economic crisis and an ordinary recession ten years after the initial shock scaled by the size of the initial shock calculated over 1,000 simulations. Dotted lines indicate 95 % confidence interval.

Comparison of Internationally Synchronized Recoveries with Not Internationally Synchronized Recoveries

In this section, I compare the strength and the dynamics of internationally synchronized recoveries with the strength and the dynamics of not internationally synchronized recoveries. Basically, I compare the results of both preceding sections. I differentiate between recoveries following domestic ordinary recessions and recoveries following domestic recessions associated with severe economic crises. For both types of recoveries I compare the strength and the dynamics of the domestic recovery when the foreign economy is not in a recovery (not internationally synchronized recovery) with the strength and the dynamics of the domestic recovery when the foreign economy is in a recovery either following an ordinary recession or a recession associated with a severe economic crisis (internationally synchronized recovery).

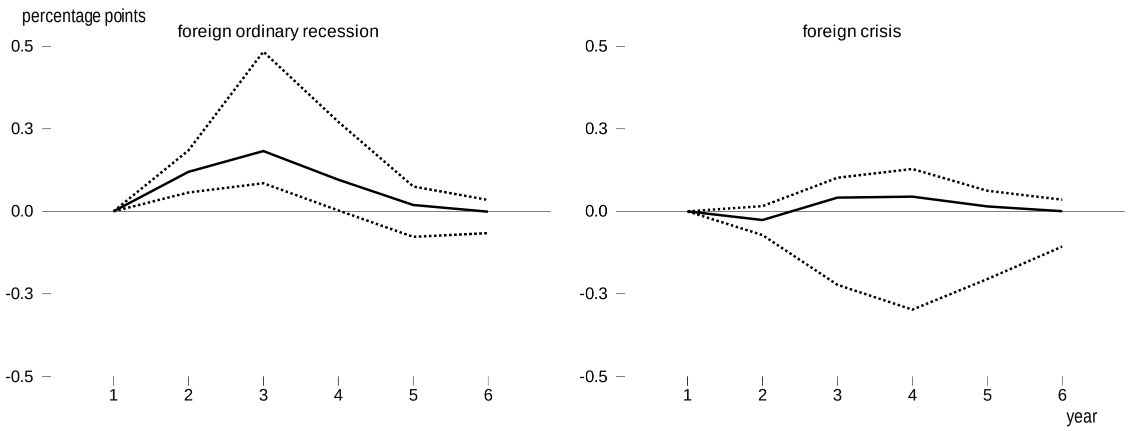
First, I compare GDP growth during the first years of a recovery. As an example I compare the results for a shock with a size of -2 percent. However, the results are qualitatively the same for shocks of various sizes. Given the domestic economy is in a recovery following an ordinary recession, GDP growth is significantly higher for two years when the foreign economy is in a recovery following an ordinary recession than when the foreign economy is not in a recovery (Figure 6.17). In contrast, the result for GDP growth during a domestic recovery when the foreign economy is in a recovery that follows a recession associated with a severe economic crisis is not significantly different from the result for GDP growth when the foreign economy is not in a recovery.

Figure 6.17:
GDP Growth after a Domestic Ordinary Recession: Difference Between International Synchronized Recovery and Not Internationally Synchronized Recovery



Notes: Dotted lines indicate 95 % confidence interval. Calculated over 1,000 simulations.

Figure 6.18:
GDP Growth after a Domestic Severe Economic Crisis: Difference Between International Synchronized Recovery and Not Internationally Synchronized Recovery

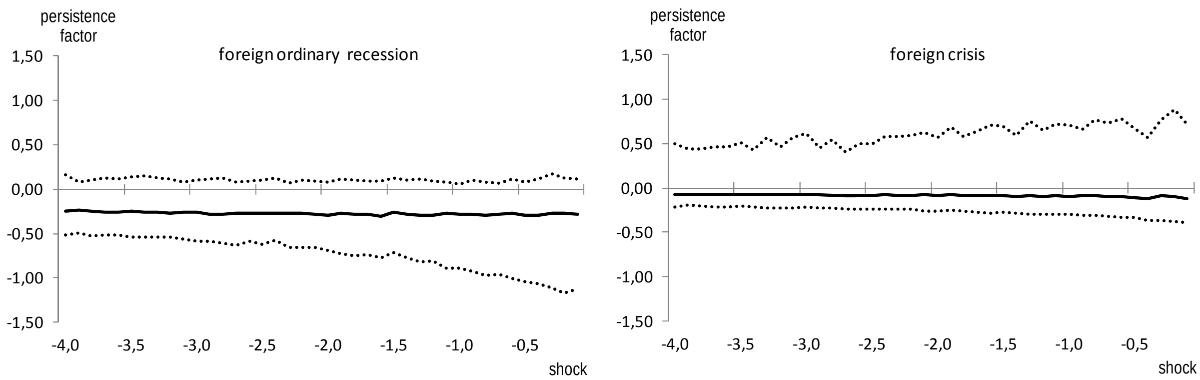


Notes: Dotted lines indicate 95 % confidence interval. Calculated over 1,000 simulations.

Given the domestic economy is in a recovery following a recession associated with a severe economic crisis, GDP growth is significantly higher for three years when the foreign economy is in a recovery following an ordinary recession than when the foreign economy is not in a recovery (Figure 6.18). Again, the result for GDP growth during a domestic recovery when the foreign economy is in a recovery following a recession that is associated with a severe economic crisis is not significantly different from the result when the foreign economy is not in a recovery.

Second, I compare the difference in GDP in the long-run calculated 10 years after the initial shock. Given the domestic economy is in a recovery following an ordinary recession GDP is considerably lower when the foreign economy is not in a recovery than when the foreign economy is in a recovery following an ordinary recession (Figure 6.19). However, the differences are not significantly different from zero at a significance level of 95 percent. When the foreign recovery is following a recession that is associated with a severe economic crisis, the point estimates indicate that the level of GDP is considerably close to the case when the foreign economy is not in a recovery.

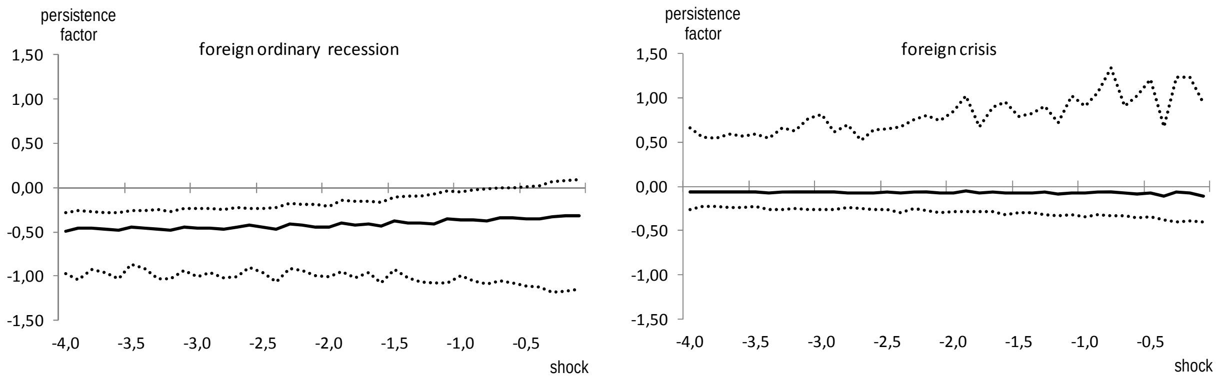
Figure 6.19:
GDP after a Domestic Ordinary Recession: Difference Between a Domestic Recovery and an International Synchronized Recovery



Notes: Calculated as difference in GDP when the foreign economy is not in a recovery and when the foreign economy is in a recovery ten years after the initial shock scaled by the size of the initial shock calculated over 1,000 simulations. Dotted lines indicate 95 % confidence interval.

Given the domestic economy is in a recovery following a recession associated with a severe economic crisis, GDP is significantly lower when the foreign economy is not in a recovery than when the foreign economy is in a recovery following an ordinary recession for initial shocks that are lower than -0.5 percent (Figure 6.20). When the foreign recovery is following a recession that is associated with a severe economic crisis, the point estimates indicate that the level of GDP is considerably close to the case when the foreign economy is not in a recovery.

Figure 6.20:
GDP after a Domestic Severe Economic Crisis: Difference Between a Domestic Recovery and an International Synchronized Recovery



Notes: Calculated as difference in GDP when the foreign economy is not in a recovery and when the foreign economy is in a recovery ten years after the initial shock scaled by the size of the initial shock calculated over 1,000 simulations. Dotted lines indicate 95 % confidence interval.

6.5 Conclusion

I analyze the impact of international synchronization of recessions and recoveries on the depth of recessions and the strength and the dynamics of recoveries. In particular, I differentiate between ordinary recessions and recessions associated with severe economic crises when I study the impact of international synchronization.

When I analyze internationally synchronized recessions, I find that recessions are to some extent an international phenomenon and usually occur in several countries at the same time. However, the results pertaining to whether internationally synchronized recessions are more severe than other recessions are sensitive to the measure that is used to estimate the degree of synchronization and to outliers in the sample. When I follow the literature and use measures that calculate the share of countries in a recession at the same time, I only find some evidence that highly internationally synchronized recessions are more severe than less internationally synchronized recessions when I control for the recessions in Finland and Switzerland as outliers. When I estimate whether a recession in a particular country is more severe the more other countries are in a recession at the same time the evidence that highly internationally synchronized recessions are more severe than less internationally synchronized recessions is stronger.

When I differentiate between ordinary recessions and recessions associated with severe economic crises, I find that countries facing a recession associated with a severe economic crisis tend to be more vulnerable to internationally synchronized recessions. Moreover, the effects of internationally synchronized recessions seem to be stronger when the foreign countries are facing ordinary recessions than when they are facing recessions associated with severe economic crises.

When I analyze internationally synchronized recoveries, I find that internationally synchronized recoveries tend to be stronger than not internationally synchronized recoveries. However a country benefits only from internationally synchronized recoveries when the foreign recoveries are following ordinary recessions, but not when they are following recessions associated with severe economic crises. The benefits are larger when the country itself was hit by a severe economic crisis.

6.6 References

Abeysinghe, T., and K. Forbes (2001). Trade-Linkages and Output-Multiplier Effects: A Structural VAR Approach with a Focus on Asia. NBER Working Paper 8600. National Bureau of Economic Research, Cambridge, MA.

Ahearne, A.G, J. Ammer, B.M. Doyle, L.S. Kole and R.F. Martin (2005). House Prices and Monetary Policy: A Cross-Country Study. International Finance Discussion Papers 841. Board of Governors of the Federal Reserve System, Washington, D.C.

Aßmann, C., J. Boysen-Hogrefe and N. Jannsen (2011). Costs of Housing Crises: International Evidence. *Bulletin of Economic Research*, forthcoming.

Baxter, M., and M.A. Kouparitsas (2005). Determinants of Business Cycle Comovement: A Robust analysis. *Journal of Monetary Economics* 52 (1): 113–157.

Beaudry, P., and G. Koop (1993). Do Recessions Permanently Change Output? *Journal of Monetary Economics* 31: 149–163.

Boysen-Hogrefe, J., N. Jannsen and C.-P. Meier (2010). The Ugly and the Bad: Banking and Housing Crises Strangle Output Permanently, Ordinary Recessions Do Not. Kiel Working Papers 1586, Kiel Institute for the World Economy.

Canova, F., M. Ciccarelli and E. Ortega (2007). Similarities and Convergence in G-7 Cycles. *Journal of Monetary Economics* 54 (3): 850–878.

Cerra, V., U. Panizza and S.C. Saxena (2009). International Evidence on Recovery from Recessions. IMF Working Papers 09/183. International Monetary Fund, Washigton, D.C.

Cerra, V., and S.C. Saxena (2008). Growth Dynamics: The Myth of Economic Recovery. *American Economic Review* 98 (1): 439–457.

Claessens, S., M.A. Kose and M.E. Terrones (2009). What Happens During Recessions, Crunches and Busts? *Economic Policy* 24 (60): 653–700.

Imbs, J. (2004). Trade, Finance, Specialization, and Synchronization. *The Review of Economics and Statistics* 86 (3): 723–734.

IMF (International Monetary Fund) (2003). When Bubbles Burst. *World Economic Outlook*. April. Washington, D.C.

IMF (International Monetary Fund) (2009). From Recession to Recovery: How Soon and How Strong? *World Economic Outlook*. April. Washington, D.C.

Jannsen, N. (2010). National and International Business Cycle Effects of Housing Crises. *Applied Economics Quarterly* 56 (2) 175–206.

Jorda, O., M. Schularick and A.M. Taylor (2011). Financial Crises, Credit Booms, and External Imbalances: 140 Years of Lessons. *IMF Economic Review* 59 (2): 340–378.

Kose, M.A., C. Otrok and C.H. Whiteman (2003). International Business Cycles: World, Region, and Country-Specific Factors. *American Economic Review* 93 (4): 1216–1239.

Kose, M.A., C. Otrok and C.H. Whiteman (2008). Understanding the Evolution of World Business Cycles. *Journal of International Economics* 75 (1) 110–130.

OECD (Organization for Economic Cooperation and Development) (2011). *Economic Outlook*. May. Paris.

Pesaran, M.H., T. Schuermann and S.M. Weiner (2004). Modelling Regional Interdependencies Using a Global Error-Correcting Model. *Journal of Business & Economic Statistics* 22 (2): 129–181.

Potter, S.M. (2000). Nonlinear Impulse Response Functions. *Journal of Economic Dynamics & Control* 24: 1425–1446.

Reinhart, C.M., and K.S. Rogoff (2008). Is the 2007 US Subprime Crises so Different? An International Historical Comparison. *American Economic Review* 98 (2): 339–344.

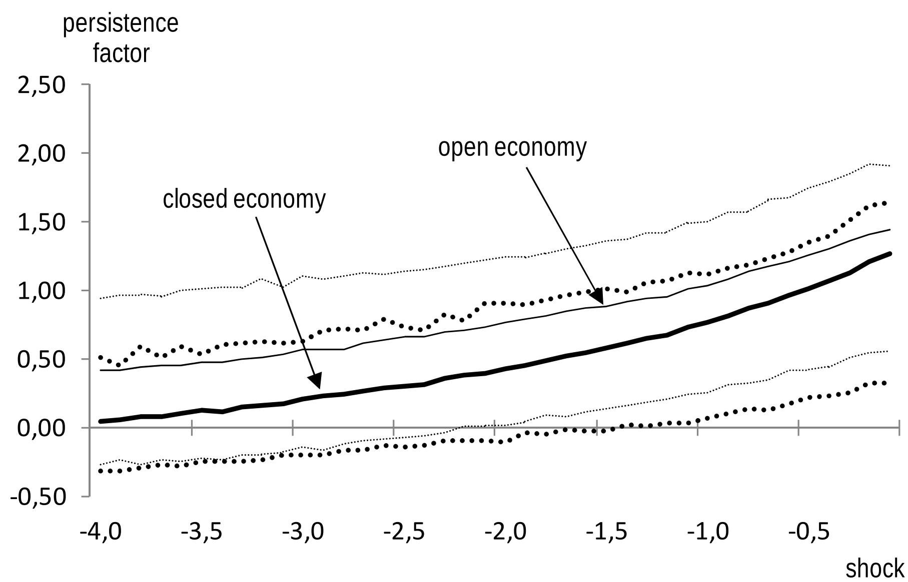
Reinhart, C.M., and K.S. Rogoff (2009). *This Time is Different: Eight Centuries of Financial Folly*. Princeton.

Stock, J.H., and M.W. Watson (2005). Understanding Changes in International Business Cycle Dynamics. *Journal of the European Economic Association* 3 (5): 968–1006.

6.7 Appendix: Differences between the Open and the Closed Economy Model

I deviate from Boysen-Hogrefe et al. (2010) in estimating an open economy model instead of a closed economy model. In Section 6.4.1, I show that both models lead to qualitatively the same result, namely that ordinary recessions are followed by a strong recovery while recessions associated with severe economic crises are not. Here, I check whether both models can lead to significantly different results in terms of GDP by means of simulation exercises analogous to the simulation exercises of Section 6.4.2.

Figure 6.A.1.1:
Persistence Factor Following an Domestic Ordinary Recession for the Closed and the Open Economy Model



Notes: Persistence factor calculated as difference between baseline and ordinary recession ten years after the initial shock scaled by the size of the initial shock calculated over 1,000 simulations. Dotted lines indicate 95 % confidence interval.

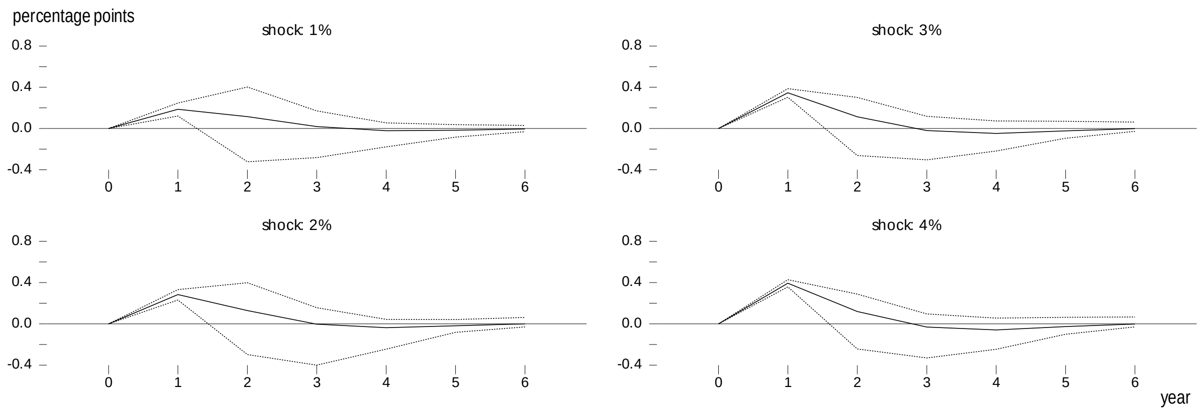
I start by comparing the persistence factors following an ordinary recession for both models. For the open economy model we assume that the foreign economy is not hit by a shock in the initial period. Overall, the persistence of ordinary recessions estimated for the open economy model is somewhat higher than estimated for the closed economy model (Figure 6.A.1.1). For the closed economy model the long-run effect of an ordinary recession on GDP is for shocks smaller than -1.5 percent not significantly different from zero, instead of

-2.0 percent for the open economy model. The point estimates show no long-run impact on GDP for shocks larger than -4 percent.

In the following, I compare the models by calculating the difference between the results of both models. GDP growth following and ordinary recession in the closed economy model is only in the first year significantly higher than in the open economy model and beginning with the third year the difference is virtually zero for the point estimates independently of the size of the shocks (Figure 6.A.1.2). The size of the shock is somewhat more important for the difference of the level of GDP. The level of GDP following an ordinary recession is significantly higher in the closed economy model from one year (for a shock of -1) to two years (Figure 6.A.1.3). However, in the long-run the difference between both models is not significantly different from zero.

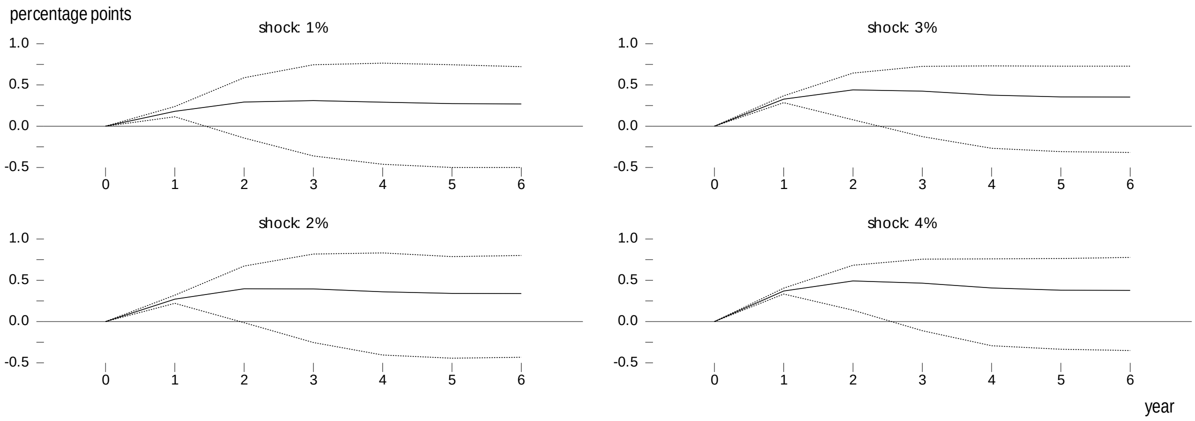
When I compare the difference between both models for the long-run impact on the level of GDP of ordinary recessions compared to the impact of severe economic crises, I find that the difference is only significantly different from zero for the first year or for the first two years (Figure 6.A.1.4). The point estimates indicate that both models lead virtually to the same results in the long-run.

Figure 6.A.1.2:
Difference of GDP Growth Following an Domestic Ordinary Recession between the Closed and the Open Economy Model



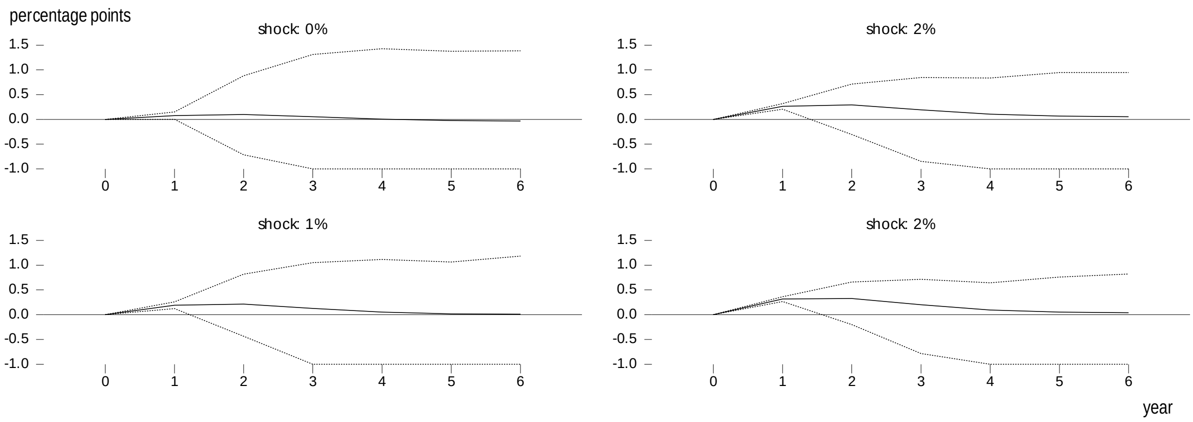
Notes: Dotted lines indicate 95 % confidence interval. Confidence interval calculated over 1,000 simulations.

Figure 6.A.1.3:
Difference of the GDP Level Following an Domestic Ordinary Recession between the Closed and the Open Economy Model



Notes: Dotted lines indicate 95 % confidence interval. Confidence interval calculated over 1,000 simulations.

Figure 6.A.1.4:
Difference Between the Closed and the Open Economy Model: Effect of Ordinary Recession Compared to Severe Economic Crisis on the GDP Level



Eidesstattliche Erklärung

Ich erkläre hiermit an Eides Statt, dass ich meine Doktorarbeit „Severe Economic Crises and the Business Cycle – An Empirical Investigation“ selbstständig und ohne fremde Hilfe angefertigt habe und dass ich alle von anderen Autoren wörtlich übernommenen Stellen, wie auch die sich an die Gedanken anderer Autoren eng anlehnenden Ausführungen meiner Arbeit, besonders gekennzeichnet und Quellen nach den mir angegebenen Richtlinien zitiert habe. Im Fall der Abschnitte, die auf einzelnen Aufsätzen basieren, welche ich in Zusammenarbeit mit anderen Autoren verfasst habe, erkläre ich, dass ich eine angemessene anteilige Leistung beim Verfassen der jeweiligen Aufsätze erbracht habe.

Ort, Datum Nils Jannsen