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Credit Expansion and Neglected Crash Risk

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Abstract

In this paper I examine the effects credit expansion has on bank equity and whether bank shareholders recognise the increased crash risk that comes with credit expansion. This is done through five regressions, each of which answers a specific element of this question. First I found that credit expansion actually increased the crash risk of bank equity. The second regression showed that bank shareholders do not demand higher returns given the increased crash risk when credit expansion was high, but rather receive lower returns. A third regression aimed to distinguish whether these lower returns were the result of elevated risk appetite or actually neglected crash risk and proved the latter to be the case. A fourth regression gave insight on the particular sentiment associated with credit expansion, yielding that it is different from the sentiment associated with the market. Lastly I analysed the effect of credit expansion on volatility, which yielded no significant results.

Contents

1 Introduction

Crises come and crises go, has been a universal truth for as long as we know. The search for the causes and remedies has delivered us a possible devil; credit expansion. A substantial body of research has linked credit expansion to banking crises, housing market crashes and economic recessions, (e.g., Borio and Lowe (2002), Mian and Sufi (2009), Schularick and Taylor (2012), and Lopez-Salido and Zakrajsek (2016)). The causes of credit expansion are discussed by Minsky (1977) and Kindleberger (1978), who emphasize overoptimism as an important cause of credit expansion. They argue prolonged periods of economic booms tend to breed optimism, which in turn leads to credit expansions. This possibly destabilizes the financial system and thereby the entire economy. A number of possible mechanisms that cause this overoptimism have already been discussed, such as neglected tail risk (Gennaioli and Vishny (2012), Gennaioli and Vishny (2013)), extrapolative expectations (Barberis and Vishny (1998)), and this-time-is-different thinking (Reinhart and Rogoff (2009)).

The negative consequences of credit expansion are further explored by Greenwood and Hanson (2013), who provide evidence that during credit booms a disproportionally large amount of low credit quality corporate bonds is issued and that this forecasts lower excess corporate bond returns. Whereas this deduction certainly is in line with debt holders being overly optimistic in times of credit booms, it does not necessarily imply causality. Another possible explanation is that the lower quality bonds are merely the result of an elevated risk appetite of investors, especially since the predicted returns are, albeit lower, still positive. This analysis restricts itself to only one group of agents in the economy however. While overoptimism might explain why debt holders neglected the financial instability associated with credit expansion, the same can not necessarily be said about other agents in the economy, equity holders in particular. Bank shareholders often face large losses during financial crises and thus have strong incentives to correctly forecast the possibility of a such a crisis. Contrary to this, a long tradition links credit booms to overoptimism (Kindleberger (1978)). It does remain hard to find concluding evidence of excessive equity valuations however.

Baron and Xiong (2016) address these issues in their paper. They use a key property of equity prices, namely that these prices reflect the current knowledge and expectations of the investors that hold and trade shares. By linking equity prices to credit expansion, we can infer whether bank equity holders correctly predict the effects of credit expansion on bank equity. Here credit expansion is measured as the past three-year change in the bank credit to GDP ratio, where bank credit is the amount of net new lending from the banking sector to domestic households and nonfinancial corporations. The data used includes 20 different developed countries, which are selected based on the availability of historical data. Baron and Xiong (2016) identify four aspects to this question, all of which are analysed with a different regression. In this paper, I replicate the regressions that form the basis of their argument and comment on the difference between our findings, after which I further analyse a different aspect to the question with a fifth regression.

The first part of the analyses concerns the question of whether credit expansions actually increase the likelihood of a bank equity crash, where a crash is defined as the value of bank equity dropping by 30%. They find this is the case, with the chances of a crisis increasing by 50% when credit expansion is one standard deviation higher than its mean. My replication provides less pronounced results, but echoes their conclusion.
In the second part of their analysis Baron and Xiong (2016) answer the question of whether bank shareholders recognise this increased crash risk. They regress credit expansion on the

future excess returns of bank equity to see whether shareholders indeed recognise the increased crash risk and thus demand higher future returns. The key argument here is that this can be accomplished by immediately lowering share prices, thereby increasing the future returns. They find credit expansion actually predicts significantly lower returns, rather than higher. My findings are in line with this. This on its own is not enough to conclude that bank shareholders neglect crash risk however, as the negative effect of credit expansion on bank equity could be explained by an elevated risk appetite.
The third question thus concerns the actual magnitude of bank equity returns subsequent to large credit booms and contractions. Baron and Xiong (2016) find that conditional on credit expansions exceeding a 95th percentile threshold, the mean excess return in subsequent two and three years is substantially negative at 17.9% and 37.3%. As shareholders of publicly traded bank equity have no commitment to hold on to stock, these shareholders are not obliged to hold on to their stock in good as well as bad times. That the expected returns turn so sharply negative can thus not be explained simply by elevated risk appetite and instead points to the presence of overoptimism or neglect of crash risk by equity holders during credit expansions.
The final part of the analysis examines how the sentiment associated with credit expansion is different from the sentiment present in the equity market, which is measured by dividend yield. Dividend yield is a robust predictor of equity returns and is thus sometimes taken as a measure of equity market sentiment. Both dividend yield and credit expansion are strong predictors of equity returns, yet their correlation is limited. Credit expansion also proves to be a strong predictor of bank equity crashes, whereas dividend yield does not. Consistent with the theoretical insight of Simsek (2013), this indicates that credit expansion and the equity market are drive by two different types of sentiment: Credit expansions are associated with neglect of tail risk, while low dividend yield is associated with optimism about the overall distribution of future economic fundamentals. There is a peculiar connection between the two however; bank equity proves to be an even stronger predictor of bank equity returns when dividend yield is low. This indicates the two predictors amplify each other, to increase the predictive power of credit expansion when equity market sentiment is high.

The aforementioned analysis restricts itself to one aspect of bank equity, namely its price. It leaves out another important aspect of stocks; their volatility. Baron and Xiong (2016) briefly mention that a possible explanation for the increased crash risk explained by credit expansion can be that credit expansion increases volatility. They dismiss this possibility by concluding that credit expansion is less effective in predicting equity booms than it is at predicting equity crashes and thus only affects the lower end of the distribution. Though this suffices for their argument, it raises the question of whether credit expansion does indeed influence the volatility of bank equity. Intuitively, unexpected low quality credit, and the problems that come with it, can easily cause large sways in bank equity. Schwert (1989) provides some useful insights in volatility modelling. Beltrattia and Morana (2006) add to this by analysing the effect of macroeconomic variables on volatility in the context of regime switching models. I use a simplified approach to see what the effect of credit expansion on volatility is, but find no significant results.

The remainder of this paper is structured as follows: section 2 provides a detailed overview of the dataset, section 3 explains the regressions used to answer the research question, section 4 shows the resulting estimations, section 5 provides a conclusion and section 6 discusses the weaknesses of this analysis.

2 Data

The data used in the replication comes in the form of a panel data set, containing quarterly observations for 20 developed economies, where an economy is defined as developed when it is classified as an advanced economy by the International Monetary Fund(IMF). The other requirement for a country to be included is that there is data available dating at least 40 years back for credit expansion as well as bank equity index returns. The data consists of three types of variables: credit expansion, bank equity index returns and control variables known to predict the equity premium. The data for the replication is provided by Baron and Xiong (2016), partly cleansed. Only observations are used where the total excess returns as well as credit expansion is available. The procedures they followed and the choices I made where there was an unclear step are explained below.

2.1 Credit expansion

The focus of this paper is the key explanatory variable in all regressions; credit expansion. Baron and Xiong (2016) define it as the annualized past three-year percentage point change in bank credit to GDP, where bank credit is credit from the banking sector to domestic households and nonfinancial corporations. In the rest of this article, credit expansion refers to bank credit expansion unless otherwise stated. It is formally expressed as

$$\Delta\left(\frac{bank\ credit}{GDP}\right)_t = \frac{(\frac{bank\ credit}{GDP})_t - (\frac{bank\ credit}{GDP})_{t-3}}{3} \tag{1}$$

Credit expansion is computed using data from two sources, (i) the "bank credit" from the Bank for International Settlements (BIS) "long series on credit to private non-financial sectors", which covers a broad range of countries, but mostly for the postwar era; and (ii) "bank loans" from Schularick and Taylor (2012), which does provide data further back but for a limited amount of countries. When the datasets overlap, BIS data is used as it is provided quarterly. Schularick-Taylor data is forward-filled 3 quarters to create quarterly data and avoid look-ahead bias. To ensure smooth overlap between datasets, the Schularick-Taylor data is scaled by an affine function.

Note that the change in bank credit is used, rather than the absolute value. This choice is made because the change in bank credit emphasizes the cyclical nature of credit expansion and represents the net new lending from the financial sector to the private sector. When new lending is high, this rapid increase may coincide with a lower quality of lending, as shown by Greenwood and Hanson (2013), which in turn increases the risk of losses for banks.

Because the magnitude of credit expansions differs between countries due to size and institutional differences, credit expansion is standardized per country. Only past information is used in this standardization to avoid look-ahead bias.

2.2 Equity Index returns

The return on bank equity is the main dependent variable in the replication part of my paper. I use the log excess total returns when I refer to returns. The price data for equity indexes is collected from Global Financial Data (GFD). The bank dividend yield is collected from Moody's Banking Manuals. Excess total returns are then constructed by adding dividend yield to quarterly price returns and subtracting the three-month short-term interest rate. For my regressions I need yearly, biannual and triannual returns. I use log returns, which are computed by simply summing the quarterly returns over the period concerned. A boom and crash dummy are also computed, where a boom is defined as a period for which the quarterly returns are higher than 30% and a crash is defined as a period for which the quarterly returns are lower than -30%.

2.3 Control variables

The last group of variables used are the macroeconomic control variables known to predict time-varying equity premium. These include dividend yield of the bank equity index, book-to-market, inflation, non-residential investment to capital and term spread. These control variables are standardised across the entire sample for space and time. As this is only a change of units, it does not introduce a looking-ahead bias. This standardisation happens before the observations for which credit expansions or excess returns are missing are deleted. The observations for which the value of certain control variables are missing in the dataset are thereafter replaced with the mean of the sample used in the regression, to ensure the missing observations do not influence the results of the estimation. A set of quintile dummies is constructed with dividend yield according to the following formula: $D_k = I_{q_{k-1}<x\leqslant q_k}$, where q is the value of the *k-th* quintile, computed with only information for the past. Note the $\leqslant$ sign, which is necessary due to the panel nature of the data as a large amount of data would be discarded if datapoints concerning the boundaries would otherwise be omitted.

2.4 Equity Index volatility

The equity index volatility is computed using daily returns from indexes representing the financial sector for each of the 20 countries. For every country for which it was available, the financial version of the national index are selected (e.g. AEX financials for the Netherlands). For the countries for which this was not available, I used the MSCI financials index of that particular country. The index values are hand-collected from Bloomberg. These values are then used to compute log returns. The index returns are then used to compute the variance of returns according to the usual formula: $\sigma^2_{t,i} = (r_{t,i} - \mu_i)^2$ Where $\sigma^2_{t,i}$ is the daily variance of the index returns in country i and μ_i is calculated using only information from the past and within the country. To use the data in the regression, I calculate the average daily volatility per quarter, per year and per 2 years. The average daily volatility is chosen as it has a more straightforward interpretation and because it is a linear transformation from the actual quarterly, yearly and biannual volatility. I also eliminate the problem of some observations having more trading days within their period as other observations. Table 6 in the appendix contains summary statistics on the volatility of these indexes.

3 Methodology

Before turning to the regression specifications, two important econometric concerns need to be addressed. Firstly, I have the issue of overlapping data. I use one-year, two-years and three-years ahead returns as well as one- and two years ahead volatility as the outcome variable in my regression, which leads to a host of econometric issues, which Hodrick (1992) and Ang and Bekaert (2007) describe. To solve this issue I take a conservative approach and delete the the intervening data, effectively creating annual, biannual and triannual observations. Hereby the first three quarters within a year are deleted, thus creating data that describes a year from beginning to end. Baron and Xiong (2016) do not provide any further information on which years exactly they select for the 2 and 3 year periods. This procedure can possibly have a strong effect on the outcome of the regression, especially for the 3 year periods as there are only around 300 observations left for this period. The algorithm I use to select these years works as follows: For each country separately it selects the last available datapoint (e.g. quarter 4 in 2013) and works its way down from there on (in this example selecting quarter 4 of 2010, quarter 4 of 2007 and onwards). For clarity, the matlab code is provided in the appendix. I use multiple period lengths as this gives insight in how the effects of credit expansion on excess returns evolve over time.

Secondly, as both explanatory and outcome variables may be correlated through time and place, shocks across a certain time period (e.g. global shocks) or persistent shocks within a country can cause correlation between residuals. Extra care should thus be taken in computing standard errors. This call for the the use of standard errors that allow correlation across time as well as countries. I therefore implement dually clustered standard errors, as derived in Thompson (2011). These are simply computed by adding the standard errors computed over a single cluster and then subtracting the general white standard errors.

3.1 Predicting Crash Risk

I start my analysis by replicating the procedure from Baron and Xiong (2016), who provide a conceptually simple framework to answer the question of whether credit expansion predicts an increased crash risk for bank equity. I estimate a probit regression with the occurrence of an equity crash as the dependent variable and credit expansion as well as the control variables as the explanatory variables.

$$Pr[Y_{i,t} = 1 | Predictor\ variables] = \Phi[\alpha_i^K + \beta^{K\prime}(predictor\ variables)_{i,t}] \tag{2}$$

Where Φ is the c.d.f. of the normal distribution and $Y_{i,t}$ is a future crash indicator, taking on the value 1 if an equity crash (defined as quarterly returns of -30%) happens in the next K years (K = 1, 2 or 3 years) and 0 otherwise. The regression is estimated for four different sets of predictor variables: only credit expansion, only bank dividend yield, credit expansion with bank dividend yield as control variable and credit expansion with all control variables. As a possible explanation for a significant coefficient might simply be increased volatility, I perform the same regression but with a boom indicator, which takes on the value 1 if the quarterly returns reach 30% over the next period. The outcome of this regression separates the actual downward risk from the possibility of increased volatility.

3.2 Predicting Mean Equity Returns

The second part of my analysis replicates the way Baron and Xiong (2016) answer the question of whether bank shareholders demand higher returns for the increased crash risk. They argue that if bank shareholders recognise this risk they will immediately lower shareprices, which leads to higher future returns in compensation for the elevated crash risk. To check this, a OLS panel regression with fixed country effects is used:

$$r_{i,t+K} - r^f_{i,t+K} = \alpha_i^K + \beta^{K\prime}(predictor\ variables)_{i,t} + \epsilon_{i,t} \tag{3}$$

which forecasts the K-year ahead excess returns of the equity index using a set of predictor values including credit expansion. We test whether the coefficient of credit expansion is different from 0. Because the model uses fixed effects, the focus is on the time-series dimension within countries.

As credit expansion may be correlated with excess returns through forces independent of the financial industry, I follow the approach in Baron and Xiong (2016) and correct for variables known to predict the time variation in the equity premium. The five main control variables are bank dividend yield, book to market, term spread, investment to capital and inflation. For a broader overview of the literature about variables that forecast the time variation in equity premium see Lettau and Ludvigson (2010). One intuitive extra control would be the market returns, as the bank equity returns most surely are highly correlated with market returns. My research question focuses on bank shareholders however, and why they hold on to bank equity during credit booms, even though the expected returns are negative. In this light, I do not first differentiate between market and financial returns but choose to solely look at financial returns.

3.3 Excess Returns Subsequent to Large Credit Expansions and Contractions

The next step in this paper focuses on the behaviour of bank equity returns subsequent to "large" credit booms and contractions. Whereas the previous regression focused on the general effect on credit expansion on bank equity returns, this analysis aims to differentiate between elevated risk appetite and overoptimism. Elevated risk appetite would not cause the average returns to go negative, as investors would simply accept more risk for the same reward but would still demand a positive return. Overoptimism would however mean that investors do not see an on average negative excess return coming. To accomplish this, we set up the following non-parametric model:

$$r_{i,t+K} - r^f_{i,t+K} = \alpha^K + \beta^{K\prime} 1_{credit\ expansion > x} + \epsilon_{i,t} \tag{4}$$

Where the threshold for credit expansion is $x \geqslant 50\%$ We then examine the expected returns that follow from the above formulation: $E(r_{i,t+K} - r^f_{i,t+K} | x = p) = \alpha^K + \beta^K$. This allows us to examine the actual magnitude of the effect a credit boom has on the expected returns of bank equity. This is equivalent to taking the mean returns for all observations for which credit expansion exceeds the threshold, but this formal setting allows me to compute dually clustered standard errors. Furthermore I apply the same method to examine the effect a credit contraction has on the expected returns, which results in the following formulation:

$$r_{i,t+K} - r^f_{i,t+K} = \alpha^K + \beta^{K\prime} 1_{credit\ contraction < x} + \epsilon_{i,t} \tag{5}$$

In this case a credit contraction is defined for $x \leqslant 50\%$

3.4 Sentiment Reflected by Credit Expansion versus Dividend Yield

As overoptimism is often present during credit booms, it is natural to wonder how exactly the optimism associated with credit expansions relates to the equity market sentiment. In this section I shed light on this subject by further relating the predictive ability of credit expansion to that of dividend yield. Due to the strong predictive power of dividend yield on equity returns, the present literature often sees dividend yield as a measure of the current market sentiment. Special interest goes to whether dividend yield and credit expansion thus amplify each others predictive ability.

Note however that credit booms and equity booms may be driven by a different kind of sentiment. The valuation of credit is especially driven by beliefs held about the lower tail of the distribution, whereas equity valuation is mainly dependent on the beliefs about the general shape of the distribution of future economic elements. Geanakoplos (2010) provides a framework in which credit cycles can be analysed by examining the difference in beliefs between creditors and borrowers. Simsek (2013) builds upon this framework and shows that a credit boom can occur in equilibrium when creditors and borrowers share a certain belief about the lower tail of the distribution of returns on credit. This optimism can then lead to borrowers becoming optimistic about the general shape of the distribution, which in turn leads to an equity boom.

This argument provides two points that are of particular interest for my analysis. First, a credit boom is mainly dependent on beliefs about the lower end of the distribution and can thus occur without being accompanied with an equity boom. This is confirmed by the negligible correlation between credit expansion and dividend yield, as shown by Baron and Xiong (2016). Also, dividend yield does not have the strong predictive power credit expansion does have when it comes to bank equity crashes. These arguments about bank dividend yield all contrast with credit expansion, providing a strong argument that credit expansion and the equity market are indeed associated with different sentiments. Second, when a credit boom occurs together with overoptimism in the equity market, the borrowers are able to use leverage to increase asset pricing, further decreasing the returns on bank equity. This would in turn thus increase the predictive ability of credit expansion.

This key insight provides the basis for my next regression, as credit expansion may interact with dividend yield to provide even stronger predictive ability, especially when dividend yield is low. This is examined through the following regression framework.

$$\begin{aligned} r_{i,t+K} - r^f_{i,t+K} = \alpha^K_i &+ \beta^{K'}_1 (credit\ expansion)_{i,t} \\ &+ \beta^{K'}_2 (bank\ dividend\ yield)_{i,t} \\ &+ \beta^{K'}_3 (interaction)_{i,t} \end{aligned} \tag{6}$$

The 'interaction' term in the equation is either the simple product of bank dividend yield and credit expansion at time t, or it is the product of credit expansion and the 4 quintile dummies of dividend yield. Note that I use only 4 quintile dummies, as adding the 5th dummy would not produce any different results and I am mainly interested in the effects of credit expansion when dividend yield is low. In accordance with the other regressions, the 1-year ahead, 2-year ahead and 3-year ahead forecasts are estimated.

3.5 Credit Expansion and Volatility

Baron and Xiong (2016) sharply analyse the effects credit expansion on the possibility of a bank equity crash. A possible and unexplored possible explanation of this is that credit expansion directly affects the volatility of bank equity. I therefore extend their analysis by regressing the volatility of bank equity on credit expansion. I do this by replacing the excess total returns in equation 3 with a measure for volatility of bank equity.

The main advantage of this simple approach is the ease of computation and interpretation. Beltrattia and Morana (2006) give a comprehensive overview of the disadvantages of this method and use a cutting edge econometric methods to solve these issues. He first filters the data by applying a long memory break factor model on the volatility and macroeconomic variables and then links these breaks, as well as the filtered volatilities, to each other. The application of this methodology to this specific problem would cause a number of problems however. Due to the panel nature of our dataset, a different break model would have to be estimated for each country. The limited data availability for daily returns of financial indexes then makes it hard to estimate the breaks within the time-series for each country. Also, Beltrattia and Morana (2006) explain the volatility in stock returns through the volatility in macroeconomic variables, not the absolute value, whereas I am mainly interested in whether a higher level of credit expansion causes a higher volatility. I thus set up a very intuitive regression, which results in the following functional form:

$$\sigma^2_{i,t+k} = \alpha^K_i + \beta^{K\prime}(credit\ expansion) + \epsilon_{i,t} \tag{7}$$

Where $\sigma_{i,t+k}$ is the average daily volatility in period $t+k$, where k is one quarter ahead, one year ahead or two years ahead. Again a country specific intercept is used, to account for different levels in stock volatility between countries. As Schwert (1989) explains, macroeconomic variables and the volatility of macroeconomic variables hardly explain the volatility in stock returns, thus the lack of control variables should not drastically alter my results.

4 Empirical results

This section describes the estimation results from the regressions as described in the previous section, with comments discussing the differences between the findings of Baron and Xiong (2016) and the results in the tables below.

4.1 Predicting Crash Risk

Table 1 estimates the regression

$$Pr[Y_{i,t} = 1|Predictor\ variables] = \Phi[\alpha^K_i + \beta^{K\prime}(predictor\ variables)_{i,t}] \tag{8}$$

All coefficients shown are the marginal effects conditional on a one standard deviation increase of credit expansion. The columns show the results for the regression on the crash dummy, boom dummy and the difference between these two regressions for the different forecast horizons. The row blocks present estimations results for the four different regressions: credit expansion without control variables, dividend yield without control variables, credit expansion with dividend yield as control variable and credit expansion with all control variables. We observe credit expansion indeed predicts a significant increase in crash risk, with a marginal effect of 1.7%, 3.3% and 4.5% for 1, 2 and 3-year ahead forecasts respectively. Credit expansion does not predict equity booms however, with marginal effects of 0.0%, 0.6% and 2.2%, non of which are significant. Adding control variables does not meaningfully change these results. Note that the marginal effects of credit expansion on crash risk increase with a longer forecast horizon, but that the effects on only the lower tail of the distribution, as represented by the difference between the marginal effects of the crash and boom regression, stay roughly the same. My findings are in line with those presented in Baron and Xiong (2016), though slightly less pronounced. They find that the marginal effects are 3.3%, 4.5% and 6.5%.

Table 1: Credit Expansion Predicts Increased Crash Risk

		1 year ahead			2 years ahead			3 years ahead		
		(1) Crash	(2) Boom	(3) Diff.	(1) Crash	(2) Boom	(3) Diff.	(1) Crash	(2) Boom	(3) Diff.
No controls	$\Delta(\frac{bank\ credit}{GDP})$	0,017***	0,000	0,017	0,033***	0,006	0,026	0,045**	0,022	0,023
		[2,723]	[-0,047]		[2,704]	[0,476]		[2,344]	[1,058]	
	N	989	989		479	479		303	303	
No controls	log(bank div. yield)	-0,013**	0,016**	-0,029	-0,027**	0,010	-0,038	-0,026	0,035	-0,061
		[-2,183]	[2,014]		[-2,132]	[0,669]		[-1,282]	[1,480]	
	N	989	989		479	479		303	303	
Bank div. yield as control	$\Delta(\frac{bank\ credit}{GDP})$	0,018***	-0,002	0,019	0,034***	0,006	0,029	0,047**	0,020	0,027
		[2,921]	[-0,238]		[2,847]	[0,409]		[2,424]	[0,956]	
	log(bank div. yield)	-0,014**	0,016**	-0,030	-0,029**	0,010	-0,039	-0,029	0,034	-0,062
		[-2,440]	[2,027]		[-2,323]	[0,623]		[-1,432]	[1,412]	
	N	989	989		479	479		303	303	
All controls	$\Delta(\frac{bank\ credit}{GDP})$	0,014**	-0,004	0,018	0,033**	0,008	0,026	0,036*	0,003	0,033
		[2,170]	[-0,525]		[2,531]	[0,521]		[1,748]	[0,125]	
	N	989	989		479	479		303	303	

*Notes: This table reports estimates specified in equation 2. The t-statistics shown in this table are computed using regular standard errors, as opposed to the dually clustered standard errors used in the remainder of the paper. This is due to the computational difficulty of computing these errors in combination with time constraints. *, ** and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.*

4.2 Predicting Mean Equity Returns

Table 2 shows the estimation results of regression

$$r_{i,t+K} - r^{f}_{i,t+K} = \alpha_i^K + \beta^{K\prime}(predictorvariables)_{i,t} + \epsilon_{i,t} \tag{9}$$

The different columns report the estimation results for regressions either with or without control variables. Columns (1-4) provide the results for the 1 year ahead returns, columns (5-8) provide the results for 2 years ahead returns and columns (9-12) provide the results for 3 years ahead returns. The first thing that catches the eye is that in nearly all cases, credit expansion has a significantly negative effect on credit expansion. For 1 year ahead forecasts, a one standard deviation increase in credit expansion predicts a 3.8% decrease in excess total returns. This effect more than doubles for 2-years ahead forecasts, in which case a one standard deviation increase predicts a 8,9% decrease in excess total returns. This is stronger than what Baron and Xiong (2016) find, which is 6.0%. Contrary to what they find however, this effect is only slightly larger for three-years ahead forecasts, being a 9.7% decrease in returns for a one standard deviation increase in credit expansion, where Baron and Xiong (2016) find a 11.4% decrease. This difference most likely is a result from the procedure for deleting the intervening observations. A difference as trivial as selecting either even or odd years in creating biannual observations can easily result in slightly different estimation results. As seen in the number of observations for each regression, I indeed select different observations for the regressions. Baron and Xiong (2016) use 957, 480 and 316 observations, whereas I use 989, 479 and 303 observations respectively.

The control variables do not meaningfully change the results of the estimations. In line with what Baron and Xiong (2016) find, the estimates change only slightly when the control variables are added to the regression. All control variables provide estimates which are in line with the existing literature, of which Baron and Xiong (2016) provide a comprehensive overview. Bank dividend yield has a positive effect on excess returns, which increases slightly when the forecast horizon expands. We do observe a relatively low R^2 for all regressions, which implies that it might be hard for policymakers to effectively combat recessions through legislations aimed at credit expansion and traders to devise effective strategies based on credit expansion.

Table 2: Credit Expansion Predicts Lower Mean Returns

	1 year ahead				2 years ahead				3 years ahead			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
$\Delta(\frac{bank\ credit}{GDP})$	-0,038*		-0,041**	-0,040**	-0,089**		-0,093***	-0,086***	-0,097**		-0,103***	-0,101***
	[-1,873]		[-2,122]	[-2,525]	[-2,371]		[-2,625]	[-3,280]	[-2,431]		[-2,735]	[-3,110]
log(bank div. yield)		0,051***	0,054***	0,054**		0,060**	0,067***	0,056*		0,062*	0,072**	0,048
		[2,789]	[3,042]	[2,566]		[2,498]	[2,599]	[1,861]		[1,873]	[2,215]	[1,288]
Inflation				-0,169				-0,034				0,100
				[-0,802]				[-0,101]				[0,205]
Term spread				0,026				0,044				0,029
				[0,910]				[0,937]				[0,675]
log(book to market)				0,039				0,090				0,116
				[1,042]				[1,249]				[1,377]
log(investment to capital)				0,019				0,040				0,028
				[0,540]				[0,651]				[0,533]
R^2	0,022	0,031	0,051	0,064	0,055	0,025	0,075	0,097	0,061	0,032	0,081	0,105
$Adj.R^2$	0,002	0,011	0,031	0,040	0,014	-0,018	0,033	0,047	-0,005	-0,037	0,012	0,024
N	989	989	989	989	479	479	479	479	303	303	303	303

*Notes: This table reports estimates specified in equation 3. t-statistics in brackets are computed from standard errors dually clustered on country and time. *, ** and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.*

4.3 Excess Returns Subsequent to Large Credit Expansions and Contractions

Table 3 estimates the regressions in equation 4 and equation 5. The various columns provide the estimations for the various thresholds of credit expansion, whereas the different rows provide the estimates for the expected returns given that credit expansion exceeds a certain threshold, a standard error for this coefficient, the adjusted R^2 as well as the number of observations for which credit expansion exceeds the threshold, all for the three different forecast horizons.

The expected returns slowly decline for the given thresholds. When credit expansion falls within its 95% quantile, the expected returns indeed become negative. When credit expansion exceeds the 98% quantile, the expected returns are -4% for 1 year ahead, -13.8% for two years ahead and -12.8% for three years ahead. Again we see that the effect becomes less strong for three years ahead. This is not in line with the result Baron and Xiong (2016) find however. They find a much more pronounced effect, with the expected returns being negative when credit expansion exceeds the 50% threshold. The current result thus do not underwrite their conclusion that the negative consequences of credit expansion indeed are the result of overoptimism instead of an elevated risk appetite. Again this difference can most likely be attributed to the selection of different observations, as I again notice different amounts of observations that exceed the thresholds, albeit it being only slight differences. Especially for the higher thresholds this can have a large impact, given the fact that only 13 observations are selected for the smallest threshold.

Table 3: Large Credit Booms Predict Negative Returns

		Expected excess returns subsequent to $\Delta(\frac{bank\ credit}{GDP})$ being:									
		$< 2\%$	$< 5\%$	$< 10\%$	$< 25\%$	$< 50\%$	$> 50\%$	$> 75\%$	$> 90\%$	$> 95\%$	$> 98\%$
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1 year ahead	$E(r_{i,t+K} - r^f_{i,t+K})$	0,127	0,188**	0,134*	0,113**	0,093*	0,033*	0,016	0,009	-0,005	-0,040**
		[1,005]	[2,187]	[1,873]	[2,203]	[1,708]	[-1,811]	[-1,398]	[-0,755]	[-0,930]	[-2,318]
	Adj. R^2	0,001	0,010	0,005	0,007	0,007	0,008	0,007	0,003	0,003	0,003
	# meeting threshold	42	68	108	236	473	510	280	128	86	39
2 years ahead	$E(r_{i,t+K} - r^f_{i,t+K})$	0,308	0,355**	0,299**	0,244***	0,197**	0,060**	0,026*	-0,004	0,015	-0,138
		[1,361]	[2,147]	[2,202]	[2,613]	[1,998]	[-2,049]	[-1,856]	[-1,453]	[-1,153]	[-1,589]
	Adj. R^2	0,006	0,017	0,015	0,019	0,019	0,020	0,017	0,011	0,004	0,011
	# meeting threshold	23	35	54	118	233	244	135	66	44	19
3 years ahead	$E(r_{i,t+K} - r^f_{i,t+K})$	0,523	0,503**	0,473***	0,294*	0,246***	0,122**	0,111*	0,021**	-0,018	-0,128**
		[1,288]	[2,098]	[2,581]	[1,945]	[2,597]	[-2,459]	[-1,755]	[-1,974]	[-1,587]	[-2,330]
	Adj. R^2	0,011	0,021	0,039	0,012	0,012	0,011	0,004	0,012	0,012	0,014
	# meeting threshold	9	17	34	71	149	153	80	40	27	13

*Notes: This table reports estimates specified in equation 4 and 5. t-statistics in brackets are computed from standard errors dually clustered on country and time. *, ** and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.*

4.4 Sentiment Reflected by Credit Expansion versus Dividend Yield

Table 4 estimates the regression

$$\begin{aligned} r_{i,t+K} - r^f_{i,t+K} = \alpha_i^K + \beta_1^{K'}(credit\ expansion)_{i,t} \\ +\beta_2^{K'}(bank\ dividend\ yield)_{i,t} \\ +\beta_3^{K'}(interaction)_{i,t} \end{aligned} \tag{10}$$

The row blocks (1-3), (4-6) and (7-9) estimate the regression for 1,2 and 3 years ahead respectively. The first row within each block estimates the regression for only credit expansion and bank dividend yield, the second row adds the simple interaction of credit expansion multiplied by bank dividend yield and the third row estimates the regression for credit expansion, bank dividend yield and the interaction term consisting of credit expansion multiplied by the quintile dummies of bank dividend yield. In the last equation, only the first four dummies are added, the fifth quintile is left for credit expansion to capture.

The first interesting result is the coefficient of the interaction term, presented in columns (2), (5) and (8). The effect of the interaction term is 0.9%, 3.1% and 2.4% for 1, 2 and 3 years ahead forecasts respectively. Though it is only significant over a 2-year horizon, the positive coefficient is in line with what I expected. A one standard deviation increase in credit expansion along with a one standard deviation decrease in dividend yield causes the interaction term to take on the value of -1. A positive coefficient thus presents the added predictive power of credit expansion when dividend yield is low, over the predictive power already presented by credit expansion and dividend yield separately.

I further expand this argument by looking at the coefficients of the interaction terms with quintile dummies. For the 1 year ahead forecasts, the effect of credit expansion is especially strong when dividend yield is in its third quintile (-3.3%). When dividend yield is in its first quintile, the effect of credit expansion is also strong at -2.2%. For the 2 year ahead forecasts, the predictive power of credit expansion is especially strong when dividend yield is within its first three quintiles, at -9%, -7.6% and -9.9% respectively, in addition to the predictive ability of -3.9% already captured by the coefficient for credit expansion. For the 3 years ahead forecast some oddities start to appear. Whereas the added predictive ability of credit expansion is only -6% when dividend yield is in its first quintile, it is a whopping -23.3% when dividend yield is in its second quintile. This result also deviates from the results obtained by Baron and Xiong (2016), who find a much smoother effect. As with all other differences between their and my results, this occurs at the 3 year ahead forecasts. This is probably again best explained by the fact that the 3 year ahead forecasts entail the least observations and that there is more opportunity to select different observations when only one in every three years is selected. Overall I can conclude that credit expansion has more predictive power when dividend yield is low, where low is best defined as within the first three quintiles.

Table 4: Predictive Ability of Credit Expansion is Higher when Dividend Yield is Low

	1 year ahead			2 years ahead			3 years ahead		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta(\frac{bank\ credit}{GDP})$	-0,041**	-0,040**	-0,027	-0,093***	-0,090**	-0,039	-0,103***	-0,102***	-0,036
	[-2,122]	[-2,029]	[-0,941]	[-2,625]	[-2,551]	[-0,773]	[-2,735]	[-2,895]	[-0,606]
log(bank div. yield)	0,054***	0,055***	0,054***	0,067***	0,073**	0,069**	0,072**	0,073**	0,070**
	[3,042]	[3,032]	[2,958]	[2,599]	[2,529]	[2,522]	[2,215]	[2,434]	[2,203]
$\Delta(\frac{bank\ credit}{GDP})$ x ...		0,009			0,031*			0,024	
log(bank div. yield)		[0,813]			[1,817]			[0,965]	
$\Delta(\frac{bank\ credit}{GDP})$ x ...									
div. yield first quintile			-0,022			-0,090			-0,060
			[-0,669]			[-1,197]			[-1,327]
div. yield second quintile			-0,014			-0,076			-0,233**
			[-0,447]			[-1,151]			[-2,017]
div. yield third quintile			-0,033			-0,099			0,006
			[-0,950]			[-1,474]			[0,073]
div. yield fourth quintile			-0,003			0,008			-0,050
			[-0,083]			[0,085]			[-0,580]
R^2	0,051	0,053	0,053	0,075	0,084	0,087	0,081	0,085	0,115
$adj.R^2$	0,031	0,031	0,028	0,033	0,040	0,036	0,012	0,013	0,035
N	989	989	989	479	479	479	303	303	303

*Notes: This table reports estimates specified in equation 3. t-statistics in brackets are computed from standard errors dually clustered on country and time. *, ** and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.*

4.5 Credit Expansion and Volatility

Table 5: Estimation results for the effect of credit expansion on volatility

	1 quarter ahead	1 year ahead	2 years ahead
credit expansion	-0,000062	0,000029	-0,000107
	[-0,694]	[0,569]	[-0,406]
R^2	0,044	0.044	0,153
Adj. R^2	0,027	-0,031	-0,001
N	1204	274	131

Table 5 estimates the following regression:

$$\sigma^2_{i,t+k} = \alpha_i^K + \beta^{K\prime}(credit\ expansion) + \epsilon_{i,t} \tag{11}$$

The estimated coefficients for the effect credit expansion has on the volatility of bank equity index returns is shown in the table above. For the 1 quarter ahead volatility, the coefficient is -6.2×10^{-5}, and is not significantly different from 0. For the 1 year ahead average daily volatility, the coefficient is 2.9×10^{-5} and for the 2 year ahead average daily volatility the coefficient is -1.07×10^{-4}. In both cases the coefficient is still not significant, mainly because the amount of observations rapidly declines for the longer forecast horizons. The observed adjusted R^2 is also negative, signaling that credit expansion has little predictive power for the volatility of bank equity. This is in line with the present literature on the predictability of volatility using macro-economic variables.

5 Conclusion

Through the use of five different regressions, I have analysed the effects credit expansion has on bank equity. The first regression estimated the predictive power of credit expansion on the risk of bank equity crashes. Credit expansion proved to significantly increase the risk of bank equity crashes.

The second regression answered the question of whether investors demand higher returns for bank equity given that credit expansion predicts an increased crash risk through checking whether credit expansion predicts higher returns. An increase in credit expansion actually predicted a decrease in the total excess returns of bank equity, fueling the idea that investors neglect this crash risk.

Another possible explanation for the fact that an increase in credit expansion predicts lower bank equity returns could be that investors simply have an elevated risk appetite. In this case, investors would still demand positive returns however. To differentiate between the two options, a third regression was estimated in which the expected returns given that credit expansion exceeded a certain threshold where computed. Contrary to what Baron and Xiong (2016) find, my estimation results do not back this hypothesis as strongly. Only after very large credit expansions do the expected returns become negative.

To give insight in the sentiment associated with credit expansion, I estimated a fourth regression that aimed to distinguish between the sentiment associated with credit expansion and that of the equity market, measured by dividend yield. The positive coefficient associated with the interaction term of credit expansion and dividend yield proved that credit expansion and dividend yield amplify each other, with the predictive ability of credit expansion increasing when dividend yield is low. In other words, when the market sentiment is high, credit expansion proved to be a better predictor of negative returns.

To add to this analysis, I proposed a very simple and intuitive way to orientate on the possibility that credit expansion adds to the volatility of bank equity. This did not provide any significant results however, making it likely that credit expansion does indeed effect the returns of bank equity and not necessarily its volatility.

6 Discussion

In this section I briefly discuss the weaknesses of the arguments made in this paper. It is structured in the same manner as the paper itself, discussing each regression separately.

The first part of the analysis concerns the effect of credit expansion on the crash risk of bank equity. A crash is defined as quarterly returns exceeding -30%. One might argue that -30% is a fairly arbitrary value. Baron and Xiong (2016) defend against this by performing a quantile regression on the returns of bank equity and thereby analysing the effect credit expansion has on the quantile levels of the returns on bank equity. As their findings are in line with the results of the probit regression on crash risk, we can conclude that the results are robust to changing this definition of an equity crash. They also note that similar (unreported) results hold for -20% and -25%.

Baron and Xiong (2016) also find much higher marginal effects in their regression; 2.7% for one year ahead forecasts and 5.4% for three year ahead forecasts against the 1.7% and 4.5% that I find. Oddly enough, the marginal effects we find for 2 year ahead are virtually the same; 3.5% and 3.3%. My findings suggest a fairly linear relations between added crash risk and forecast horizon, whereas their results do not. They also find a negative coefficient for the marginal effect of credit expansion on equity booms, whereas I find insignificantly positive coefficients. This discrepancy in results is thus best explained by the fact that they are not significantly different and thus may as well be different iterations of the same thing.

The second part of this paper concerns the predictive ability of credit expansion on bank equity returns over subsequent years. Baron and Xiong (2016) provide a comprehensive description of issues that could arise with the empirical framework that is chosen to answer the question at hand, such as the choice between market dividend yield and high betas in the financial industry, which both do not have significant effects on their results. The most interesting oddity of my results is the fact that I find a lower coefficient in 3 years ahead forecasts (-0.097 against -0.114) whereas the other coefficients I find are higher. Baron and Xiong (2016) note that the coefficient levels off for forecast horizons longer than three years. This seems thus seems to occur earlier in my findings. Note that in some of my other unreported findings, the coefficient for three year ahead forecasts proved to be sensitive to the choice of quarters around which to center a year, where there were only changes in magnitude, not in significance or sign.

The third part of my analysis yielded the results that deviated most from those obtained by Baron and Xiong (2016). Whereas they find that the expected returns on bank equity become negative when credit expansion falls within the upper 50% quantile or higher, I find that this only happens when credit expansion falls within its upper 95% quantile or higher. We do find roughly the same amount of observations for which credit expansion exceeds a certain quantile and the results are easily checked by taking the average returns of the observations for which credit expansion exceeds that quantile, as this is equivalent to the results of the regression, which leaves little room for errors. This means the results obtained are apparently very sensitive to what years are selected in the dataset. Further research on the used dataset could yield better explanations for these discrepancies.

Baron and Xiong (2016) note that the results for the different quintiles in the fourth regression "increase somewhat monotonically" when looking at observations for which dividend yield falls in higher to lower quintiles. This is certainly not echoed by the results I find, with the coefficients for the quintile dummies mostly varying from coefficient to coefficient and not showing a general pattern. This is especially true for the results of the 3 years ahead forecasts, which brings me to the next point. Baron and Xiong (2016) go to great lengths to show their research is robust to small changes within their empirical framework. No stone is left unturned when it comes to the internal validity of their paper, yet little information is given on how these results fare when different data is selected. Given the fact that most data currently available about the economies of the developed world is used to construct a mere 316 observations for 3 year ahead forecasts, one naturally wonders how selecting different data would influence their results. The lack of information about how these 3 year ahead forecasts were put together thus made their results hard to replicate.

Finally, the fifth regression explored the possibility of credit expansion affecting the volatility of bank equity. Sadly the time consuming process of collecting and formatting data limited me to implementing a very crude model. Beltrattia and Morana (2006) give a comprehensive overview of the difficulties of modelling volatility. Implementing their methodology on this problem could yield different results than those I obtained. Related to this is the technical difficulty in modelling volatility that comes with its distinct autoregressive properties. Daily volatility usually exhibits properties captured in a GARCH-model and although this is less important when looking at averages spanning an entire quarter, these theoretical properties are insufficiently highlighted by the current model.

7 Appendix

Table 6: Summary statistics for the average daily volatility of financial indices for 20 countries over quarterly periods

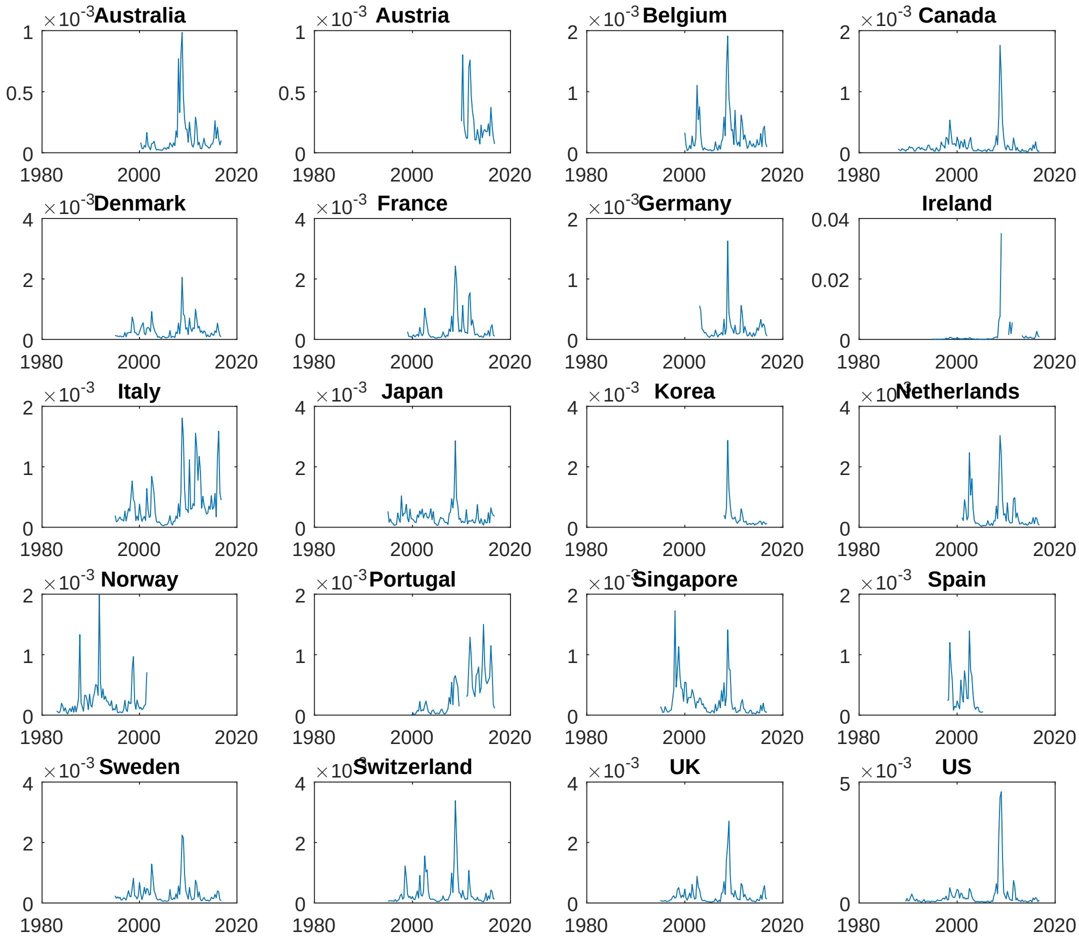
	Australia	Austria	Belgium	Canada	Denmark
mean	1.310×10^{-4}	2.522×10^{-4}	2.683×10^{-4}	1.213×10^{-4}	2.918×10^{-4}
min	1.971×10^{-5}	7.199×10^{-5}	2.925×10^{-5}	1.361×10^{-5}	3.421×10^{-5}
max	9.854×10^{-4}	8.020×10^{-4}	1.913×10^{-3}	1.758×10^{-3}	2.053×10^{-3}
median	7.086×10^{-5}	1.825×10^{-4}	1.385×10^{-4}	6.520×10^{-5}	2.239×10^{-4}

	France	Germany	Ireland	Italy	Japan
mean	3.437×10^{-4}	1.867×10^{-4}	1.176×10^{-3}	3.794×10^{-4}	3.628×10^{-4}
min	4.492×10^{-5}	3.317×10^{-5}	3.164×10^{-5}	2.695×10^{-5}	6.307×10^{-5}
max	2.425×10^{-3}	1.628×10^{-3}	3.517×10^{-2}	1.805×10^{-3}	2.860×10^{-3}
median	1.699×10^{-4}	1.092×10^{-4}	2.812×10^{-4}	2.557×10^{-4}	2.801×10^{-4}

	Korea	Netherlands	Norway	Portugal	Singapore
mean	3.338×10^{-4}	4.278×10^{-4}	2.377×10^{-4}	3.354×10^{-4}	2.325×10^{-4}
min	7.576×10^{-5}	3.238×10^{-5}	2.044×10^{-5}	1.057×10^{-5}	2.167×10^{-5}
max	2.875×10^{-3}	3.030×10^{-3}	1.988×10^{-3}	1.500×10^{-3}	1.727×10^{-3}
median	1.837×10^{-4}	2.050×10^{-4}	1.561×10^{-4}	1.749×10^{-4}	1.236×10^{-4}

	Spain	Sweden	Switzerland	UK	US
mean	3.580×10^{-4}	3.136×10^{-4}	3.378×10^{-4}	2.751×10^{-4}	3.037×10^{-4}
min	4.696×10^{-5}	5.385×10^{-5}	4.348×10^{-5}	2.699×10^{-5}	2.973×10^{-5}
max	1.393×10^{-3}	2.242×10^{-3}	3.384×10^{-3}	2.706×10^{-3}	4.599×10^{-3}
median	2.387×10^{-4}	1.907×10^{-4}	1.529×10^{-4}	1.576×10^{-4}	1.247×10^{-4}

Figure 1: Graphs depicting the volatility of different countries over time



Matlab function used for computing K-year ahead forecasts

```
function [data_out, years_out, quarters_out, break_indices] = ...
    select_only_quarters(data, years, quarters, quart_to_select, years_ahead, countryindices)

year_indices = [];

%remove unnecessary years
if(years_ahead > 1)

    for j = 1:20
        temp_years = years(countryindices{j});
        if (temp_years/years_ahead) == floor(temp_years/years_ahead)
            d = 0;
        elseif ((temp_years+1)/years_ahead) == floor((temp_years+1)/years_ahead)
            d = 1;
        else
            d = 2;
        end

        temp_year_indices = countryindices{j}((temp_years+d)/years_ahead == floor((temp_years+d)
        year_indices = [year_indices,temp_year_indices];
    end
    years = years(year_indices);
    quarters = quarters(year_indices);
    data = data(year_indices,:);
end

%select quarter and remove all other observations
quart_indices = find(quarters == quart_to_select);
data_out = data(quart_indices,:);
years_out = years(quart_indices);
quarters_out = quarters(quart_indices);

%find breaks
previousobservations = lagmatrix(years_out,1)+years_ahead;
break_indices = find(previousobservations ~= years_out);
```

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