M.Sc. Thesis

Financial Economics

Developing an early warning indicator for the Icelandic financial system

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Faculty of Economics

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HÁSKÓLI ÍSLANDS

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A thesis towards an M.Sc. degree in Financial Economics

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Foreword

This essay is a 30 ECTS credit thesis towards a M.Sc. degree in Financial Economics at the University of Iceland, School of Social Sciences, Faculty of Economics. I would like to express gratitude to my thesis advisor, Dr. Hersir Sigurgeirsson, Associate Professor at the Faculty of Business Administration, School of Social Sciences, University of Iceland. I would also like to thank my colleagues at the Financial Supervisory Authority of Iceland for their assistance and understanding during the process of writing this thesis. Finally I thank my family and friends for their assistance and support.

Executive summary

This essay reviews theories on developments during financial booms that lead to financial imbalances and possible crises. Those theories are put to the test with a statistical model that is used to forecast the probabilities of banking crises. We find that domestic indicators of financial imbalances, such as credit to the private sector, real house prices and bank financing as well as their international counterparts, are useful predictors of crises in a multivariate framework. The resulting model displays good crisis predicting properties in sample and seems to combine risks emanating from many sectors logically. Risks stemming from the financial sector in Iceland are low according to the fitted model (as of Q1 2017).

The strength of the model lies in combining multiple risk factors into a comprehensive measure. The weakness, which applies in Iceland especially, is that the model does not provide much interpretable information during tranquil times. For that reason, we draw the conclusion that the model is best considered a helpful tool in combination with multiple univariate models but not a measure that can be used in isolation.

As with other indicators that are based on historical data, the logistic regression models developed in this thesis are only useful to predict crises that are similar in nature to those that have taken place in the past. Since systemic banking crises happen infrequently it’s necessary to use data from many countries to gather varied enough crisis observations so that the model can anticipate as many future crises as possible.

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1 Preface

The Basel III accord brought about many innovations in capital regulations. Notable among those is the Countercyclical Capital Buffer (Basel, 2011) which is intended to counteract the buildup of cyclical risks associated with excessive credit growth (Financial Stability Forum Working Group, 2008). Financial institutions are required to maintain the Countercyclical Capital Buffer (CCyB) as well as other capital buffers on top of minimum capital requirements so that they do not breach those minimum requirements during times of financial stress. The Basel accord gives domestic policymakers discretion to decide the specific level of the CCyB but it should be between zero and 2.5% unless special circumstances dictate that it needs to be higher. The rate is set four times per year and institutions that are required to maintain it are given 12 months to implement it.

The consequences of breaching capital buffers are not as serious as with minimum capital requirements. Restrictions are placed on outflows such as dividend payments and bonus payments but there is no need for capital restructuring. In the event of financial distress this helps financial firms in maintaining regular business and allows them to build up their capital level over time.

The rationale for a time varying capital buffer is to increase robustness of the financial sector while having minimal drag on the economy. Rather than obliging financial firms to maintain high levels of capital at all times the CCyB is only activated when policymakers detect that risk awareness may be low and financial imbalances growing.

The decision process for the policymaker poses difficult challenges, the difference between tranquil periods and those that later turn out to be the calm before the storm may be subtle. It must also be taken into account that decisions made by the policymaker are in some cases based on data that is at worst a few months old and the decision won't be fully implemented for up to 12 months after it's been made. That is where early warning indicators play a key role. The purpose of this thesis is to combine risk indicators that have been proven to be informative on their own with econometric methods and make a single indicator that has a broad perspective and reliable forecasting capabilities.

The essay is constructed as follows:

- The second chapter describes the cyclical process that brings about the necessity for time varying capital buffers.
- The third chapter outlines the statistical methods that are used in this thesis, both the model building framework and the actual estimation process.
- The fourth chapter outlines the individual risk indicators that are used in the model and the theoretical background for them.
- The fifth chapter inspects how the individual risk indicators behave around crises and the temporal properties.
- The sixth chapter contains the regression results and brief interpretations.
- The seventh chapter contains an analysis of the Icelandic risk environment.
- The eighth chapter contains robustness checks and out of sample analysis.
- The ninth chapter concludes the essay with discussions.

2 The financial cycle

In the same way that the business cycle can be described as the alternation of periods when economic activity is high and low, the financial cycle can be described as the alternation of periods when asset prices are high and credit flows freely on the one hand and periods when losses are high and credit market freeze up on the other.

Drehmann et al. (2012) evaluated a large number of indicators for seven advanced economies between 1960 and 2011 and found that the financial cycle could be adequately described with the medium term trends of real house prices, private credit growth and the ratio of private credit to GDP (Drehmann, et al., 2012).

In figure 1 a stylized measure of the financial cycle has been plotted for Iceland and some of its most important trade partners. The long term trends of each variable are calculated with the Christiano-Fitzgerald filter[1] and then a simple average of them is used to approximate the financial cycle.[2] The business cycle is also plotted for comparison but that is approximated with the short term trend of GDP growth.

The result of the filtering process has no interpretable unit and is therefore standardized to have a zero mean and standard deviation of 1 in the case of the business cycle and zero mean but standard deviation equaling 2 in the case of the financial cycle. This is done for demonstration purposes but Drehmann, et al. (2012) found that the standard deviation of the financial cycle is seven times larger than the business cycle's at short term frequencies and more than twice and a half times if the business cycle is calculated at medium term frequencies.

[1] The Cristiano-Fitzgerald filter is a frequency based filter that decomposes time series and discards fluctuations that are outside the desired frequency. For the financial cycle the range is between 8 and 30 years but for the business cycle it's from 1 to 8 years (Christiano & Fitzgerald, 1999).

[2] The Central bank of Iceland has experimented with using principal component analysis to weigh the variables (Einarsson, et al., 2016).

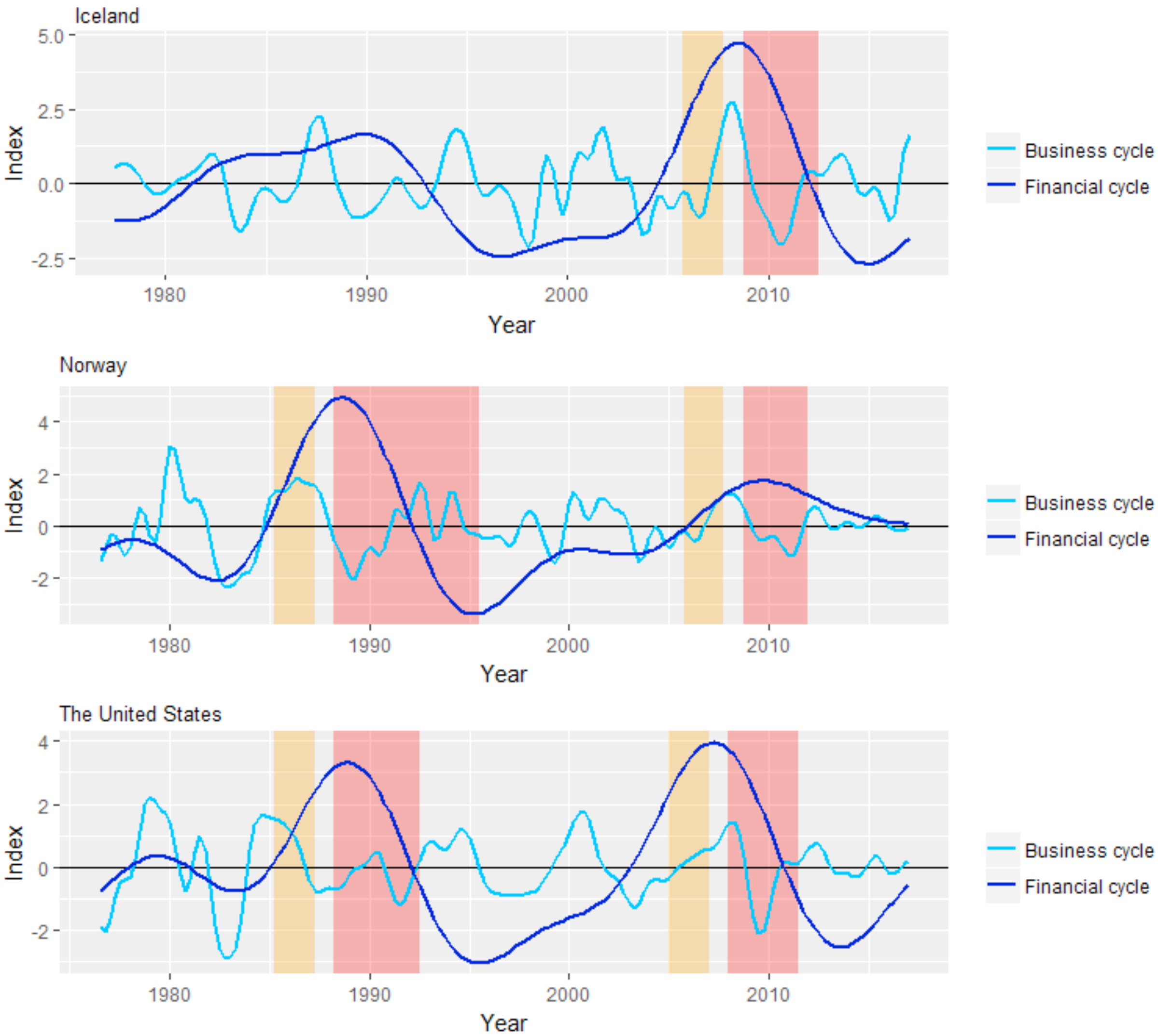

Figure 1. Comparison of business and financial cycles (Source: Author's calculations)

In contrast to the business cycle, which typically lasts between six quarters and eight years, the financial cycle can last more than 20 years. Einarsson, et al. (2016) found that the duration of the Icelandic financial cycle has been getting longer, the average cycle length since 1875 is 16 years but since 1980 the cycle length has been 24 years. The correlation of the Icelandic financial cycle with the US financial cycle was also found to have increased significantly over the period (Einarsson, et al., 2016).

Recent history has lent support to the view that the financial system amplifies both up- and downturns of the real economy through feedback mechanisms. As the real economy grows and both incomes and asset prices rise, risk aversion is at its lowest and credit is readily available which leads to even more growth and consequently even higher incomes and asset prices and the process repeats. When a banking crisis takes place the cycle is reversed (Financial Stability Forum Working Group, 2008).

Economic theory suggests that banks are so central to the flow of credit that if they are stressed to the point that they can't provide credit to the economy it will have a severe and protracted impact on productivity. Ariccia, et al. (2004) found evidence in support of this hypothesis in a study covering 20 countries. Their conclusion was that the greater the reliance of a sector on external financing was, the more it was impacted in banking crises. They also found that this relationship was weaker in countries where access to other means of financing was available.

Banking crises are superimposed in the figure 1 as red areas and it is evident from the picture that they are often associated with deep and protracted recessions. Reinhart & Rogoff (2014) find that it takes countries on average 8 years to reach pre-crisis GDP per capita following financial crises.

With that in mind it's clearly important for policymakers to take preventative action as soon as procyclical developments start having an effect. The yellow areas in figure 1 represent an interval that starts 3 years prior to systemic banking crises and ends 12 months before it. The statistical model developed in this thesis compares the development of key variables during such pre-crisis states with those same variables during tranquil periods. The model can then be used to calculate the probability that the latest data points correspond with stressed or tranquil times. If the probability breaches a predetermined threshold the policymaker knows there is a real risk of a systemic banking crisis occurring in the next 12 to 36 months.

3 Methodology

To put the usefulness of the models studied in this thesis into perspective they need to be compared with an established alternative (Behn, et al., 2013). The signaling approach is a convenient benchmark as it's one of the most commonly used early warning systems according to Detken et al (2014). The univariate and discrete binary choice models are described in this chapter as well as the methods that are used to compare their usefulness.

3.1 Univariate models

Policymakers commonly analyze trends in indicators such as house prices and credit growth directly. They can either be interpreted as is or converted into a binary signal with the signaling approach. The signaling approach is used to find a threshold value of the variable in question and issue a warning signal if that threshold is breached. Variables are usually not combined into a single indicator but many individual models are used simultaneously to establish a comprehensive risk assessment.

The positive aspects of this method are that it's easy to implement and interpret and depending on the variable chosen it's not reliant on computational methods that may distort the development of the underlying risk factor.

A drawback of this method is that each indicator only takes into account risk emanating from one direction. When multiple aspects of the financial system display different levels of stress this method doesn't offer a unified interpretation. Instances where indicators A and B are critical can't readily be compared with instances where indicators C and D are (Bussiere & Fratzscher, 2002).

Drehmann & Juselius (2013) compared a range of indicators that were suspected to be informative leading up to crises and found that the credit to GDP gap gave a robust signal across a large number of countries. The credit to GDP gap is the difference between the actual credit to GDP ratio and its long term trend. This indicator is used for demonstration in the following chapters and as a benchmark for the multivariate model to beat, both since it is the most useful in a global context and established as a *common reference guide* by the Basel committee (Basel, 2010).

3.2 The signaling approach

If the threshold for a risk indicator is set arbitrarily low, it should be expected that it constantly signals crises even though they are unlikely to materialize in reality (type II error). If it's set too high, it may not give any indication of an imminent crisis (type I error). Finding an optimal level means weighing up the costs of either and expressing them with a loss function that can be optimized (Behn, et al., 2013).

P1 represents the unconditional probability of pre-crisis periods in the sample and P2 the complement. T1(τ) represents the ratio of type I errors relative to the total number of crisis periods and T2(τ) the ratio of type II errors relative to the total number of non-crisis periods. The relative cost of missing crises and the action taken to prevent crises that don't materialize is represented with μ. The perceived cost, L, is then calculated with formula 3.1.

$$L(\mu, \tau) = \mu P_1 T_1(\tau) + (1 - \mu) P_2 T_2(\tau) \tag{3.1}$$

If the cost of enduring a crisis and preventing it are equivalent, μ will be equal to 0.5 but if the cost of crises are much higher than the cost of preventative action μ will be closer to 1. Since the cost of banking crises can be substantial it's fair to assume that policy makers have a high preference towards not missing a crisis. For this reason the following analysis uses μ=0.9 and μ=0.95 as a baseline.

Finding the threshold level, τ, is a simple optimization problem once μ has been chosen. To make the threshold applicable for a range of heterogeneous countries it's defined as a percentile of the distribution within each country rather than an absolute value.

In figure 2 the credit to GDP ratio has been plotted with a threshold corresponding to μ=0.95. While it does issue a clear signal in the years leading to the crisis it would have issued a lot of false signals in the decades prior to the actual crisis.

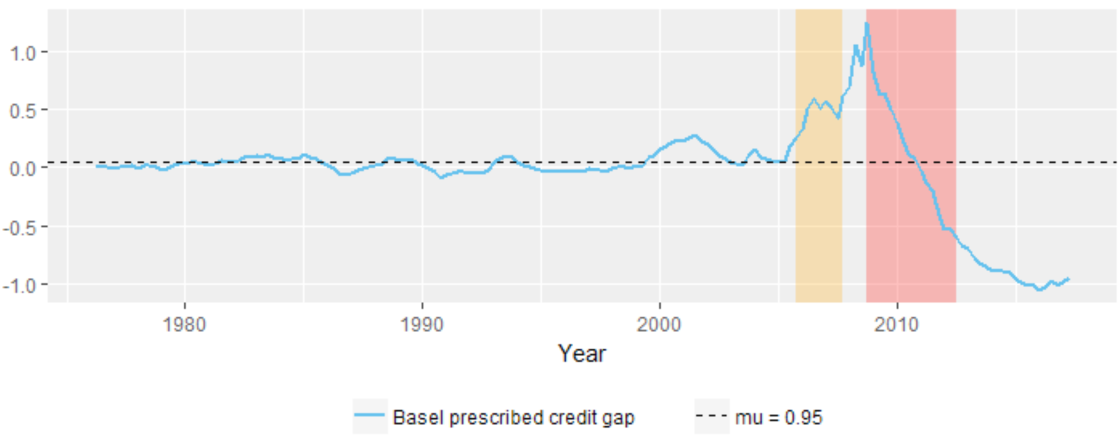

Figure 2. The credit-to-GDP gap as a risk indicator (Source: Central Bank of Iceland, Author's calculations)

Rather than relying on a visual inspection of the indicator in a single country we inspect its usefulness when applied to all the countries in the sample. Table 1 lists the proportion of type I and II errors in the complete sample.

Table 1. Type I and II error rates at different values of μ

Credit to GDP gap	μ=0,90	μ=0,95
Type I error rate	32,1%	24,8%
Type II error rate	29,5%	37,2%

It's important to clarify that the type I error rate is not the absolute probability of missing a crisis. The probability of missing a crisis can be estimated by multiplying the probability of type I errors with the unconditional probability of crises (Demirgüc-Kunt & Detragiache, 2000). Since crises occur rarely the actual probability is considerably lower than the type I error rate. The actual coincidence of pre-crisis observations is 7.55% of the sample so the unconditional probability of missing a crisis is 2.4% when μ=0.9 and 1.87% when μ=0.95.

3.3 AUROC

In some cases, it may be preferable to compare model usefulness without making any assumptions about the preference for type I and II errors. The Receiver Operating Characteristic curve (ROC curve) plots the true positive and false positive rates for every value of μ.

If μ=0 the threshold is very high and no signals are issued, the rate of false positives and true positives are therefore 0% and the corresponding point on the graph is (0,0). If μ=1 the model issues a signal in every quarter and both true and false positives are equal to unity, the corresponding point on the graph is (1,1). These two points are fixed no matter how good or bad the model is but the shape of the curve between them describes how useful it is.

If the risk indicator is no better than tossing a coin, a positive signal is just as likely to be false or true. The true positive and false positive rates are therefore equal at every level of μ and the ROC curve is a straight line from (0,0) to (1,1). The better the risk indicator, the fewer false positives it makes for every true positive and the curve stretches upwards as depicted by the colored curves in figure 3.

The area under the Receiver Operating Characteristic (AUROC) conveniently converts this characteristic into a single number. The area under the curve is 0,5 in the case of the coin toss and tends towards 1 for models that can reliably predict crises without issuing false signals (Detken et al., 2014).

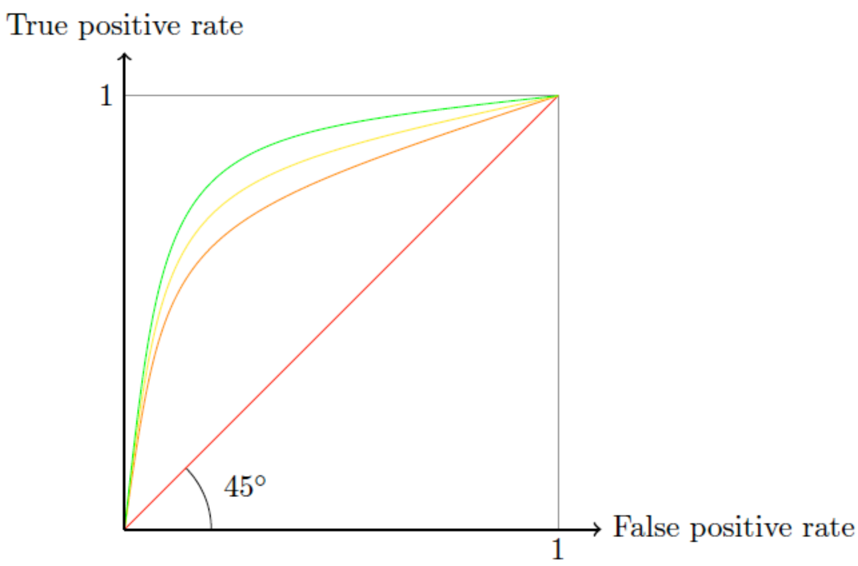

Figure 3. Example of a ROC curve

If a risk indicator turns out to be worse than tossing a coin and gets an AUROC value less than 0,5 it is conceivable to just do the opposite of what the indicator says and thereby get an AUROC value above 0,5.

3.4 Multivariate discrete choice models

One of the most basic ways to combine variables in a statistical model is with linear regression. It's commonly used to estimate probabilities when observed values lie within a narrow range. However there is nothing that prevents the estimated probability of an event to be less than zero or greater than one when the model is used on data that's much higher or lower out of sample (Bussiere & Fratzscher, 2002).

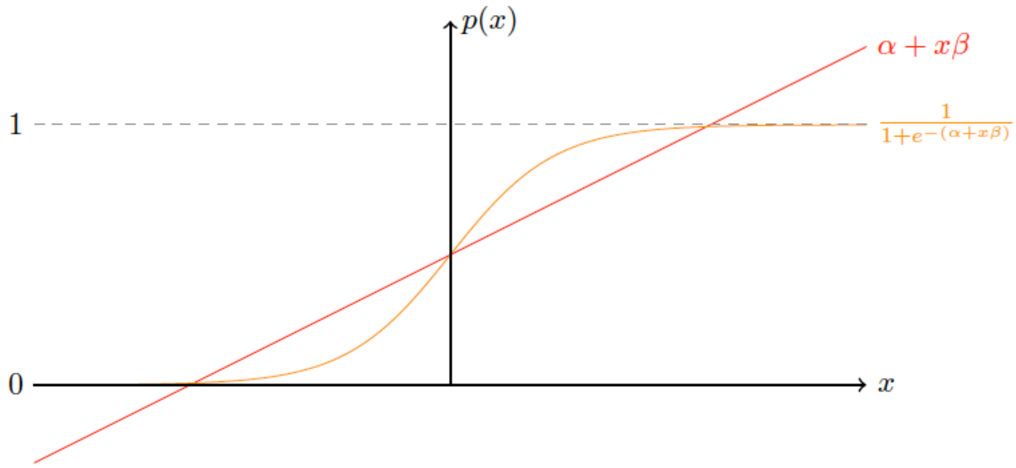

Figure 4. Comparison of linear and non-linear (logit) models

The probit and logit models prevent this from occurring by applying a non-linear transformation to the right hand side variables, as seen in figure 4. The marginal effects of the regressors decrease as the estimated probability tends closer to either 0 or 1. This has the effect that the estimated probability can never be greater than one or less than zero. In this thesis the logistic function is adopted:

$$p_i = Pr(Y_{i,t} = 1) = logit(\alpha_i + \beta'\mathbf{x}_{i,t}) = \frac{1}{1 + e^{-(\alpha_i + \beta'\mathbf{x}_{i,t})}} \tag{3.2}$$

The logit model has been used to estimate probabilities of economic and financial crises for decades and is more convenient to work with than the peobit model while having similar characteristics. Lastly the main inspirations for this paper, Anundsen et al (2014), Behn et al. (2013) and Bussiere & Fratzscher (2002) all used logistic regression.

The marginal effects of each variable can't be taken at face value because of the nonlinear nature of the model. In linear regression an arbitrary change in the covariate $x_{i,j}$ can simply be estimated as β_i ($x_{i,j,t}$- $x_{i,j,t-1}$) where *i* denotes the country and *j* identifies the element of vector $\mathbf{x}_{i,t}$. The marginal effect of $x_{i,j,t}$ in the logistic regression depends on the values of all the covariates at any given time as the partial derivative shows:

$$\frac{\partial p_i}{\partial x_{j,i}} = \frac{e^{-(\alpha_i+\beta'\mathbf{x}_{i,t})}}{\left(1+e^{-(\alpha_i+\beta'\mathbf{x}_{i,t})}\right)^2} * \beta_j \tag{3.3}$$

Although this property makes it harder to distinguish the effects of single variables on the probability estimate it serves a vital role in the model. It makes sense economically that marginal increases of individual risk indicators would have a greater impact when risks from other sectors of the economy are already high.

Steps need to be taken to account for the heterogeneous nature of the countries in the sample. The statistical model cannot account for all variables that effect crisis probabilities as some of them are intangible, such as properties of the political environment and institutions. That may lead to permanent under- or overestimation of crisis probabilities in some countries. Adding fixed effects to the model equates to estimating a dummy variable for each country. This allows for further variability in the crisis probability across countries.

$$y_{it} = \mathbf{X}_{it}\beta + \alpha_i + u_{it} \tag{3.4}$$

This process can be taken one step further by letting the country effects be random. By defining the country affects that way they can vary over time which is reasonable in the context of a 40-year data set. Bussiere & Fratzscher (2002) point out that this method is likely to produce biased results when macroeconomic variables are used since it assumes that the country effects are uncorrelated with the independent variables. They observe that if the country effects arise because of political reasons macroeconomic variables on the right hand side of the model are also likely to be affected by the political situation (Bussiere & Fratzscher, 2002). For this reason the fixed effects model was chosen.

4 Choice of variables

The first iteration of this model was based on a narrow range of countries but it proved important to gather a larger sample to avoid overfitting. Banking crises are rare and the collection of detailed data is a relatively new development. The core indicators are in most cases available since 1976, see Appendix A for detailed information on data availability. In that time half of the countries have only suffered one systemic banking crisis and the other half two. A sufficiently long dataset for the multivariate analysis is only available for about 20-25 countries.

The time series need to be standardized across countries for the regression to have any meaningful results. Statistical databases provided by international organizations proved essential as they provide data with consistent definitions. We endeavored to make Icelandic data conform to the rest of the data in the cases it was not included in the databases.

4.1 The independent variable

The definition of a systemic banking crisis used in this model is borrowed from Valencia & Laeven (2008) who define it as the occurrence of a large number of defaults and the difficulty of financial institutions to repay contracts on time. The accompanying database for banking crises was used as a starting point in designating the crisis periods. Some of the crises dates were adjusted manually since the database has not been updated since 2012, when some banking crises had not yet conclusively ended. The start of a systemic banking crisis is marked by a run on the banks, a deposit freeze or blanket guarantee or extensive liquidity support or bank interventions. The last year of the crisis is defined as the last year before both real GDP growth and credit growth are positive for at least two consecutive years. The maximum length of a crisis is five years (Valencia & Laeven, 2012). The crisis dates were also compared with those from Behn et al. (2013) and Babecký et al. (2012).

Table 2. Crisis dates

Australia	Q4 1989	Japan	Q1 1992
Belgium	Q3 2008	Korea	Q3 1997
Canada	Q1 1983	Netherlands	Q3 2008
Denmark	Q1 1987, Q3 2008	Norway	Q1 1997, Q3 2008
Finland	Q1 1991	Spain	Q3 1997, Q3 2008
France	Q3 1993	Sweden	Q2 1991, Q3 2008
Germany	Q1 1997, Q3 2008	Switzerland	Q1 1991, Q3 2008
Iceland	Q3 2008	Great Britain	Q3 1990, Q3 2007
Ireland	Q1 2008	United States	Q1 1988, Q4 2007
Italy	Q1 1994, Q3 2008		

The dependent variable is defined as unity 5 to 12 quarters before the crises and zero at all other times since the periods of interest are actually the pre-crisis periods. This definition of the dependent variable is based on crisis observations up to 12 quarters into the future and therefore the regression is only estimated with data up until the fourth quarter of 2013 even though the independent variables are available through 2016.

$$Y_{i,t} = \begin{cases} 1 & if\, FC_{i,t+k} = 1\ for\ k \in [5, 12] \\ 0 & otherwise \end{cases} \tag{4.1}$$

The goal of the model is to distinguish pre-crises from tranquil periods so the last 4 quarters prior to the crisis are omitted from the sample, as well as the crisis itself as they do not represent tranquil times. Bussiere and Fratzscher (2002) found that discarding an additional 6 quarters after the crises officially end prevents post-crisis bias so they are excluded as well.

4.2 Credit and house prices

The first stage of model development should always be to suggest a theory or hypothesis that explains how the data being examined came about. The specification of the model can be considered a test of the hypothesis that's based on theory (Ouliaris, 2017).

The interaction effects between asset prices and credit growth is often considered the main driver of the financial cycle. The theory is that credit facilitates asset purchases which lead to price increases, which weakens financial restraint and a positive feedback loop is established. Borio (2012) found that house prices were the best measure of asset prices in this context since their variability is at a low frequency matching the financial cycle as opposed to stocks and other financial assets that can be a distraction since they have large short term fluctuations.

We experiment with several measures of credit. The most basic indicator is annual growth of credit adjusted for inflation. One way to make the comparison between countries and different time periods more informative is using the ratio of credit to GDP. We also use the credit to GDP gap, which is found by subtracting the long term trend from the observed time series, this method is explained in more detail in chapter 4.7. Since previous analyses found that the results could be improved by differentiating credit to households and credit to non-financial enterprises (NFE's) those measures are examined as well.

The majority of the time series for credit and credit to GDP were sourced from the Bank for International Settlements database. Credit was adjusted for inflation with consumer prices, also sourced from the Bank for International Settlements. Icelandic data was compiled with credit data from the Central Bank of Iceland while GDP and consumer prices are both sourced from Statistics Iceland.

House prices are also measured in several ways; annual growth of house prices adjusted for inflation, annual change of the house prices to income ratio and the house price to income gap.

House prices and income were both sourced from the Federal Reserve Bank of Dallas, which collects international house prices in a publicly available database. Icelandic data was sourced from the QMM database that the Central Bank of Iceland makes available on its website.

4.3 Bank financing variables

The literature suggests that banks seek non-core financing when their traditional financing sources can't keep up with accelerated credit growth (Shin & Shin, 2011). If risk premiums rise when the banks face heightened defaults, they may face additional pressure from their liability side. If this theory holds it's an important variable as it would directly contribute to financial instability.

A common measure of stress in banks' balance sheets is the ratio of non-core financing, which for the purpose of this analysis is defined as the ratio of customer deposits and equity to total assets as the data according to this definition is readily available and comparable across countries. It may be beneficial to tailor the definition to the domestic economy for in depth monitoring of non-core liabilities. The Icelandic Systemic Risk Committee has defined core financing to exclude foreign deposits and include long duration bonds (Financial Stability Council, 2017).

Aggregated data from banks' balance sheets was obtained from OECD bank profitability statistics which is available online. No data was available for Australia, Britain and Ireland so they are excluded from all models that contain banking variables. Time series for Icelandic banks were sourced from the Central Bank of Iceland.

4.4 Current account balance

Current account deficits are by definition accompanied with capital inflows since the domestic economy becomes indebted to its trade partners. If the capital flows are used to finance credit growth it may lead to overheating of the economy and a dependence on foreigners' willingness to finance the deficit (Barrell, et al., 2010).

We measure the trade balance as a percentage of GDP, the data was sourced from OECD quarterly national accounts.

4.5 Global variables

As the global economy becomes increasingly interconnected the effects of a systemic banking crisis in one country can be felt in the countries around it. This became evident in the global financial crisis of 2007 and 2008 as contagion effects were felt through most of the western world. Einarsson et al. (2016) found that the correlation of the Icelandic financial cycle with the financial cycle in the United States grew over time.

The global variables are constructed with the methodology from Anundsen et al. (2014). Rather than constructing a single iteration of the global variable that proxies global development, the method assumes that global effects are locally felt through developments in the country's banking and trade partners.

The method allows the weights to change over time which is beneficial since trade patterns and interdependencies are presumed to be continually changing. If $\mathbf{x}_t$ is a vector of country specific indicators, such as credit gaps, and $\mathbf{w}_i$ is a vector of weights, the global variable for country i at time t is defined as:

$$x_{i,t}^{*s} = \mathbf{x}_t^s \mathbf{w}_i' \qquad (4.2)$$

We elected to only use global house price to income gaps and global credit to GDP gaps to estimate the impact of global developments on the domestic probability of banking crises since they are the most fundamental variables in the analysis.

The global variables were constructed with the house price and credit data that had already been collected for the domestic variables. The trade weights were constructed from gross merchandise import and export volume, which was sourced from IMF direction of trade statistics.

4.6 Other variables

Since the purpose of the model is to approximate the true data generating process we experiment with other available variables from financial markets and the real economy (Ouliaris, 2017). Share prices are a measure of asset prices but are seldom used as risk indicators for financial crises since they fluctuate at a much higher frequency than the financial system as a whole. The exchange rate can be expected to be strong before a crisis if international capital flows contribute to credit growth. Inflation and GDP were included because they are commonly elevated in an overheating economy.

Inflation and exchange rate data were sourced from the Bank for International Settlements while share prices and GDP were sourced from the OECD.

4.7 The HP filter

The Hodrick-Prescott filter was first devised as a tool to study business cycles. In their original paper, Robert J. Hodrick, and Edward C. Prescott (Hodrick & Prescott, 1997) explained their theory that the long term growth of GDP is driven by slow moving factors such as investment and increased productivity but cyclical fluctuations are the result of cyclical demand and working hours. Since the observed output is the sum of the growth and cyclical component, business cycles could theoretically be determined by estimating the growth trend and detracting it from the observed data. This was not feasible since the errors of deterministic models of the growth component are large relative to the cyclical component. The solution put forth in the aforementioned paper is to draw on more fundamental characteristics of the growth component, namely that it grows slowly and smoothly.

The formula for the Hodrick-Prescott trend (HP trend) optimizes the trend estimate in two respects. Firstly the trend, μ_t, should be close to the observed data, y_t. The first part of function 4.3 imposes this restriction by summing the squares of the distance between the observed data and the trend component. The second condition is that the trend should be smooth. This restriction is imposed on the trend by summing the squares of its gradient between times t-2, t-1 and t. This restriction is multiplied by the constant λ which adjusts the relative emphasis on smoothness and closeness, larger values of λ result in a straighter trend. The value of λ is commonly set as 1,600 for business cycle analyses and 400,000 for financial cycle analyses (Gerdrup et al., 2013; Basel, 2010). The HP trend is found my minimizing function 4.3 with respect to μ.

$$\min_{\{\mu_t\}_{t=-1}^{T}} \left(\sum_{t=1}^{T} (y_t - \mu_t)^2 + \lambda \sum_{t=1}^{T} ((\mu_t - \mu_{t-1}) - (\mu_{t-1} - \mu_{t-2}))^2 \right) \tag{4.3}$$

Analogous to the business cycle anecdote, the theory is that financial systems grow slowly and smoothly while financial markets deepen and the economy matures but short term fluctuations are driven by other factors. Periods of credit growth above trend are sometimes associated with irrational exuberance which can mean lower lending standards and increased risk appetite.

The credit gap, measured by detracting the HP trend from the ratio of credit to GDP, was found to be an effective risk indicator in a panel study covering 26 countries over a period of 32 years (Drehmann & Juselius, 2013). The Basel committee also expects member countries to calculate the credit to GDP gap as a common reference when making decisions on the countercyclical capital buffer (Basel, 2010). The trend is estimated recursively which means that only information up until time t is used to calculate the trend at time t and it is not revised retrospectively when new data points are added to the sample.

$$y_{t+h} = \frac{1}{4} \sum_{s=t-3}^{t} y_s \tag{4.4}$$

In this analysis we enhance the filtering procedure with a simple moving average forecast (function 4.4) which has been shown to reduce endpoint uncertainty (Gerdrup, et al. 2013). This method is particularly suitable for Icelandic data as is evident in figure 5. The actual time series is shown in black. In the third quarter of 2008 there is a large structural shift and the ratio has declined continuously since then. The orange line is the traditional one sided HP trend which did not adjust to the continuous decline of the credit to GDP ratio until the series crossed and the gap is currently so large that it can't realistically become positive for a number of years. The augmented HP filter, depicted in blue, adjusts to the new norm much quicker without sacrificing any of the signaling properties prior to the crisis of 2008.

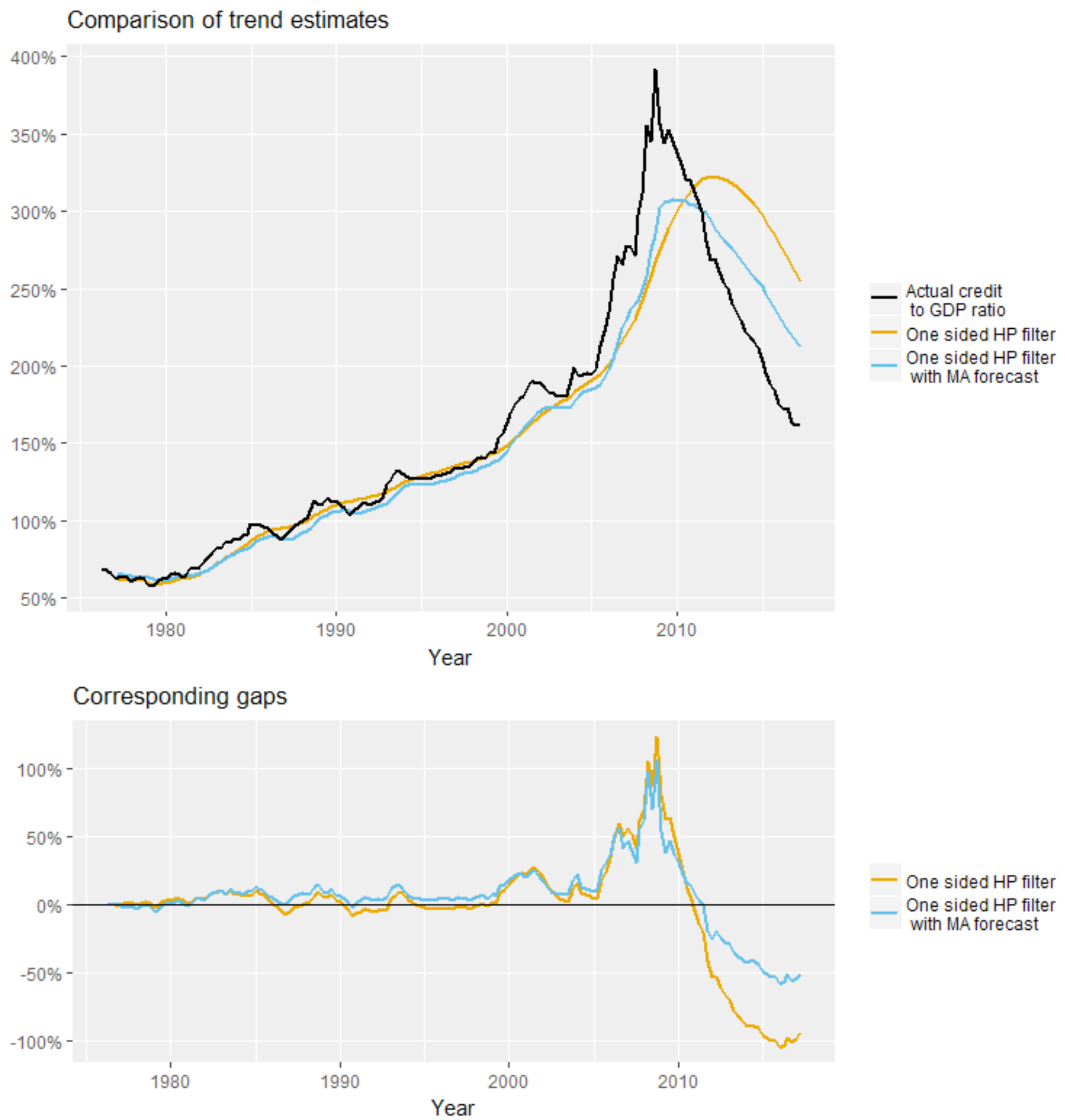

Figure 5. Comparison of trend estimates (Source: Central Bank of Iceland, Author's calculations)

In order to assess which filtering technique should be used for each indicator, all gap measures were estimated with both the regular HP trend and the HP trend with MA forecasts. Each version was tested across a variety of models and the version that had better signaling properties was chosen. The results are shown in table 3.

Table 3. Trend estimation techniques

Indicator	Trend estimation technique	λ
Credit to GDP gaps	HP filter with MA forecast	400.000
House price to income gap	HP filter	400.000
Bank non-core financing ratio gap	HP filter with MA forecast	400.000
Global credit to GDP gap	HP filter	400.000
Global house price to income gap	HP filter	400.000
Output gap	HP filter	1.600

5 A closer look at the data

5.1 Conditional effects

Before the logistic regression is applied to the data the behavior of individual variables around banking crises is inspected. This is done by estimating the conditional effects with a linear regression (Gourinchas & Obstfeld, 2011):

$$x_{j,i,t} = \alpha_{j,i} + \beta_{j,s}\delta_{j,i,s} + \varepsilon_{j,i,t} \tag{5.1}$$

The conditional effect is measured by defining an indicator variable, $\delta_{s,}$ to take the value 1 for s ϵ[-16:16] quarters from the starting date of each crisis in the sample. The estimated coefficient β is the measure of the conditional effect and is mapped in figures 6 and 7 along with a 95% confidence interval.

All of the credit growth measures are statistically significant from zero prior to a banking crisis, however there are subtle differences in their attributes. Real credit growth is positive until just before the crisis, the credit to GDP ratio prevails longer since GDP falls early in the crisis (see figure 6). The credit gap displays similar characteristics around the crisis period as the annual change in the credit to GDP measure although its signaling is slightly more significant. If total credit to the private sector is split up into two parts, households and non-financial firms (NFE's) it becomes apparent that household credit growth precedes the NFE credit growth and the NFE credit gap does not peak until after the crisis has taken place.

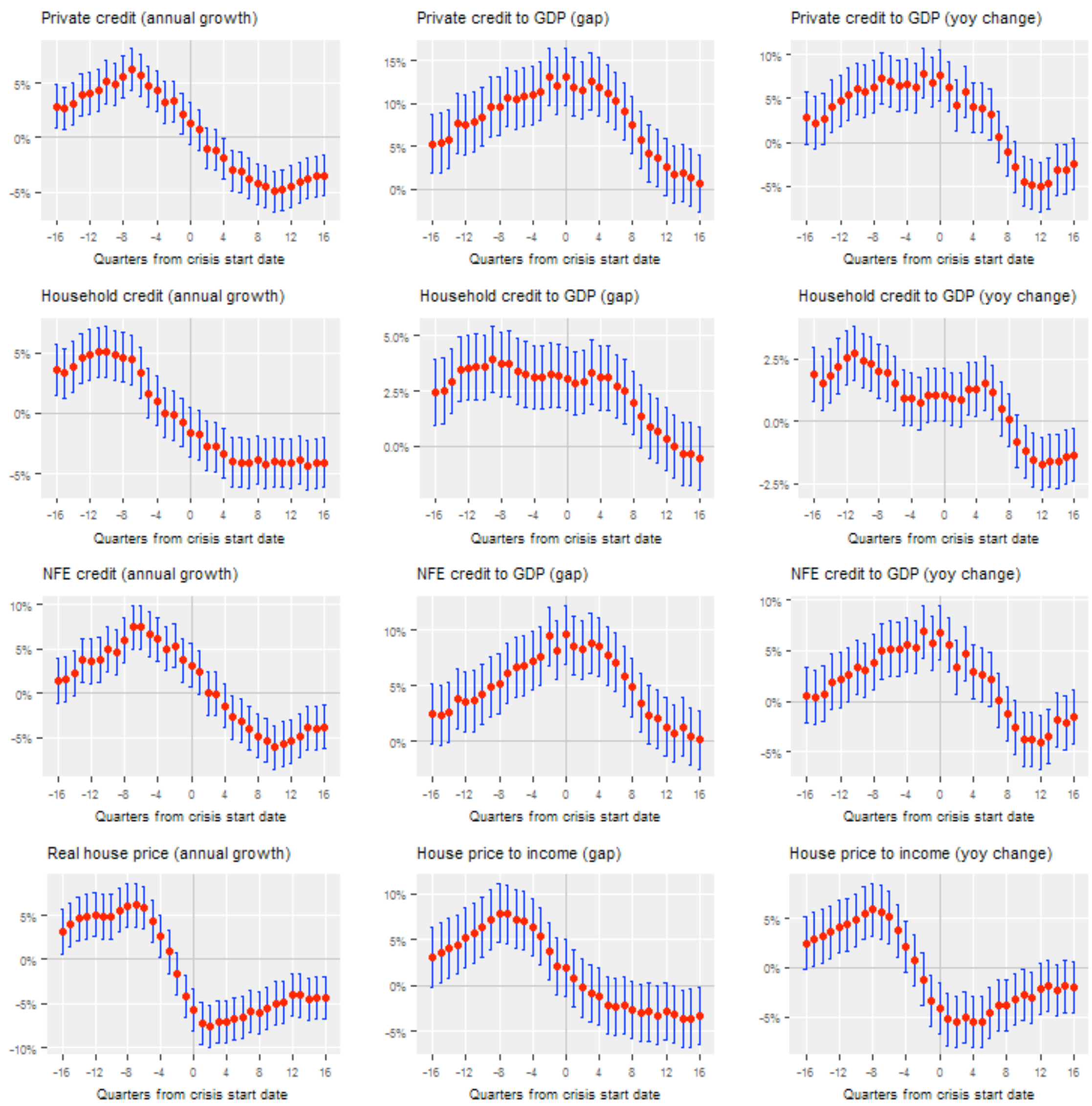

Figure 6. Conditional effects, part 1 (Source: Author's calculations)

Real house prices are most significantly above zero about 1 to 4 years prior to the average crisis. Since the house price to income ratio is also above trend before the crisis takes place it can be inferred that house prices rise faster than income during those periods.

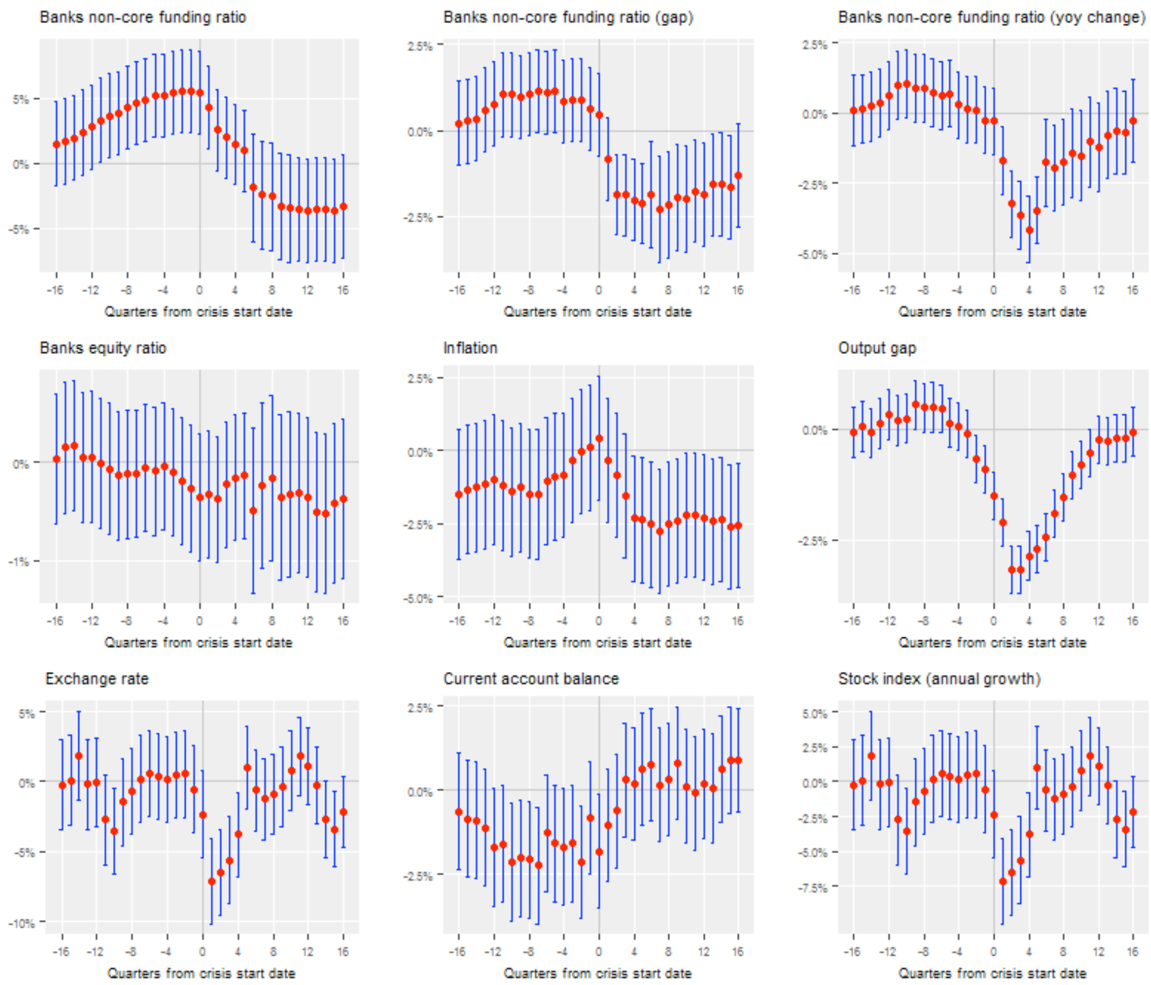

Figure 7. Conditional effects, part 2 (Source: Author's calculations)

Although the ratio of banks' non-core funding is significantly different from zero prior to the crisis, the year-on-year growth and gap measures are not. We will nevertheless include them in the statistical model since their interaction with other variables could make them significant.

The current account balance is below trend in the lead up to crises although the significance is unclear. Stock prices, exchange rates and the output gap don't show any distinguishable characteristics until after the crisis hits.

5.2 Stationarity

As with linear regression, the use of non-stationary data can result in biased inference with logistic regression. Park & Phillips (2000) found that regression results will hover around 0 and 1 for a disproportionate portion of cases when non-stationary data is used.

We employ two methods to test for stationarity in the dataset. First we test each variable with the Augmented Dickey-Fuller test (Davidson & Mackinnon, 2009) and report the percentage of countries for which stationarity was not rejected at 10% significance.[3] Our most important variables are stationary in more than 50% of cases except for the gap measures of credit to households. The results for bank equity ratio and non-core financing ratio are also that they are non-stationary in most cases.

Next the data was tested with the Im-Pesaran-Shin test, which takes into account that each variable is part of a data panel (Im, et al., 2003). The test rejects stationarity of the gap measures of credit to households but does not reject stationarity of the bank financing ratios. The complete list of results is shown in Appendix B.

[3] We use AIC criterion to decide lag lengths with a maximum of 8 lags.

6 Regression results

6.1 Baseline regression

The first regression is based on the characterization of the financial cycle by Drehmann et al. (2012) discussed at the beginning of the essay. All signs are consistent with economic theory, credit growth, positive credit gaps and real house price growth are all associated with higher risk levels.

The second regression builds on that by using gap measures when applicable, this gives a measure of excessiveness in the growth rates rather than absolute growth rates. The AUROC of the new model indicates that signaling properties are modestly improved. The relative importance of credit to GDP, credit growth and house price to income is preserved from first model.

The next step is to evaluate whether there is any progress made by separating credit to households and non-financial enterprises (NFE's). Since shorter time series are available with this separation model 2 is reevaluated with the same sample and the results of that are shown in column 3. Experimentation led to the conclusion that splitting the credit growth into credit growth to firms and households was preferred to splitting the credit gap. Non-stationarity concerns of the credit to households' gap cemented the choice to go with this specification.

The improvement in performance is only marginal if it is measured in terms of AUROC. However, the Type I error rate for higher values of μ is markedly improved. Model 4 is therefore preferred of the models that only take account of credit and house prices.

Table 4. Regression results, part 1

Baseline regression results

	Dependent variable:			
	Crisis indicator			
	(1)	(2)	(3)	(4)
Real credit growth (YoY)	8.7^{***}	11.9^{***}	13.9^{***}	
	(2.6)	(2.1)	(2.3)	
Change in credit-to-GDP (YoY)	12.3^{***}			
	(2.0)			
Real house price growth (YoY)	7.7^{***}			
	(1.4)			
Growth in real credit to households (YoY)				5.0^{**}
				(2.3)
Growth in real credit to NFE's (YoY)				10.0^{***}
				(2.1)
Credit-to-GDP gap		14.1^{***}	16.5^{***}	16.0^{***}
		(1.9)	(1.8)	(1.9)
House price to income gap		5.4^{***}	4.7^{**}	5.0^{**}
		(2.1)	(1.9)	(2.0)
AUROC	0.801	0.833	0.846	0.85
Type I error rate (μ = 0.9/0.95)	0.33/0.20	0.32/0.17	0.28/0.23	0.20/0.16
Type II error rate (μ = 0.9/0.95)	0.27/0.43	0.15/0.35	0.20/0.25	0.20/0.25
R^2	0.265	0.340	0.362	0.369
Observations	2,217	2,178	1,813	1,813

Notes: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Heteroskedasticity robust standard errors are reported in parenthesis below the point estimates. Country fixed effects are not shown.

6.2 Regression with banking data

When additional variables were added to the models variations in the signs of credit variables were observed, which is probably due to multicollinearity. Multicollinearity is a result of regressing variables that are correlated and the model can't tell which variable is affecting the outcome. This does not affect the overall quality of the model but it can lead to dramatic shifts in the coefficients with slight variability of the data. Since the coefficient for growth in real credit to NFE's became negative in more cases than growth in real credit to households and the conditional effects analysis pointed to household credit as an earlier indicator we elect to keep the credit growth to households in the model.

Model 4 is re-estimated with a reduced sample to serve as a benchmark for models incorporating banking variables since the banking variables are only available for a limited time range within the sample. The next step is to add measures of stress of banks' balance sheets. As in the first models, all signs conform to our expectation based on the literature. Higher bank capitalization is associated with less risk of banking crises whereas increased non-core financing is associated with higher risk.

Table 5. Regression results, part 2

Regression results with banking data

	Dependent variable:			
	Crisis indicator			
	(5)	(6)	(7)	(8)
Growth in real credit to households (YoY)	15.8***	15.9***	16.3***	16.0***
	(2.9)	(2.9)	(2.9)	(2.9)
Growth in real credit to NFE's (YoY)	2.0			
	(2.6)			
Credit-to-GDP gap	21.6***	23.9***	23.2***	23.6***
	(2.6)	(2.5)	(2.7)	(2.5)
House price to income gap	1.9*	1.4	1.3	1.4
	(1.0)	(1.0)	(1.1)	(1.0)
Banks equity ratio		-21.0**	-22.8**	-19.2**
		(9.0)	(9.5)	(9.1)
Banks non-core funding ratio			2.0	
			(1.8)	
Banks non-core funding gap				9.8
				(7.5)
AUROC	0.868	0.871	0.871	0.872
Type I error rate (μ = 0.9/0.95)	0.27/0.15	0.13/0.12	0.15/0.15	0.15/0.12
Type II error rate (μ = 0.9/0.95)	0.23/0.37	0.22/0.23	0.21/0.21	0.21/0.25
R^2	0.426	0.430	0.431	0.433
Observations	1,112	1,112	1,112	1,112

Notes: *p<0.1; **p<0.05; ***p<0.01

Heteroskedasticity robust standard errors are reported in parenthesis below the point estimates. Country fixed effects are not shown.

There is a slight improvement in most of the comparison metrics when banking variables are added to the model. The reduced sample size makes it a difficult comparison however and the signal from these models lack stability.

The house price to income variable becomes insignificant when banking variables are added to the model. We keep it in the model since its sign still conforms to the theory and the results from previous regressions showed that it's a significant variable overall. Furthermore, it's not a specific requirement of the model that every variable be statistically significant but rather that the model as a whole is correctly specified.

6.3 Regression with global variables

Overall the models that include global variables show appreciable performance gains over the standard models. The global variables are also available for the whole duration of the sample period so the good performance is not just a result of a reduced sample.

The coefficients for the global variables are highly significant. That is to be expected since 13 out of the 28 systemic banking crises in the sample took place in 2007 and 2008 and will therefore have similar reliance on global variables.

Table 6. Regression results, part 3

Regression results with global variables

	Dependent variable:			
	Crisis indicator			
	(9)	(10)	(11)	(12)
Growth in real credit to households (YoY)	5.0**	4.0	7.8***	5.0*
	(2.3)	(2.6)	(2.5)	(2.8)
Growth in real credit to NFE's (YoY)	10.0***			
	(2.1)			
Credit-to-GDP gap	16.0***	20.5***	18.5***	19.4***
	(1.9)	(1.5)	(1.7)	(1.6)
House price to income gap	5.0**	1.7	3.9***	2.1*
	(2.0)	(1.0)	(1.4)	(1.1)
Global house price to income gap		15.4***		12.5***
		(2.2)		(2.5)
Global credit-to-GDP gap			16.9***	10.5***
			(2.9)	(3.7)
AUROC	0.85	0.87	0.862	0.876
Type I error rate (μ = 0.9/0.95)	0.20/0.16	0.25/0.10	0.22/0.12	0.16/0.12
Type II error rate (μ = 0.9/0.95)	0.20/0.25	0.20/0.34	0.21/0.35	0.26/0.30
R^2	0.369	0.413	0.388	0.424
Observations	1,813	1,817	1,817	1,817

Notes: *p<0.1; **p<0.05; ***p<0.01

Heteroskedasticity robust standard errors are reported in parenthesis below the point estimates. Country fixed effects are not shown.

6.4 Comparing ROC curves

The area under the ROC curve for the optimized logistic regression models varies between 0.85 and 0.88 which is a rather narrow range. For comparison the AUROC for the credit to GDP gap is 0.75. The individual ROC curves are plotted in Figure 8 to give an enhanced sense of the models' attributes.

While model 12 has the highest true positive rate for a broad range of false positive rates, both models 4 and 8 outperform it for the lowest quadrant of false positive rates. This evidence doesn't conclusively point to one model above another so we need to look at other attributes such as signal stability.

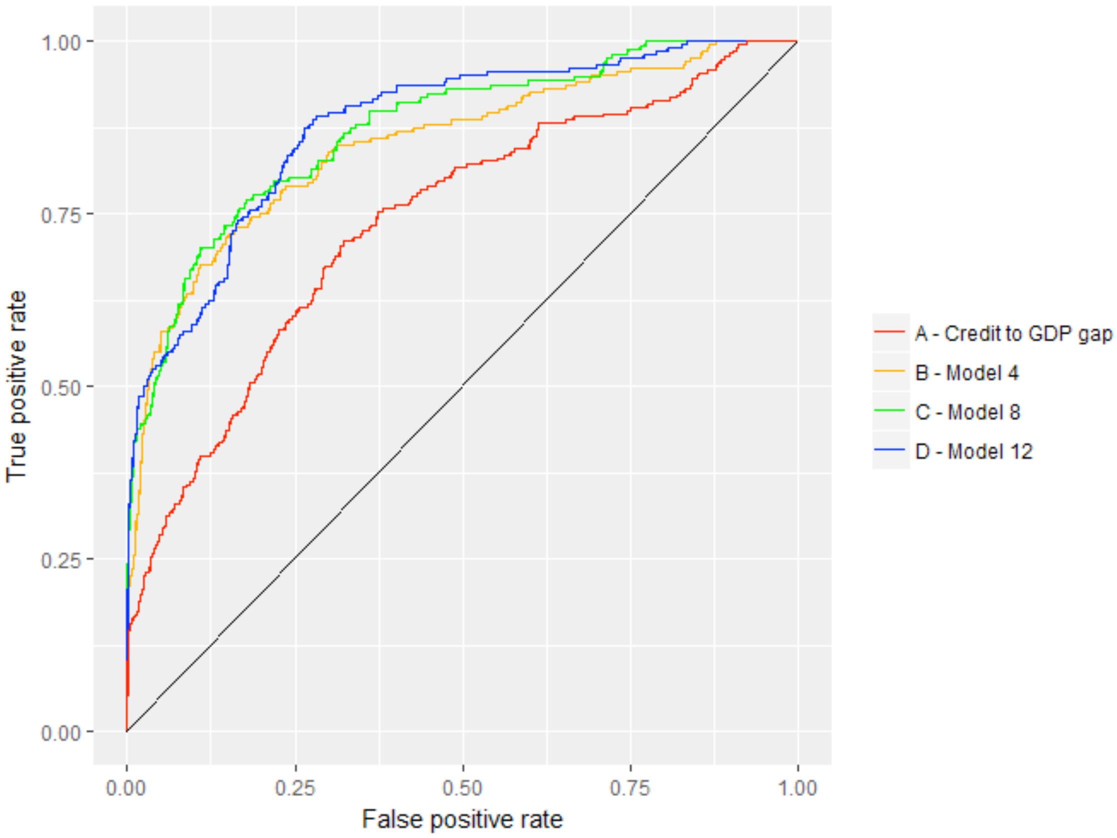

Figure 8. Comparison of ROC curves (Source: Author's calculations)

7 Estimating crisis probabilities with Icelandic data

After the best performing model from each category has been picked based on minimizing type I and II errors and the AUROC, they are fitted with Icelandic data with two objectives in mind. Firstly, we are interested in seeing how well the results conform to our understanding of economic history. Secondly we make a visual inspection of how stable the signal is.

In the top graph of figure 9 we show the results of fitting model 4 with Icelandic data. The indicator does indicate the pre-crisis era between 2005 and 2007 rather well but it ascends suddenly and is not very stable. It gives a misleading signal by dipping back down by the end of 2007. Analysis of the underlying data showed that the credit to GDP gap is unstable near its peak which resulted in this fluctuation.

The middle graph of figure 8 corresponds to model 8. The model displays similar signal instability as model 4. The definition of non-core banking liabilities used in the model doesn’t capture the events that unfolded in 2007 when Icelandic banks sought foreign deposits which actually resulted in lower non-core financing ratios in the run up to the crisis according to the definition used.

Model 12 (bottom of figure 9) displays the most stable signal of the three models. The global variables have a much smoother development than the domestic ones which serves to increase the stability.

The signals are rather binary in nature in all of the models which arouses some suspicion that non-stationarity effects might be present, as discussed in the first paragraph of chapter 4.2. Upon closer inspection it was concluded that other properties of the Icelandic data accounted for this anomaly. A key indicator, the house price to income gap, is only available since 1987 and the relatively high fluctuations in some indicators result in a larger negative value of the fixed effect than in other countries. For this reason only relatively large developments register as heightened crisis probabilities in the case of Iceland.

The fitted crisis probabilities are plotted for a sample of other countries in figure 12 (Appendix C). As the fixed effect gets weaker, the less binary the result becomes. This was taken as a satisfactory explanation.

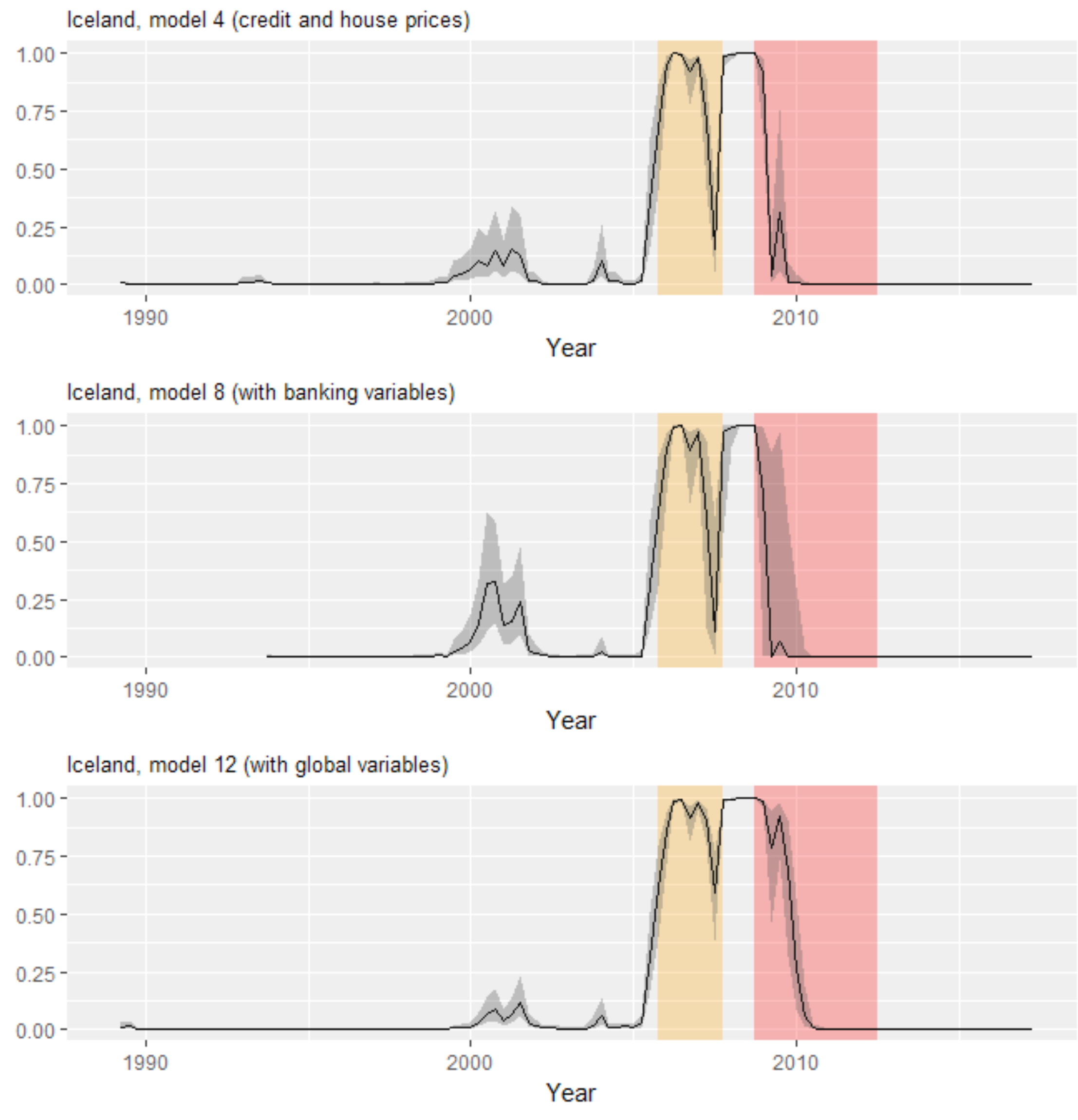

Figure 9. Fitted crisis probabilities (Source: Author's calculations)

As figure 9 clearly shows, risks emanating from the Icelandic financial system are not elevated enough to register according to the model with the latest observation being Q1 2017.

8 Out-of-sample analysis and robustness check

The choice of countries in the sample and time periods can have a large effect on the regression results since systemic banking crises are so rare. Therefore, it's prudent to try different samples and observe the effect this variation has on the outcome and usefulness of our models.

8.1 Out-of-sample analysis

We estimate the three main models with data from 1976 to 2000 and see whether they are useful in predicting the global financial crisis. It should come as no surprise that the coefficients change substantially since a third of the countries don't even have a systemic banking crisis within the reduced sample (Behn, et al., 2013) and the total number of crises drops from 28 to 15.

Interestingly the model predicts the systemic financial crisis in Iceland reasonably well even though the coefficients have changed considerably.

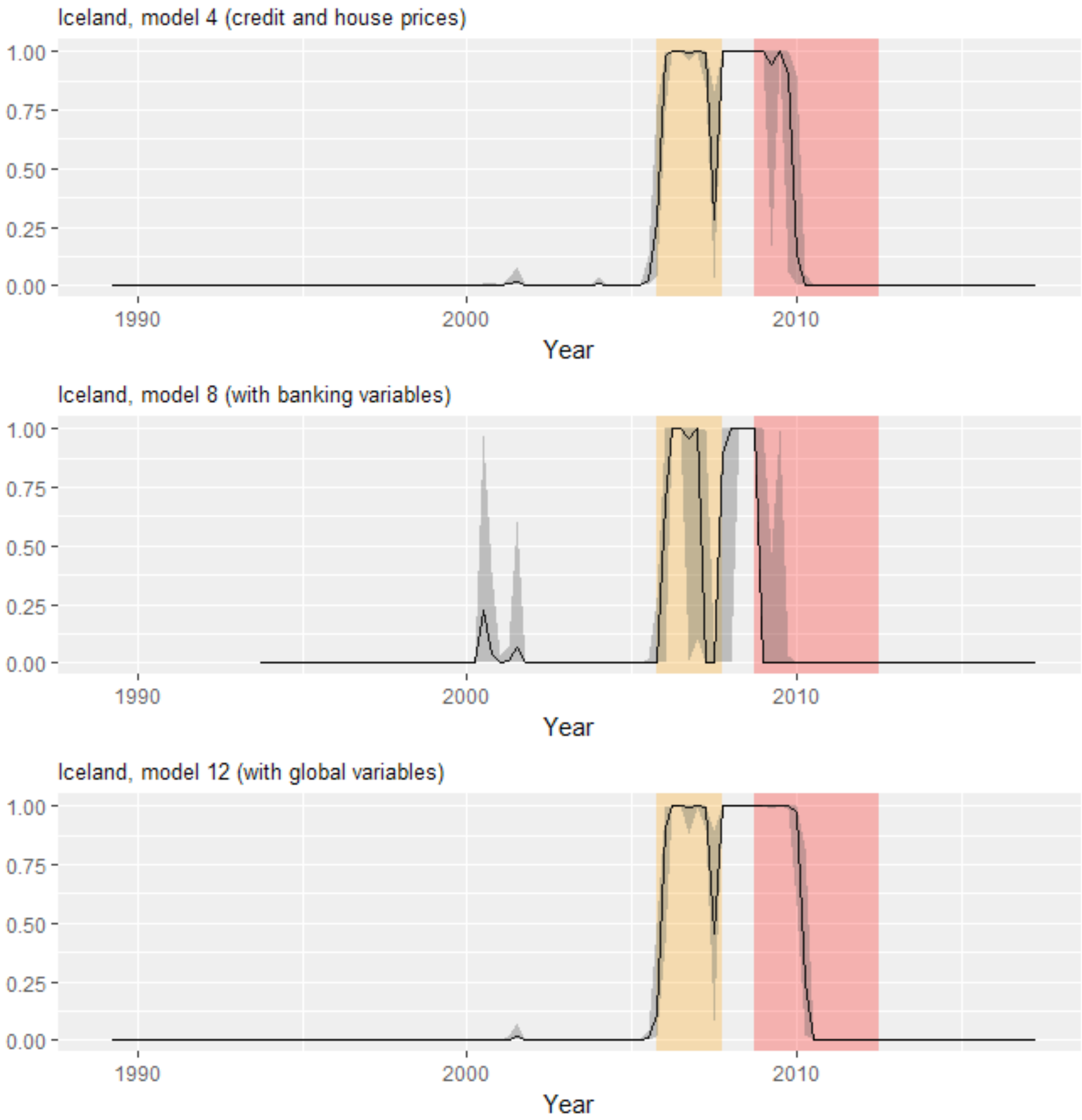

Figure 10. Out-of-sample test (Source: Author's calculations)

8.2 Robustness check

The robustness check is performed by dropping each country from the sample one by one and estimating the parameters to see how much they vary. As is evident in figure 8 the results are more or less stable. Korea seems to be a significant outlier in terms of bank equity ratio and house price to income gap. However, the signs of the variables do not change so we accept this as natural variability in the model.

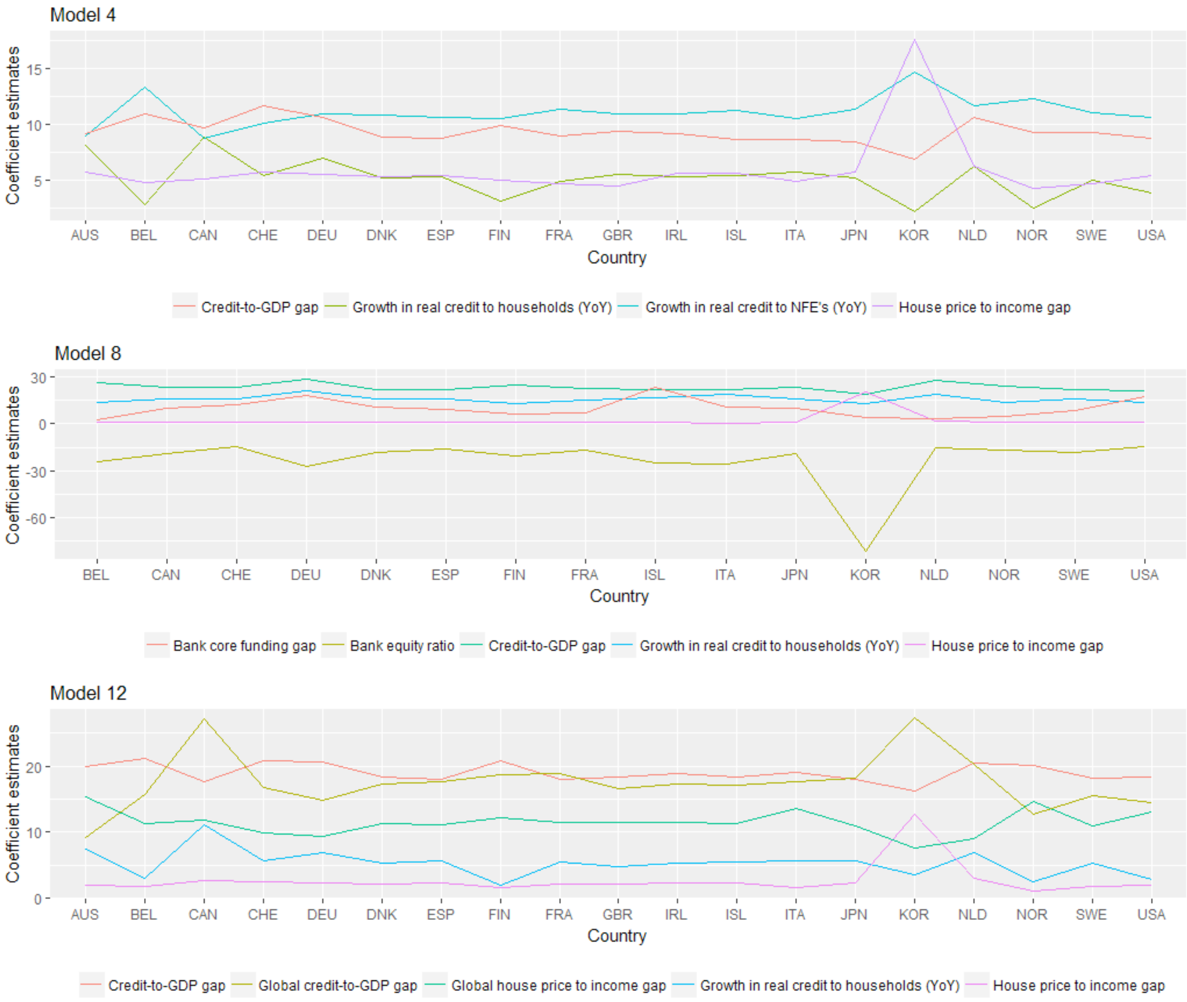

Figure 11. Cross sectional stability (Source: Author's calculations)

9 Conclusion

The models that have been developed in this thesis display good crisis predicting properties in sample. Overall the multivariate framework greatly improves crisis predictions above the univariate method. When the best performing logistic model is compared to the benchmark indicator, the credit to GDP gap, it becomes apparent that the type I error rate is halved from 32% to 16% when μ=0.9. The area under the ROC curve also increases significantly from 0.75 to 0.85.

When the models are used to estimate crisis probabilities with the most current data, Q1 2017, the result is that the overall picture of the financial cycle gives little indication that a financial crisis is imminent. That result should be taken with the caveat that historically the Icelandic financial sector went through a rather extreme period of excess before crisis struck so the model can be interpreted in such a way that the financial sector is comparatively resilient.

As with other models that are based on historical data, the logistic regression models developed in this thesis are only useful to predict crises that are similar in nature to those that have taken place in the past. Since systemic banking crises happen infrequently it's necessary to use data from many countries to gather varied enough crisis observations so that the model can anticipate as many types of future crises as possible. Stress tests may be better suited to evaluate risks from scenarios that have not yet taken place.

When an analysis is based on many different indicators it can be difficult to find the appropriate weights to give to any single one of them. We find that the role of the models developed in this thesis is to find this balance methodically. The model should therefore be considered a helpful tool in combination with multiple univariate models but not a measure that should be used in isolation.

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Appendix A – Data availability

The following tables list the starting date for each time series broken down by country. The total number of observations that were useful for the regression analysis is also included.

Table 7. Core data availability

	Private credit	Credit separated by households and NFE's	House prices	House price to income
Australia	Q1 1976	Q4 1977	Q1 1976	Q1 1976
Belgium	Q1 1976	Q4 1980	Q1 1976	Q1 1976
Canada	Q1 1976	Q1 1976	Q1 1976	Q1 1976
Denmark	Q1 1976	Q4 1994	Q1 1976	Q1 1976
Finland	Q1 1976	Q1 1976	Q1 1976	Q1 1976
France	Q1 1976	Q4 1977	Q1 1976	Q1 1976
Germany	Q1 1976	Q1 1976	Q1 1976	Q1 1976
Iceland	Q1 1976	Q1 1986	Q1 1976	Q4 1987
Ireland	Q1 1976	Q1 2002	Q1 1976	Q1 1976
Italy	Q1 1976	Q1 1976	Q1 1976	Q1 1976
Japan	Q1 1976	Q1 1976	Q1 1976	Q1 1976
Korea	Q1 1976	Q1 1976	Q1 1976	Q1 1976
Netherlands	Q1 1976	Q4 1990	Q1 1976	Q1 1976
Norway	Q1 1976	Q1 1976	Q1 1976	Q1 1976
Spain	Q1 1976	Q4 1980	Q1 1976	Q1 1976
Sweden	Q1 1976	Q4 1980	Q1 1976	Q1 1976
Switzerland	Q1 1976	Q4 1999	Q1 1976	Q1 1976
Great Britain	Q1 1976	Q1 1976	Q1 1976	Q1 1976
United States	Q1 1976	Q1 1976	Q1 1976	Q1 1976
Number of observations	2888	2444	2888	2841

Table 8. Additional data availability

	Bank balance sheet data*	Trade balance to GDP	Share prices	Exchange rate	Inflation	Output
Australia	-	Q1 1997	Q1 1993	Q1 1995	Q1 1976	Q1 1976
Belgium	Q4 1981	Q1 1997	Q1 1993	Q1 1995	Q1 1976	Q1 1976
Canada	Q4 1988	Q1 1997	Q1 1993	Q1 1995	Q1 1976	Q1 1976
Denmark	Q4 1979	Q1 1997	Q1 1993	Q1 1995	Q1 1976	Q1 1976
Finland	Q4 1979	Q1 1997	Q1 1993	Q1 1995	Q1 1976	Q1 1976
France	Q4 1988	Q1 1997	Q1 1993	Q1 1995	Q1 1976	Q1 1976
Germany	Q4 1979	Q1 1997	Q1 1993	Q1 1995	Q1 1976	Q1 1976
Iceland	Q3 1993	Q1 1997	Q1 1993	Q1 1995	Q1 1976	Q1 1976
Ireland	-	Q1 1997	Q1 1993	Q1 1995	Q1 1976	Q1 1976
Italy	Q4 1984	Q1 1997	Q1 1993	Q1 1995	Q1 1976	Q1 1976
Japan	Q4 1989	Q1 1997	Q1 1993	Q1 1995	Q1 1976	Q1 1976
Korea	Q4 1990	Q1 1997	Q1 1993	Q1 1995	Q1 1976	Q1 1976
Netherlands	Q4 1979	Q1 1997	Q1 1993	Q1 1995	Q1 1976	Q1 1976
Norway	Q4 1979	Q1 1997	Q1 1993	Q1 1995	Q1 1976	Q1 1976
Spain	Q4 1979	Q1 1997	Q1 1993	Q1 1995	Q1 1976	Q1 1976
Sweden	Q4 1979	Q1 1997	Q1 1993	Q1 1995	Q1 1976	Q1 1976
Switzerland	Q4 1979	Q1 1997	Q1 1993	Q1 1995	Q1 1976	Q1 1976
Great Britain	-	Q1 1997	Q1 1993	Q1 1995	Q1 1976	Q1 1976
United States	Q4 1980	Q1 1997	Q1 1993	Q1 1995	Q1 1976	Q1 1976
Number of observations	1705	1292	1596	1691	2888	2888

**The OECD bank profitability statistics database was discontinued in 2008, only Icelandic time series were extended beyond that date.*

Appendix B – Stationarity test results

The percentage of countries for which stationarity was not rejected at 10% significance is reported in column 2. The p-values for rejection of stationarity in the Im-Pesaran-Shin test are reported in column 3. Values below 0.10 and 0.05 indicate that stationarity is not rejected at 5% and 10% significance levels respectively.

Table 9. Stationarity test results

Variable	Augmented Dickey-Fuller test % of total stationary	Im-Pesaran-Shin test p-values
Real credit growth	52,6 %	0,0000
Real credit growth to households	52,6 %	0,0001
Real credit growth to NFE's	68,4 %	0,0000
Credit to GDP gap	84,2 %	0,0000
Credit to GDP gap (households)	57,9 %	0,0022
Credit to GDP gap (NFE's)	89,5 %	0,0000
Credit to GDP gap*	47,4 %	0,0002
Credit to GDP gap* (households)	31,6 %	0,2074
Credit to GDP gap* (NFE's)	73,7 %	0,0002
Change in credit to GDP ratio	89,5 %	0,0000
Change in credit to GDP ratio (households)	31,6 %	0,2496
Change in credit to GDP ratio (NFE's)	84,2 %	0,0000
Real house price growth	100,0 %	0,0000
House price to income gap	84,2 %	0,0013
House price to income gap*	94,7 %	0,0666
Change in the house price to income ratio	100,0 %	0,0000
Bank equity ratio	0,0 %	0,0518
Bank non-core financing ratio	6,3 %	0,0186
Bank non-core financing gap	62,5 %	0,2308
Bank non-core financing gap*	62,5 %	0,2223
Change in non-core financing	68,8 %	0,0004
Output gap	100,0 %	0,0000
Current account balance	15,8 %	0,0599
Inflation	73,7 %	0,0036
Exchange rate change	94,7 %	0,0000
Stock index change	5,3 %	0,0350

Appendix C – Cross country comparison

The fitted crisis probabilities, along with a 95% confidence interval, according to model 12 are plotted in graph 12. Norway, Great Britain and The United States were chosen since they are important trade partners of Iceland and the country fixed effect is progressively weaker for each of them. Norway has the strongest effect after Iceland, then Great Britain and lastly the United States is least impacted by it.

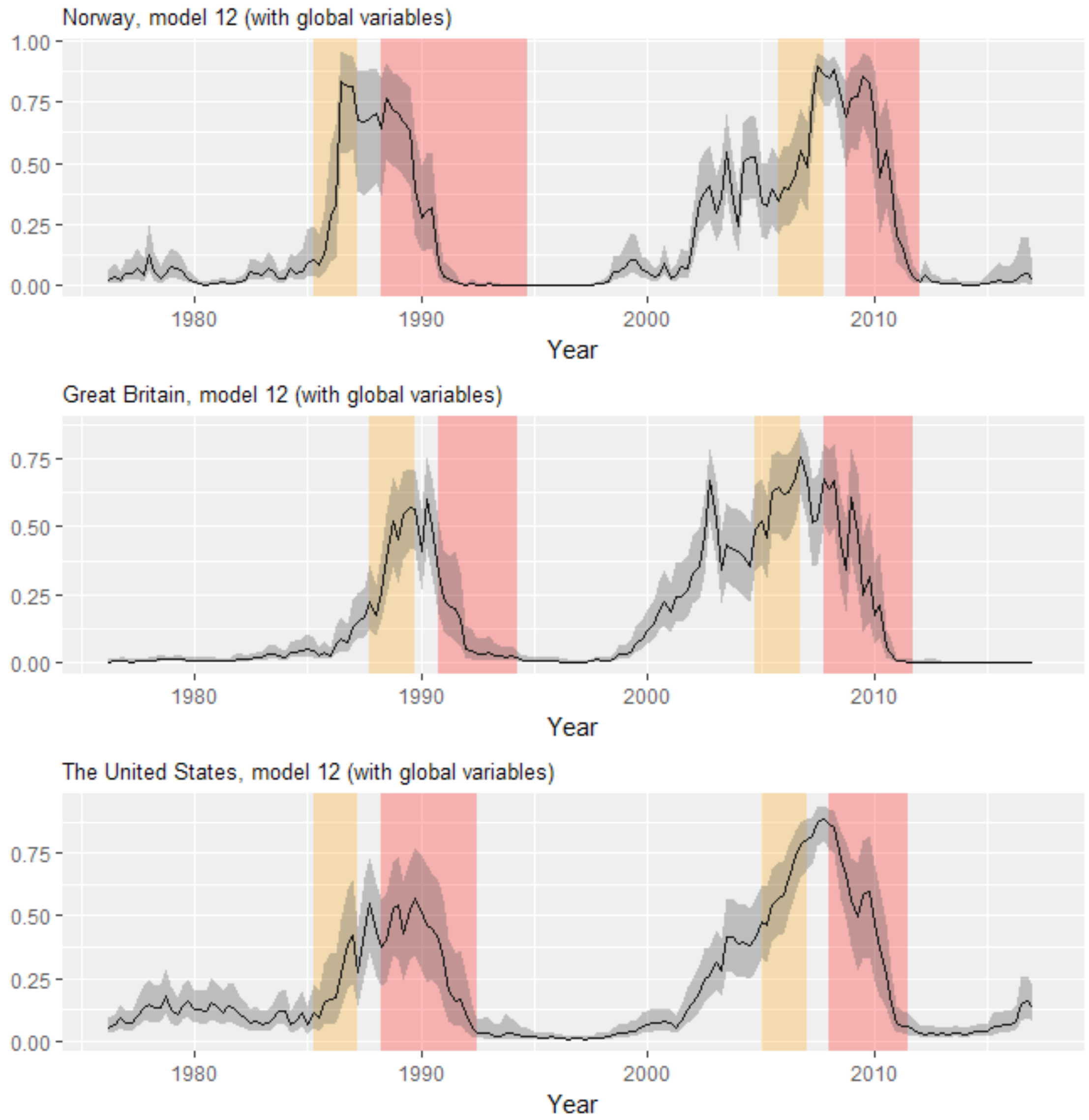

Figure 12. Fitted crisis probabilities for some of Iceland's trade partners (Source: Author's calculations)