Is Risk Mispriced in a Credit Boom?*

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Abstract

I review and extend the literature on credit booms and asset pricing by examining the pricing of risky assets (equities, housing, and credit) during a credit boom in an international panel spanning 140 years. Credit booms are associated with low risk premiums (credit growth negatively forecasts excess returns), but are also associated with more risk in terms of higher likelihood of a left tail events in returns and GDP and higher probability of a financial crisis. Thus, the effective pricing of risk (e.g., risk aversion) needs to be quite low to rationalize asset price behavior in credit booms. While there is no definitive evidence of mispricing, typical theories of varying risk-aversion don't easily reconcile the evidence, suggesting a role for risk being *underpriced* in credit booms. Models that suggest mispricing through extrapolation from past risk appear promising as credit booms are preceded by low risk in asset markets even though they forecast high future risk. I consider the idea that agents do not take into account endogenous risk through their actions of taking higher leverage in credit booms.

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1 Introduction

Credit booms tend to precede financial crises (Jordà *et al.*, 2011, Schularick and Taylor, 2012). A key question is how expectations of agents and their attitude toward risk may drive credit booms. This paper studies how those expectations and attitudes toward risk may manifest themselves in asset prices. I take the asset pricing framework that expected risk premiums should equal quantity of risk times price of risk (e.g. "effective risk aversion") and then study how each of these channels move in a credit boom. The main conclusion, echoing and summarizing a broader literature, is that risk premiums fall in credit booms while quantity of risk appears to rise, suggesting a very low price of risk.

I begin by summarizing, and then extending, the existing literature on credit booms, asset prices, and financial crises. In an international panel spanning 17 countries over 140 years, credit growth negatively forecasts excess returns on housing and equity returns, meaning risk premiums are low in credit booms. The relationship is economically large: a one standard deviation increase in credit growth is associated with about a 2% lower expected excess return for equities and 1-1.5% lower return for housing. Thus, as a broader literature has found, asset prices appear to be significantly elevated in credit booms and in the run up to financial crises so that expected returns going forward are low. Krishnamurthy and Muir (2018) document low credit spreads in the years preceding a financial crisis (about 25% lower than average levels), and show that low spreads actually positively forecast crises. Baron and Xiong (2017) find that credit growth significantly negatively forecasts bank equity returns, suggesting mispricing of bank equity in the lead up to crises. Brunnermeier *et al.* (2019) find that high equity and real estate prices rises appear to contribute to increased systemic risk. López-Salido *et al.* (2017) find high credit growth negatively predicts returns on corporate bonds.

Next, I analyze the quantity of risk channel during credit booms. High credit growth predicts financial crises (Jordà *et al.*, 2011, Schularick and Taylor, 2012) as well as drops in economic activity (e.g., GDP) and it also predicts heightened probability of a significant decline in asset values for multiple broad asset classes, consistent with the work Baron and Xiong (2017) who focus on bank stocks. This is important because it signifies that the low risk premiums are not easily explained by low future risk in asset returns, i.e., by the quantity of risk channel. Taken together, low risk premiums and higher risk suggest that the pricing of risk (effective risk aversion in the economy) appears very low in credit booms. This is an important feature that equilibrium asset pricing models should aim to match.

Mispricing is always difficult to cleanly document, as one needs a model of "correct" prices (Fama, 1970).[1] This paper takes several views to think about the possibility that risk is mispriced – and in particular *underpriced* during credit booms. However, there is no definitive evidence of mispricing without taking a stronger view on agents effective risk aversion which may vary through time (e.g., low enough risk aversion from agents can rationalize a higher quantity of risk and lower risk premium). Thus, a main open question is whether this lower effective risk aversion is due to belief distortions (so that it reflects mispricing), or whether it is consistent with rational models of risk pricing with time-varying risk aversion. In my analysis, there is no "smoking gun" to rule out stories of time-varying risk aversion without more structure: while average returns are quite low when credit growth is high they do not appear robustly negative. Hence, there is still some positive price of risk that can rationalize these episodes so it is difficult to say definitively that there is a clear underpricing of risk. Note that this conclusion differs from Baron and Xiong (2017) who reliably forecast *negative* returns for bank stocks when credit growth is above a specified threshold (which appears inconsistent with any positive price of risk, and hence clearly indicates mispricing), but this is because I consider equity returns and housing returns broadly rather than just bank stocks. However, the low risk premiums do not seem to be driven by standard models with time-varying risk aversion (e.g., Campbell and Cochrane (1999)). This leads me to explore what factors drive credit booms and if they are instead consistent with more behavioral views of mispricing.

A main result is that low past risk in asset returns is positively associated with credit booms despite the fact that booms predict increased future risk. Putting these facts together paints a potential story for the financial crisis episode and credit boom bust cycle in credit, though I don't argue it is the only potential story. Low measures of risk in the past (e.g., low volatility of asset returns) may lead agents to view the world as safe and be overoptimistic about risk going forward resulting in low premiums. In doing so they may take excessive leverage resulting in a credit boom and high asset prices. The result of this collective action is increased fragility through increased leverage and can result in higher risk ex-post. This would explain why low past risk predicts credit booms, which are associated with low risk premiums, but predict increased quantity of risk going forward (see Gennaioli *et al.* (2012), Greenwood *et al.* (2019), and Moreira and Savov (2014) for models along these lines and similar arguments in Minsky (1977), Kindleberger and Aliber (2011), and Reinhart and Rogoff (2009)). However, as with the rest of the results in this paper, the results are meant to be suggestive and I do not claim the regressions show low volatility causes credit growth

[1] See Santos and Veronesi (2018) for an example where many results can obtain in a frictionless setting with time-varying risk aversion.

(see Gomes *et al.* (2018a) or Santos and Veronesi (2018)).

These results relate to the work on credit growth and crises more broadly.[2] However, the focus here is specifically on asset price movements associated with credit growth, most closely in the vein of Baron and Xiong (2017), Brunnermeier *et al.* (2019), López-Salido *et al.* (2017), and Krishnamurthy and Muir (2018). The closest paper is Baron and Xiong (2017) who focus mostly on pricing of bank stocks, though I extend much of their analysis to the broader equity market, real estate returns, and credit markets. Because this is a short article and this literature is large, many more relevant references are omitted to save space.

The paper proceeds as follows. First, I outline a general framework for thinking about asset prices as linking risk premiums, quantity of risk, and price of risk in Section 2. Section 3 describes the data. Section 4 documents empirically that credit growth is associated with low risk premiums and higher future risk. I then revisit the price of risk from the perspective of standard models and consider which models best match the facts. Section 5 concludes.

2 Framework

To better consider mispricing of risk, we need to start with a benchmark model of how agents should price risk. For simplicity, the analysis can't consider all possible models of risk pricing, though still my goal is for a simple benchmark framework that captures the main features of such models. I begin with a broad framework where risk premiums are determined by quantity and price of risk. That is,

$$(Risk\ Premium)_t = (Quantity\ of\ Risk)_t \times (Price\ of\ Risk)_t \tag{1}$$

For example, in a classic mean-variance representative agent equilibrium, this equation would be: $(Risk\ Premium)_t = \sigma_t^2 \times \gamma$ where γ is the agents risk aversion and σ_t^2 is the conditional variance of returns and measures the quantity of risk (see Merton (1980)). The prediction is that, all else equal higher quantity of risk or higher risk aversion should lead to higher risk premiums.

For $(Quantity\ of\ Risk)_t$ I consider downside risk, or risk of a crash, as the main object of interest, that is, the chance of significant drops in asset returns going forward. The crash probability captures "left tail" events and is the object of interest in models with rare disasters (Barro, 2006, Wachter, 2012), though it is also related to volatility or variance. I

[2] A non-exhaustive list includes (Bordo *et al.*, 2001, Cerra and Saxena, 2008, Reinhart and Rogoff, 2009, Claessens *et al.*, 2010, Bordo and Haubrich, 2012, Jordà *et al.*, 2011, Schularick and Taylor, 2012, Romer and Romer, 2014) studying the aftermath of financial crises and (Schularick and Taylor, 2012, Jordà *et al.*, 2011, Baron and Xiong, 2017, López-Salido *et al.*, 2017, Mian *et al.*, 2017) studying credit growth.

focus on real economic activity (e.g., GDP) and asset returns being below roughly the 10th percentile for each asset class as an indicator of quantity of risk. One can look at lower percentiles as well though this gives me substantially more power in my tests. This is also strongly related to volatility of asset returns as well so I choose to focus mainly on this indicator for the analysis.

Admittedly, the object $(Price\ of\ Risk)_t$ is even harder to assess without significantly more structure due to the joint hypothesis problem (Fama, 1970). That is, we need a null hypothesis on the pricing of risk to make progress. In the most basic economic models (e.g., representative agent models with CRRA preferences), the object $(Price\ of\ Risk)_t$ is equal to a fixed constant γ and does not vary through time. I argue that this can't be consistent with the credit boom facts because it appears both that risk premiums fall and quantity of risk, if anything, rises. However, many models feature time-varying risk aversion. I characterize the pricing of risk behavior consistent with the data and then see how much progress can be made by comparing this to predictions of such models. Many rational models predict a positive association between the quantity of risk and risk aversion which is inconsistent with the evidence in credit booms.

3 Data description

Data are from Jordà *et al.* (2017) who construct a database on macro quantities on credit and GDP together with returns for housing and equities as well as dividend yields (dividend to price) and rental yields (rent to price). The database covers 17 advanced economies since 1870 on an annual basis (see http://www.macrohistory.net/data/). I omit summary statistics or other descriptive statistics to save space. The data set also includes dates for financial crises – periods where the banking system suffered large losses, bank runs, and bank failures. Return data are winsorized at the 0.1% level. This has implications only for equity returns where the non-winsorized data show one or two major outliers (in particular, Germany in the early 1920's shows equity returns of several thousand percent which I remove).

I study excess returns as the (log) returns minus the (log) risk free rate taken as the short term interest rate in each country. Excess log returns are of interest because this measures the risk premium, but practically this also deals with the fact that returns are given in nominal units and are in different currencies and the log excess returns net these effects out. I also construct real per capita GDP growth and define credit to GDP as the log of total loans divided by GDP (both nominal). I consider three and five year changes in credit to GDP as measures of credit growth, that is, of indicators that credit in the economy is growing.

I supplement this data with data on credit spreads from Krishnamurthy and Muir (2018), though this data does not allow me to construct credit returns. The main reason is that I don't have data on observed defaults so we can't assess the actual returns from spreads alone. Still, I will use the spread as a proxy for expected returns in keeping with a longer literature that finds variation in credit spreads is driven more by risk premiums rather than default (see Giesecke *et al.* (2012)). Another limitation of the credit spread (and quantity data) is that is at the aggregate level and doesn't allow me to study cross-sectional dispersion in credit quality Gomes *et al.* (2018b).

In all regressions below I include a dummy for pre and post war data, that is, I include a dummy that takes the value of 1 after 1945. This is important in capturing different means of returns and differences in economic growth rates before and after this period. Further, I include country fixed effects to account for cross country differences in means. Finally, I drop the major world wars (1914-1918 and 1939-1945) from the analysis.

4 Empirical Analysis

4.1 Predicting Risk and Returns in Credit Booms

Table 1 regresses future excess returns for housing and equities on lags of credit growth. I use cumulative returns over three years for both housing and equities though one year returns give qualitatively similar results. I construct credit to GDP following Schularick and Taylor (2012) and consider the level of credit to GDP, as well as the three and five year changes in this variable. In addition, I consider controls for the predictive regressions which include the equity dividend yield and housing rental yield (rent to price) as both are known forecasters of returns, as well as country fixed effects and a dummy for the post war period (post 1945). The point here is not to say that credit growth drives out these predictors but to assess if it has some additional forecasting power beyond these variables.

In both cases, credit growth strongly negatively forecasts returns. That is, credit booms are followed by lower than average stock and housing returns. This result is robust to including the asset class predictors (equity dividend yield and housing rental yield). Returns are in percent and credit growth is standardized in all cases, so the coefficients represent the drop in risk premiums from a one standard deviation change in credit growth. The results are economically large: for equity returns a one-standard deviation change in credit growth implies about 2% lower excess returns while for housing the coefficient implies about a 1%

drop (unconditional excess equity and housing returns are both around 5% so this is high relative to the mean).

While intriguing, nothing in these regressions rules out, or even addresses, a basic risk-based story. Perhaps credit booms predict low returns because they also predict low risk. That is, if periods of high credit growth are associated with *safer* future returns then it makes sense that investors would require low premiums for holding these assets. In the language of the framework earlier, perhaps the quantity of risk drops to explain the fall in risk premiums, leaving the pricing of risk unchanged.

Table 2 indicates that this is not the case. Panel A runs regressions of financial crisis indicators on credit growth, confirming the findings of (Jordà *et al.*, 2011) who find high credit growth predicts financial crises (similar results are found using probit or logit specifications though I stick to OLS for this analysis). Thus credit growth is associated with high future macroeconomic risk, possibly due to fragility created by leverage in the credit growth episode. Panels B and C run regressions of future crashes (a crash in any of the next three years) in equity and housing returns over the following three years (again, using one year results produces qualitatively similar results). I define "crashes" for equities as a dummy indicator of returns being below -20% in a given year. This occurs about 10% of the years in my sample, so should not be viewed as an abnormally large crash. Similarly, a housing crash is defined as housing returns being below -5% – the lower threshold is due to the lower standard deviation of housing returns, though this definition also means a housing crash occurs about 10% of the years in the sample. More severe crashes give fairly similar results though the tradeoff is there are then fewer observations.

A one standard deviation increase in credit growth suggests a crash over the next three years is about 10% more likely (slightly smaller for equities and slightly larger for housing, depending on controls). These results echo the findings in Baron and Xiong (2017) who use similar dummies to assess credit growth on crash risk and find elevated probability of a crash following high credit growth. We thus see for both housing and equity returns that credit growth has information for the left tail of the return distribution: a crash is more likely if credit growth is high. This gets directly at the rare disaster type story, and suggests that low risk premiums during credit booms are not only reflecting the likelihood of a crash. Of course, it does not say that time-varying risk premiums more generally (e.g., outside credit booms) don't relate to agents view of disaster probabilities.

Table 3 repeats this analysis using declines in consumption and GDP over the next three years where a significant drop is defined as consumption or GDP growth being below 2.5% (again this threshold is chosen to represent about the 10th percentile for both series). For

GDP, higher credit growth signifies an elevated chance of a decline. For consumption the results also go in the same direction though they are notably noisier.

Taken together, both results indicate credit booms are associated with lower average returns but effectively more risk in terms of a more spread out distribution of returns with increased probability of a downside event in terms of returns, a financial crisis, or a decline in consumption or GDP. These results suggest a standard risk story alone is unlikely in driving the predictability results, one needs variation in the pricing of risk or risk aversion to account for these facts.

I next summarize the behavior of credit spreads during credit expansions and preceding crises. I then turn to risk premium stories where the pricing of risk, rather than its quantity, varies over time due to changes in effective risk aversion of agents.

4.2 Credit Spread Data

I use data from Krishnamurthy and Muir (2018) on credit spreads for the same set of countries, though the dataset is much more limited then what is presented here. The data constructs the equivalent of riskier (higher yield) bonds over government bonds for the same set of countries, thus giving a sense of the pricing of credit risk.

I provide evidence straight from the Tables in Krishnamurthy and Muir (2018) which in many ways echoes the above findings, and is presented in Table 4. First, credit spreads before a financial crisis are low, around 23% lower than their average as shown in the table. Importantly, we control for a post crisis dummy as well which is equal to 1 in the five years after a crisis. This means the pre-crisis dummy should be judged relative to other "normal times" and is not mechanically low because spreads during crises are high.

Second, the flip side of this result is that low spreads (in conjunction with high credit growth) are a significant predictor of financial crises. That is, periods where credit grows strongly and risk premiums in credit markets are low suggest significantly higher chance of a crisis going forward.

This is notable for a few reasons. First, though we don't observe data on realized defaults, it is reasonable to assume that they increase if anything during financial crises. That implies that the low spreads before a crisis are not easily reconciled by the expected default channel. This implies – just as in the other asset price data seen so far, that the credit risk premium is low and the quantity of risk is high in the lead up to a crisis. This would imply that the pricing of risk is especially low.

Second, credit spreads appear to decouple from fundamentals in these periods. More specifically, in our paper we regress credit spreads regressed on GDP growth and other variables that track the macroeconomy and correlate with spreads. We take the residual from this regression as the "abnormal" spread. The information in predicting crises seems to come from the abnormal spread piece – that is, crises are especially likely when abnormal spreads appear low. Again, this suggests a pricing of risk channel that is distinct from the usual channels we consider driving macroeconomic measures of risk pricing.

4.3 Pricing of Risk in Credit Booms

Taken together, these results suggest that the object $(Risk\ Premium)_t$ is lower during credit booms. Further, the evidence is that the object $(Quantity\ of\ Risk)_t$ does not appear to be lower during credit booms, and in most of the specifications appears to be higher if anything. Thus, from the framework $(Risk\ Premium)_t = (Quantity\ of\ Risk)_t \times (Price\ of\ Risk)_t$, it appears that the price of risk must be substantially lower in credit booms. This is important because it indicates that one can not easily view asset price behavior in these episodes from the view of a constant risk aversion type of model.

Is this low pricing of risk rational or does it reflect "mispricing" in the sense that risk is underpriced during these episodes? This is hard to fully gauge as one needs a model for what the price of risk should be (the "Joint Hypothesis Problem" Fama (1970)). A leading theory is the habits model (Campbell and Cochrane (1999)) where risk premiums are low when the economy is booming, and specifically when consumption growth in the past has been high. If credit booms are associated with economic booms in general, it is therefore natural that risk premiums could be low in such episodes.

To assess this issue, I next see whether the results change if I include past GDP growth or consumption growth in the regressions as a proxy for the time-varying risk aversion coming from a Campbell and Cochrane (1999) model. In that model, surplus consumption (defined as cumulative consumption relative to a habit level) drives risk premiums where high surplus consumption implies low effective risk aversion (though it is worth noting in the main calibration of their model this also implies low asset volatility going forward which we don't appear to see in credit booms). I consider cumulative GDP growth over the past five years as a control in the predictive regressions (past lags beyond this don't appear to change the results, nor does including lags of GDP growth individually by year). This is imperfect, though the results indicate that credit growth continues to provide about the same forecasting power as before (results are omitted to save space, though see Muir (2017) for a more in depth treatment using consumption data rather than GDP and considering other models with time-varying risk aversion). Hence, there is no indication that the price of risk is low in credit booms simply because the economy has been strong in the credit boom episodes. It is also worth nothing that these predictions are at odds with models of intermediation and financial frictions driving risk premiums (He and Krishnamurthy, 2013) because those models generally predict higher risk premiums when the likelihood of a crisis is high. Those models do, however, describe the behavior of risk premiums *during* a financial crisis episode well (see Muir (2017)).

A full answer to the mispricing story would make even weaker assumptions on the rational pricing of risk. In particular, Baron and Xiong (2017) use the weak restriction that in standard asset pricing models $(Price\ of\ Risk)_t \geq 0$. That is, risky assets always deserve a weakly positive premium. They then show that high thresholds of credit growth (e.g., above the 95th percentile) actually forecast negative returns, violating the above inequality. However, they show this primarily for bank stock returns. In the housing and equity return data that I have available this prediction doesn't appear to be true. If I condition on credit growth being above 1.5 standard deviations above its mean (but condition on no other factors), I find mean returns for stocks to be about -1% (not statistically significant) and for housing to be about 2%, where both have unconditional average returns near 5%. Thus, there is evidence that mean returns are quite low following a credit boom and even negative for equities. Further, given the increased risk associated with these episodes, this would imply a much lower price of risk than average. However, it does not provide any "smoking gun" evidence for mispricing since the average returns are not reliably negative in a statistical sense.

In summary, I don't find direct evidence for the idea that the price of risk inferred from models of time-varying risk aversion explains why credit growth predicts returns with a negative coefficient. However, using weak restrictions on prices of risk does not lead me to the conclusion that risk is clearly underpriced either.

To make more progress on this issue, I turn to explicit models of mispricing to assess whether they are able to account for these facts, and specifically I analyze behavioral stories where agents extrapolate from past returns.

4.4 Behavioral Stories with Return Extrapolation

I explore whether extrapolation from past returns can help us understand credit booms (Barberis *et al.*, 2015, Malmendier and Nagel, 2011). That is, perhaps agents see high past returns and then view future returns as being high. This may lead them to push up prices even further and possibly to take on more risk. Are credit booms associated with high past returns in the data? I find mixed results. Regressions of credit growth on cumulative asset returns over the past five years don't provide strong evidence for this channel.

Column (1) of Table 5 presents these results where I regress futures credit growth over the coming fives years on lags of GDP growth and returns over the previous five years. There is not much evidence that high returns are associated with high future credit growth. This cuts against the extrapolation story based on past experience of good times as being associated with low pricing of risk, high credit growth, and lower future risk premiums.

4.5 Drivers of Credit Growth and Low Volatility

I now explore the idea that low volatility is a key driver of credit booms. The idea is that if the economy looks relatively safe, then agents may view the quantity of risk to be low (overoptimism), leading them to take excess risk in the form of leverage and also driving risk premiums down. This increased borrowing can generate a credit boom. What I have in mind, however, is that the act of taking leverage generates endogenous risk which is not properly accounted for since high leverage can lead to more fragility in the system (see Gennaioli *et al.* (2012)). Thus, even though things look fairly safe, they may actually be fairly risky through the fragility created by leverage.

To assess this story, I run regressions of future credit growth on lags of volatility in GDP growth, stock returns, and housing returns over the trailing five years. The main prediction is that low volatility positively predicts credit growth. Table 5 Columns (2) and (3) present these results which are mixed to some extent. Equity market volatility is associated with future credit growth meaning low equity volatility is associated with a credit boom. Similarly, past crashes in asset markets for both equity and housing are negatively associated with credit growth as is past incidence of a crisis.

These regressions support the idea that perhaps agents extrapolate the quantity of risk dimension. That is, suppose agents base their expectations on the quantity of risk based on past experience. Then it seems natural they will take more leverage and borrow and lend more aggressively, possibly resulting in a credit boom. However, this could lead to more fragility from the resulting higher leverage and actually generate more risk in the future. Thus, the objective quantity of risk going forward could be high even though things have looked safe in the past. This would mean the agents subjective view of the quantity of risk is below the true objective quantity of risk going forward through the channel of endogenous actions. This would then show up empirically as an abnormally low price of risk in credit booms. While more work would be needed to fully flesh out this channel, the results here indicate this may be a promising avenue. Models consistent with this view include Gennaioli *et al.* (2012) who study neglected risk, Moreira and Savov (2014) who study an agent who learns about disaster probabilities over time, and Greenwood *et al.* (2019).

4.6 Risk Premiums After a Crisis

So far, the analysis documents low risk premiums during high credit growth periods and in the run up to financial crises. I now study the behavior of risk premiums *after* a financial crisis. The results presented here mirror those in Muir (2017) though using slightly different data on dividend yields and rental yields over somewhat different countries to be consistent with the analysis presented in the rest of this paper. However, the conclusions are the same. Specifically, I run regressions of the dividend yield, rental yield, and credit spreads on an indicator for whether there was a financial crisis in the last five years. I control for five lags of GDP growth in the regressions as well. This is very important because it helps differentiate if financial crises are "special" for risk premiums or not. That is, if risk premiums just go up when the economy is doing poorly, and financial crises are just instances where the macroeconomy declines, then the rise in premiums may have little to do with the crisis. Other analysis pursued in Muir (2017) includes recession dummies to compare the financial crises, whereas here I just include GDP declines directly into the analysis though this produces similar results. Thus, one can't explain the increase in risk premiums during financial crises just through the lens of the economy doing poorly and supports models of risk premiums in crisis episodes such as He and Krishnamurthy (2013).

Table 6 gives the results. We see significant increases in the dividend yield and credit spreads after a crisis of close to 30%. The point estimate for rental yields suggests an increase though this is not statistical significant.

The results paint a clearer picture of the results earlier: financial crises are preceded by credit growth which is associated with low risk premiums. Hence, asset prices are high leading into a crisis and credit spreads are low. However, these effects on risk premiums dramatically shift after the crisis begins and spreads and risk premiums appear to rise substantially (which also means prices and realized returns will fall dramatically). This would not affect pricing of risk stories if crises themselves were not predictable, though the evidence indicates that they are. I view this effect as in part explaining the quantity of risk facts that high credit growth appears to predict low mean returns as well as heightened chances of a significant decline in asset values. Further, it suggests that agents update their view on risk following crisis episodes. These results put more structure on the time-varying risk aversion stories as risk aversion needs to fluctuate substantially to be very low in the lead up to a crisis and then spike to high levels following a crisis. The dramatic shift in risk premiums is also consistent with agents significantly updating beliefs in a crisis as in behavioral models mentioned earlier.

5 Conclusion

This paper studies the pricing of risk during credit booms by studying the behavior of equities, housing, and credit spreads in these episodes. It summarizes and echoes much of the empirical work on asset prices in credit market booms. First, credit growth negatively predicts asset market returns for stocks and housing, and is associated with low credit spreads before a financial crisis. These results all indicate low risk premiums in a credit boom. However, at the same time, the quantity of risk, defined by considering left tail events in returns, appears to rise during credit booms.

The way to square these facts is with the pricing of risk by agents in the economy: that is, by effective risk aversion in the economy being abnormally low in credit booms. Because the risk premium falls and risk itself rises, effective risk aversion needs to fall substantially to reconcile the evidence. This provides an important piece of evidence for asset pricing models aimed at explaining these episodes. Using only the restriction that effective risk aversion must be positive, I can not definitively rule out a risk pricing story because the evidence doesn't support reliable forecasts of negative returns, only that returns are well below average in credit expansions. At the same time, there is not strong evidence of time-varying risk aversion from typical structural asset pricing models that match the data. Thus, whether the evidence points to behavioral biases or low rational effective risk aversion remains open.

The results do support the idea of neglected risk (Gennaioli *et al.* (2012), among others) and suggests neglected risk may come from low past risk (rather than, say, high past returns). In particular, because low asset volatility in part predicts credit growth, a potential explanation is that agents update their views on risk based on the past and are overoptimistic about risk going forward. This could lead them to take excessive risk, resulting in fragility and raising the future likelihood of a bad event. At the same time, it could explain why risk premiums appear low in credit booms. While more work would be needed to fully flesh out this channel, the results here indicate this may be a promising avenue for future work.

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Table 1: **Forecasting excess returns with credit growth**. I run predictive regressions of returns on lagged credit to GDP across countries. I consider the level of credit to GDP as well as 3 and 5 year changes. As dependent variables I use the equity risk premium and housing risk premium over a three year period (each computed as log total return over short term interest rates). Standard errors in parentheses are double clustered by country and time.

Panel A: Predicting Equity Excess Returns

	(1)	(2)	(3)	(4)	(5)	(6)
credit/gdp	-2.01			-1.40		
	(0.98)			(0.91)		
Δ_3(credit/gdp)		-2.26			-2.47	
		(0.71)			(0.80)	
Δ_5(credit/gdp)			-1.99			-2.41
			(0.68)			(0.77)
dividend yield				1.93	2.07	2.13
				(0.37)	(0.41)	(0.40)
N	1,614	1,588	1,561	1,546	1,521	1,496
R-squared	0.05	0.07	0.07	0.10	0.13	0.13

Panel B: Predicting Housing Excess Returns

	(1)	(2)	(3)	(4)	(5)	(6)
credit/gdp	-1.60			-0.45		
	(0.38)			(0.30)		
Δ_3(credit/gdp)		-0.98			-0.49	
		(0.29)			(0.27)	
Δ_5(credit/gdp)			-1.26			-0.66
			(0.34)			(0.31)
rental yield				1.54	1.54	1.53
				(0.19)	(0.19)	(0.19)
N	1,401	1,384	1,367	1,394	1,377	1,361
R-squared	0.17	0.16	0.17	0.31	0.31	0.31

Table 2: **Forecasting crises and crashes with credit growth**. I run predictive regressions of crash and crisis indicators (defined as a financial crisis in the next 3 years or a crash in returns in the next 3 years) on lagged credit to GDP across countries. I consider the level of credit to gdp as well as 3 and 5 year changes. Standard errors in parentheses are double clustered by country and time.

Panel A: Predicting Financial Crises						
	(1)	(2)	(3)	(4)	(5)	(6)
credit/gdp	4.94			4.32		
	(1.95)			(2.28)		
Δ_3(credit/gdp)		5.58			6.45	
		(1.26)			(1.24)	
Δ_5(credit/gdp)			4.58			5.51
			(1.16)			(1.22)
dividend yield				0.10	-0.31	-0.25
				(1.05)	(1.04)	(1.07)
rental yield				-1.55	-1.96	-1.94
				(0.82)	(0.83)	(0.82)
N	2,114	2,030	1,978	1,531	1,499	1,481
R-squared	0.06	0.08	0.07	0.07	0.10	0.09
Panel B: Predicting Equity Crashes						
credit/gdp	10.00			7.11		
	(4.87)			(4.78)		
Δ_3(credit/gdp)		7.23			8.41	
		(2.68)			(2.87)	
Δ_5(credit/gdp)			4.65			5.84
			(2.03)			(2.39)
dividend yield				-7.56	-8.14	-8.35
				(1.63)	(1.81)	(1.80)
N	1,671	1,645	1,618	1,598	1,573	1,548
R-squared	0.08	0.08	0.08	0.12	0.12	0.12
Panel C: Predicting Housing Crashes						
credit/gdp	9.16			0.85		
	(4.51)			(4.75)		
Δ_3(credit/gdp)		12.11			8.71	
		(3.37)			(3.63)	
Δ_5(credit/gdp)			13.77			9.63
			(3.75)			(4.06)
rental yield				-11.37	-10.72	-10.89
				(3.27)	(3.29)	(3.33)
N	1,445	1,428	1,411	1,438	1,421	1,405
R-squared	0.09	0.11	0.12	0.16	0.18	0.18

Table 3: **Forecasting consumption and GDP drops with credit growth**. I run predictive regressions of an indicator for a substantial decline in consumption and GDP (defined as a significant drop in each series in the next 3 years) on lagged credit to GDP across countries. I consider the level of credit to gdp as well as 3 and 5 year changes and include controls for dividend yields and rental yields. Standard errors in parentheses are double clustered by country and time.

Panel A: Predicting GDP Declines						
	(1)	(2)	(3)	(4)	(5)	(6)
credit/gdp	3.50			1.28		
	(3.73)			(4.04)		
Δ_3(credit/gdp)		5.41			4.51	
		(2.54)			(2.73)	
Δ_5(credit/gdp)			5.02			3.97
			(2.35)			(2.72)
dividend yield				0.47	0.27	0.20
				(1.74)	(1.71)	(1.86)
rental yield				-2.94	-2.75	-3.09
				(1.75)	(1.82)	(1.82)
N	1,882	1,853	1,824	1,412	1,396	1,382
R-squared	0.16	0.17	0.18	0.14	0.15	0.16

Panel B: Predicting Consumption Declines						
	(1)	(2)	(3)	(4)	(5)	(6)
credit/gdp	4.67			0.90		
	(3.86)			(4.50)		
Δ_3(credit/gdp)		6.70			6.09	
		(3.09)			(3.46)	
Δ_5(credit/gdp)			6.32			4.77
			(3.97)			(4.77)
dividend yield				3.27	3.35	3.12
				(1.51)	(1.41)	(1.48)
rental yield				-5.41	-4.94	-5.22
				(2.51)	(2.31)	(2.33)
N	1,825	1,799	1,772	1,389	1,373	1,359
R-squared	0.23	0.23	0.23	0.23	0.24	0.24

Table 4: **Spreads before a crisis (Source: Krishnamurthy and Muir (2018))**. This table is a direct reproduction of Krishnamurthy and Muir (2018). Are spreads before a crisis too low? We run regressions of our normalized spreads on a dummy which takes the value 1 in the 5 years before a financial crisis (labeled $1_{t-5,t-1}$) in order to assess whether spreads going into a crisis are low. Importantly, we control for a post crisis dummy as well which is equal to 1 in the 5 years after a crisis, the means the pre-crisis dummy should be judged relative to other "normal times" and is not mechanically low because spreads during crises are high. We show the univariate results, as well as the results controlling for time fixed effects. We then add changes in credit growth and GDP to control for fundamentals that could drive spreads. We then split this result by severe versus mild crises based on the median drop in GDP in a crisis. It thus asks whether spreads are especially low before crises which are particularly severe. Standard errors clustered by country in parenthesis.

	Spreads before a crisis		
	(1)	(2)	(3)
$1_{t-5,t-1}$	-.23		
	(0.11)		
$1_{t-5,t-1}$ × Severe		-0.43	
		(0.20)	
$1_{t-5,t-1}$ × Mild		-0.18	
		(0.11)	
$1_{t-5,t-1} \times \Delta Credit_{t-1}$			-1.58
			(0.72)
$\Delta Credit_{t-1}$	0.98	0.92	1.18
	(0.58)	(0.52)	(0.70)
ΔGDP_{t-1}	-0.16	-0.18	-0.22
	(1.68)	(1.68)	(1.54)
Observations	621	621	621
R-squared	0.40	0.40	0.40
Country FE	Y	Y	Y
Year FE	Y	Y	Y

Table 5: **What drives credit growth?**. This table runs regressions of credit growth over five years on lags of GDP growth and returns over the trailing five years to see if credit growth is high following a period of high economic growth or high returns in asset markets (Column (1)). Columns 2 and 3 repeat this exercise but instead use trailing volatility of each of these series to see if low volatility is associated with high future credit growth. Column (4) uses dummies for whether there has been a crash in equity markets, housing markets, or a financial crisis over the past five years. The result is that periods of low risk are associated with higher credit growth whereas high past growth or high returns themselves do not appear to be. Standard errors in parentheses are double clustered by country and time.

	(1)	(2)	(3)	(4)
Past GDP growth	0.58		0.73	0.49
	(0.46)		(0.48)	(0.46)
Past Equity Returns	0.10		0.08	0.11
	(0.07)		(0.08)	(0.07)
Past Housing Returns	-0.14		-0.11	-0.10
	(0.19)		(0.18)	(0.18)
Past GDP Volatility		0.08	-0.39	
		(0.39)	(0.41)	
Past Equity Volatility		-1.91	-1.63	
		(0.79)	(0.75)	
Past Housing Volatility		-13.52	-3.75	
		(20.11)	(21.34)	
Past Equity Crash				-0.03
				(0.02)
Past Housing Crash				-0.06
				(0.02)
Past Financial Crisis				-0.09
				(0.02)
Observations	1,275	1,275	1,275	1,275
R-squared	0.09	0.09	0.10	0.13

Table 6: **Risk Premiums After a Financial Crisis**. I run regressions of measures of risk premiums for stocks, housing, and credit, on a dummy equal to one if a financial crisis has occurred in the last five years. Included are lags of each variable before the crisis began (e.g., five year lags), as well as GDP growth for each of the last five years. The latter is important in distinguishing financial crises from other bad times like recessions. In particular, the coefficient below indicates how high risk premiums are even controlling for the fact that GDP growth is low through a financial crisis. Standard errors in parentheses are double clustered by country and time.

	(1) Dividend Yield	(2) Rental Yield	(3) Credit Spread
Crisis Past 5 Years	0.28	0.15	0.31
	(0.10)	(0.13)	(0.13)
Observations	1,628	1,437	682
R-squared	0.31	0.57	0.14