Financial Markets with Frictions and Belief Distortions

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HANDELSHØJSKOLEN

Financial Markets with Frictions and Belief Distortions

Jakob Ahm Sørensen

A thesis presented for the degree of Doctor of Philosophy

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Ph.D. School in Economics and Management
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Abstract

The three essays of this thesis investigate the role of frictions and belief distortions as determinants of asset prices and macroeconomic outcomes. The essays are the product of my PhD studies at the Department of Finance and the Center for Financial Frictions (FRIC) at CBS. The essays are self-contained and can be read independently.

In my first paper, Risk Neglect in the Corporate Bond Market, I present an equilibrium model of corporate bonds and stocks that distinguishes the effects of rational risk aversion from the effects of extrapolative beliefs on asset prices. From the model, I construct a novel measure of credit market sentiment denoted yield-for-risk, which measures the compensation investors require for credit risk in the cross section of corporate bonds. In a panel of bonds and stocks spanning more than 40 years, I find strong evidence of risk neglect; When yield-for-risk is low, the expected return on credit is low and the risk-return relationship inverts for both corporate bonds and stocks. The evidence is consistent with extrapolative beliefs, but inconsistent with canonical asset pricing models with rational expectations.

My second paper, Predictable Financial Crises (coauthored with Robin Greenwood, Samuel G. Hanson, and Andrei Shleifer), uses historical data on post-war financial crises around the world to show that financial crises are substantially more predictable than previously thought. Specifically, the combination of rapid credit and asset price growth over the prior three years, whether in the nonfinancial business sector or the household sector, is associated with about a 40% probability of entering a financial crisis within the next three years. Our evidence cuts against the view that financial crises are unpredictable "bolts from the sky" and points toward the Kindleberger-Minsky view that crises are the byproduct of predictable, boom-bust credit cycles. As in my first essay, the evidence suggests that extrapolative beliefs are important determinants of economic outcomes. The predictability favors macroprudential policies that lean against incipient credit-market booms.

My last paper, Asset Driven Insurance Pricing (coauthored with Benjamin Knox), considers the investment strategies of insurance companies and their impact on the pricing of insurance contracts. In the paper, we develop a theory that connects insurance premiums, insurance companies' investment behavior, and equilibrium asset prices. Consistent with the model's key predictions we show empirically that: (1) insurers with more stable insurance funding take more investment risk and, therefore, earn higher average investment returns; (2) insurance premiums are lower when expected investment returns are higher, both in the cross section of insurance companies and in the time series. We show our results hold for both life insurance companies and, using a novel approach, for property and casualty insurance companies. Consistent findings across different regulatory frameworks helps identify asset-driven insurance pricing while controlling for alternative explanations.

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I have received more help and support during the course of my studies than I can possibly account for here. I find myself deeply indebted to the many people who have generously shared their time and wisdom with me. Here, I can only acknowledge the few I owe the most.

First and foremost, I am profoundly grateful to my advisor Lasse Heje Pedersen for his steadfast patience and encouragement. Lasse has saved me from countless confusions and disciplined my thinking and my research in the process. Lasse took me under his wing at a critical point in my studies, where I lacked direction and the belief that I would make it to where I am at today. This thesis would not have been possible without him.

Many other people were crucial in getting me through my PhD. David Lando hired me in as a research assistant and got me interested in pursuing a career in academia. My co-advisors, Robin Greenwood and Andrei Shleifer, kept me in shape physically and mentally during my time at Harvard. My co-author, Sam Hanson, invested a great deal in my education. Further, I would like to thank all my colleagues at Copenhagen Business School. It has been a fantastic place of work and fun, and I count myself lucky for the many friends I have made among both the faculty and my fellow PhD's. In this regard, my coauthor Benjamin Knox deserves a special thanks for sharing the ups and downs of PhD life with me as both class mate, office mate, and occasionally travel mate.

Finally, I am grateful to my family and friends. To my parents for always believing in me. To my friends for the good times shared. To Karen for keeping me in the present moment. My greatest debt is to my fiancé, Anne Sofie, who has supported my dream of a career in academia from the beginning and who has kept me afloat. Thank you for always reminding me what's important in life. This thesis is dedicated to you.

Summaries

1 Summaries in English

Risk Neglect in the Corporate Bond Market

This paper studies the determinants of credit spreads and returns on financial assets. A credit spread is the difference between the yield of a risky bond issued by a corporation and safe bond issued by the U.S. Government. The riskier the bond, the higher the credit spread demanded by investors. The question is therefore whether investors can accurately assess the true risk of a bond, or whether they suffer from behavioral biases which disconnects credit spreads from fundamental risks. The question is important as a mispricing of risk can cause markets to overheat when investors are too optimistic, and markets to freeze when investors are too pessimistic.

To identify the determinants of credit spreads, I first present a unified model of risk aversion and extrapolative beliefs. While the two mechanisms share many implications for the relationship between credit spreads and returns on financial assets, only extrapolative beliefs are consistent with risk neglect by investors. Risk neglect is a situation where investors underestimate the expected losses of bonds and charge a credit spread which is too low compared to the true risk of the bond. This causes expected returns to become negative, and the cross sectional relationship between risk and return to invert as the riskiest bonds are most affected by the risk neglect.

To test the model, I extract a novel measure of credit market sentiment named *yield-for-risk* (YFR_t) which measures the compensation required by investors for credit risk in the cross section of bonds at a given point in time. In a panel spanning more than 40 years, I find that YFR_t is a strong predictor of returns to credit risk in both the time series and in the cross section of both bonds and stocks. Further, periods of low YFR_t coincide with negative expected returns on the bond market as a whole, and an inversion of the risk-return relationship in both bonds and stocks. This finding is inconsistent with leading rational asset pricing models, but consistent with models of extrapolative beliefs.

Predictable Financial Crises

How predictable are financial crises? An important line of thought, shared by prominent policy makers and academics alike, postulates that they are largely unpredictable.[1] This line of thought is supported by early empirical studies showing that even if most crises are preceded by weak economic fundamentals, they

[1] Cole and Kehoe (2000); Chari and Kehoe (2003); Gorton (2012); Geithner (2014)

are not especially predictable.[2] An alternative view, attributed to Minsky (1977) and Kindleberger (1978), postulates that financial crises are instead the predictable byproducts of joint credit expansions and asset price booms. However, while this view received renewed attention in the wake of the 2008 Global Financial Crisis, precise estimates of the probability of a financial crisis following credit and asset price booms remain unavailable. More importantly, how high the probability of a crisis should be permitted to climb before prompting preemptive policy action remains an open question.

In this paper, we combine historical data on the growth of outstanding credit to nonfinancial businesses and households with data on the growth of equity and home prices to estimate the future probability of a financial crisis in a panel of 42 countries over the period 1950 to 2016. We find that the combination of high debt growth *and* high asset price growth is in fact a strong predictor of financial crises. The result holds for both the nonfinancial business sector and the household sector. That is, when nonfinancial business debt and stock market valuations have risen sharply, or when household debt and home prices have risen sharply, the risk of a subsequent crisis is substantially elevated. We call these episodes of heightened risk *R-Zones*.

Second, we address the question of how high we should allow the probability of a crisis to be by calibrating a simple model of macroprudential policymaking under uncertainty. The decision facing the policy maker is a trade-off between the two types of classification errors: false positives, *R-zones* not followed by financial crises, and false negatives, financial crises not preceded by an *R-zone*. We show that given the level of predictability documented, policymakers should adopt a do-nothing strategy only if they think that the cost of a false positive is extremely large relative to the cost of a false negative. In conclusion, our findings support the Kindleberger-Minsky view of credit cycles and financial crises, and favor proactive macroprudential policies that lean against incipient credit booms.

Asset-Driven Insurance Pricing

Traditional theories of insurance pricing have little consideration for the investment decisions of insurance companies. They assume that insurance companies invest solely is risk-free government bonds, despite the fact that these make up only around 10% of insurance companies' actual investment portfolios. Instead, illiquid credit securities make up the bulk of insurance companies' portfolios. This investment behavior motivates the two main questions in the third chapter of my thesis: (1) Why do insurers have such high exposure to credit and liquidity risk in their asset portfolios? (2) Do the expected investment returns on these portfolios affect how they set premiums?

We address these questions by developing a model of insurance premia and asset prices in which insurance underwriting works as a stable source of funding for insurance companies. The stable funding provided by insurance underwriting allows insurance companies to earn a liquidity premium caused by other investors forced selling. The central result of the model is that a higher liquidity premium will result in lower insurance premia as insurance companies compete for funding. As a consequence, part of the value generated by the stable funding of insurance underwriting is channelled back to the policyholders in the form of lower insurance prices. We name this mechanism *asset-driven insurance pricing*.

We test the model in two markets: (1) the market for life insurance contracts and (2) the market for property and casualty (P&C) insurance. In both markets we find compelling evidence of asset driven insurance pricing in both the time series and the cross section. Specifically, when liquidity premia are high in aggregate,

[2]Kaminsky and Reinhart (1999)

insurance prices are low for both life insurance contracts and P&C contracts. Further, insurance companies with more investment risk and higher expected returns set lower prices on their insurance policies.

In summary, we propose a new theory of insurance pricing which highlights the interaction between insurers' assets and liabilities. We find empirical evidence consistent with the model's predictions in both life insurance contracts and P&C insurance contracts.

2 Summaries in Danish

Risk Neglect in the Corporate Bond Market

I denne artikel studerer jeg de faktorer som bestemmer kreditspænd og afkast på financielle aktiver. Et kreditspænd er forskellen i udbytte givet på en risikabel obligation udstedt af en virksomhed, og en sikker obligation udstedt af den amerikanske stat. Jo mere risikabel obligationen er, des højere et kreditspænd vil investorer afkræve. Spørgsmålet er derfor om investorer kan vurdere risikoen i en given obligation korrekt, eller om de ligger under for psykologiske bias hvilket vil få kreditspænd til at være ude a trit med obligationers fundamentale risici. Dette er et vigtigt spørgsmål da en forkert prissætning af risici kan få finansielle markeder til at overophede når investorer er for optimistiske, og til at fryse til når investorer bliver for pessimistiske.

For at kunne identificere faktorerne som bestemmer kreditspænd præsenterer jeg først en samlet model, som inkluderer både rationel risikoaversion og ekstrapolative forventninger. Mens de to mekanismer har mange af de samme implikationer for forholdet mellem kreditspænd og afkast på finansielle aktiver, kan kun ekstrapolative forventninger lede til at investorer negligerer risikoen ved deres investeringer. Negligering af risiko opstår når investorer er for optimistiske omkring virksomheders evne til at honorere deres gæld, og derfor afkræver kreditspænd som er for lave i forhold til obligationernes sande risici. Dette vil lede til negative forventede afkast, og til en inversion af sammenhængen mellem risiko og afkast tværs af obligationer.

For at teste modellen udleder jeg et nyt mål for temperaturen på kreditmarkedet som jeg kalder udbytte-for-risiko (YFR_t), som måler hvor meget kompensation investorer kræver for kreditrisiko på tværs af virksomhedsobligationer på et givent tidspunkt. Ved brug af over 40 års data finder jeg at YFR_t forudsiger afkastet på kreditrisiko både over tid, og på tværs af aktier og obligationer. Ydermere finder jeg at perioder med lav YFR_t falder sammen med negative forventede afkast på det samlede marked for virksomhedsobligationer, samt en inversion af risiko-afkast relationen. Disse resultater er inkonsistente med førende rationelle modeller for prisning af finansielle aktiver, men konsistent med modeller med ekstrapolative forventninger.

Predictable Financial Crises

Hvor forudsigelige er finansielle kriser? Et synspunkt, som deles af både prominente akademikere og centralbanksdirektører, er at de i høj grad er uforudsigelige.[3] Dette synspunkt understøttes af tidlige empiriske studier som viser at selvom kriser som regel efterfølger en svag økonomisk udvikling, så er de svære at forudsige.[4] Et alternativt synspunkt fremført af Minsky (1977) og Kindleberger (1978) postulerer i stedet at finansielle kriser er forudsigelige biprodukter voldsomme ekspansioner i den udestående gæld, med tilhørende booms i priserne på finansielle aktiver. På trods af den øgede interesse for Minskys og Kindlebergers teorier

[3] Cole and Kehoe (2000); Chari and Kehoe (2003); Gorton (2012); Geithner (2014)
[4] Kaminsky and Reinhart (1999)

som fulgte i kølvandet på den globale finansielle krise i 2008, findes der ikke noget præcist estimat for sandsynligheden for at ende i en finansiel krise efter kreditekspansioner og prisbooms. Vigtigere endnu, vi har intet svar på hvor høj man bør tillade sandsynligheden for en krise at være før man som regulatorisk myndighed intervenerer i økonomien.

I dette papir kombinerer vi historisk data fra 42 lande i perioden 1950-2016 på vækst i udestående gæld til ikke-finansielle virksomheder og husholdninger med data på aktie- og husafkast, og estimerer derefter sandsynligheden for en fremtidig krise. Vi finder at kombinationen af høj gældsvækst koblet med høj prisvækst er en stærk prædiktor for fremtidige finansielle kriser. Resultatet holder både når vi bruger data fra den private virksomhedssektor og når vi kigger på data fra husholdninger. Det vil sige at vi dokumenterer en betydeligt forøget risiko for en finansiel krise både når ikke-finansielle virksomheders gæld og aktiepriser er steget voldsomt, og når husholdningers gæld og huspriser er steget voldsomt. Vi kalder disse episoder for *R-zoner*.

I anden del af papiret adresserer vi spørgsmålet om hvor høj en sandsynlighed for en krise man bør tillade ved at kalibrere en simpel model for makroprudentiel politik under usikkerhed. Vi bemærker at man som regulatorisk myndighed må afveje omkostningerne ved de to typer klassifikationsfejl man kan lave: falske positiver, *R-zoner* som ikke efterfølges af en finansiel krise, og falske negativer, finansielle kriser som ikke forudsiges af en *R-zone*. Vi viser at med graden af forudsigelighed som vi dokumenterer, bør man kun undlade at intervenere i en overophedet økonomi såfremt man tror at omkostningerne ved en falsk positiv er meget høje, sammenholdt med omkostningerne ved en falsk negativ. Alt i alt understøtter vores resultater Minskys og Kindlebergers hypotese om krisers forudsigelighed, og promoverer en mere proaktiv makroprudentiel politik som modvægt til kreditbooms.

Asset-Driven Insurance Pricing

Tradionelle teorier om forsikringspræmier tager meget lidt højde for forsikringsselskabers investeringsstrategier. Det antages som regel at forsikringsselskaber udelukkende investerer i risikofri statsobligationer på trods af at disse kun udgør omkring 10% af forsikringsselskabernes faktiske investeringsporteføljer. I virkeligheden køber forsikringsselskaber primært illikvide virksomhedsobligationer. Denne investeringsstrategi er motivationen bag de to hovedspørgsmål i min afhandlings tredje kapitel: (1) Hvorfor er forsikringsselskabers investeringer i høj grad eksponerede mod kredit- og likviditetsrisici? (2) Påvirker forsikringsselskabernes forventede afkast deres forsikringspræmier?

Vi adresserer disse spørgsmål ved at opstille en model for forsikringspræmier og priser på finansielle aktiver, hvori forsikringspræmier fungerer som en stabil finansieringskilde for forsikringsselskaber. Denne stabile finansiering gør det muligt for forsikringsselskaber at høste en likviditetspræmie, som skyldes andre investorers tvungne frasalg af aktiver. Modellens vigtigste resultat er at en højere likviditetspræmie vil resultere i lavere forsikringspræmier når forsikringsselskaber konkurrerer om finansiering. Konsekvensen er at en del af den værdi som skabes ved den stabile finansiering fra forsikringsudstedelse, leveres tilbage til forsikringstagere i form af lavere forsikringspræmier. Vi kalder denne mekanisme *aktiv-drevne forsikringspræmier*.

Vi tester vores model i to markeder: (1) markedet for livsforsikringer og (2) markedet for indbo- og ulykkesforsikringer. I begge markeder finder vi bevis for aktiv-drevne forsikringspræmier både over tid, og på tværs af forsikringsselskaber. Specifikt finder vi at når likviditetspræmier er høje er forsikringspræmier lave på både livsforsikringer og indbo-/ulykkesforsikringer. Ydermere finder vi at forsikringsselskaber med højere investeringsrisici og dermed højere forventede afkast har lavere forsikringspræmier.

Kort sagt præsenterer vi en ny teori for forsikringspræmier som lægger vægt på interaktionen mellem forsikringsselskabers aktiver og passiver. Vi finder empirisk bevis for denne teori i markederne for både livs- og indbo-/ulykkesforsikring.

Contents

Chapter 1

Risk Neglect in the Corporate Bond Market

Abstract

I present an equilibrium model for valuing corporate bonds and stocks to distinguish investors' rational risk aversion from extrapolative expectations. Motivated by the model, I construct a novel empirical measure of credit market sentiment, denoted yield-for-risk (YFR_t), which measures the compensation investors require for credit risk in the cross-section of corporate bonds. I find evidence of extrapolative expectations in the form of risk neglect: Low YFR_t predicts low returns to credit and an inversion of the risk-return relationship among both corporate bonds and stocks. Firms exploit this effect by increasing their debt issuance when YFR_t is low, especially high-risk firms.

I would like to thank Pedro Bordalo, Jens Dick-Nielsen, Peter Feldhütter, Robin Greenwood, Sam Hanson, Ben Knox, David Lando, Peter Maxted, Lasse Heje Pedersen, Dagfinn Rime, Andrei Shleifer, Jeremy Stein, Adi Sunderam, Niels Joachim Gormsen, Theis Jensen, and participants at the Bocconi Virtual PhD Conference 2020, the NFN PhD Workshop 2021 at Aarhus University, the Young Scholars Nordic Finance Workshop, Tilburg University, Purdue University, University of Toronto, HEC Paris, Bocconi University, Boston College, BI Oslo, and at Copenhagen Business School for valuable comments. I gratefully acknowledge support from FRIC Center for Financial Frictions (grant no. DNRF102).

1 Introduction

The credit spread (i.e., the yield of corporate bonds minus the yield of Treasuries) is a well-known predictor of economic activity and returns on financial assets (Gilchrist and Zakrajšek, 2012).[1] While variation in credit spreads has traditionally been explained by time-varying credit risk and risk aversion (Merton, 1974; Chen et al., 2008), a newer strand of theoretical models propose that credit spread variation is instead driven by investors' extrapolation of news about firm fundamentals and recent default rates (Bordalo et al., 2018; Greenwood et al., 2019). This paper presents a unified model of risk aversion and extrapolation, and shows that both mechanisms imply low credit spreads in good times, but only extrapolative beliefs are consistent with risk neglect by investors. Using a newly constructed panel of bond and stock returns and a novel measure of credit market sentiment, this paper identifies periods of risk neglect in both the bond and the stock market, indicating a significant role for extrapolative beliefs in determining the credit spread of corporate bonds.

To identify periods of risk neglect, I introduce a new measure of credit market sentiment, the yield-for-risk (YFR_t), which measures the compensation required by investors for credit risk at a given point in time. I show that YFR_t fluctuates substantially over time and strongly predicts the returns to credit risk in the cross-section of both the bond and the stock market. In particular, I identify periods of almost complete disconnect between risk and credit spreads, and document that these periods coincide with an inversion of the risk-return relationship as high-risk assets carry lower expected returns than low-risk assets. Further, I show YFR_t to be a strong predictor of aggregate bond market returns, and that this predictive relationship is explained by the predictable repricing of credit risk. Finally, I find that YFR_t predicts net debt issuance, and that this is driven in particular by the riskiest firms in the economy, who take advantage of the high values of their debt by increasing their leverage.

To understand how I arrive at these results, I first develop a model of asset prices, where a risk-averse representative investor extrapolates news about the fundamental values of a cross-section of firms, who all have debt and equity outstanding. The model builds on the insights of Merton (1974) to price the debt and equity issued by each firm as contingent claims on the firms' underlying assets. Extrapolation is embedded in the model via diagnostic expectations as developed by Bordalo et al. (2018), which is a systematic way of modeling that investors are too optimistic following good news and too pessimistic following bad news. I show that, in equilibrium, extrapolation of fundamentals causes low credit spreads and low expected returns on both bonds and stocks following good news about firm fundamentals. In fact, when extrapolation is severe enough, the risk-return relationship inverts and this inversion is a key distinguishing feature of extrapolation versus rational models. Further, I show that this inversion is even stronger for equities, since equities are more information sensitive than bonds.

Motivated by the model, I estimate yield-for-risk (YFR_t) by regressing the cross-section of credit spreads on the cross-section of risk at every date, where risk is measured by (the negative value of) a firm's distance-to-default.[2] Distance-to-default combines a firm's leverage with the volatility of its assets to measure how many standard deviations the firm is from default, meaning that YFR_t measures how much investors require in additional yield for holding a bond that is one standard deviation closer to default at a given point in time. To measure YFR_t, I construct a panel of investment grade corporate bonds from January 1976, through February 2019, by combining data from three data sources: the Lehman/Warga database, the ICE Fixed

[1]Further, see Stock and Watson (1989), Fama and French (1989), Bernanke (1990), Friedman and Kuttner (1993), Gertler and Lown (1999), Mueller (2009).

[2]Distance-to-default is measured empirically using the methodology of Bharath and Shumway (2008).

Income database, and the TRACE database. A key advantage of YFR_t as a measure of sentiment is that it has a clear economic interpretation, and therefore periods of potential risk neglect become evident from a simple time-series plot. For example, in May 2007, YFR_t was 0.01%, meaning investors required only 0.01% in additional yield for moving a standard deviation closer to default right before the Global Financial Crisis of 2008. Given that expected losses form a lower bound on credit spreads, a YFR_t of 0.01% also means that, in May 2007, investors think the expected losses on a bond increase by at most 0.01% when a bond moves a standard deviation closer to default. Less than two years after, in March 2009, YFR_t had increased almost thirtyfold and topped out at 0.29%. While the 2008 Financial Crisis is the epitome of this boom-bust dynamic, the pattern is not unique to this period. Figure 1 presents a time-series plot of YFR_t and shows that YFR_t is low immediately before economic recessions, but increases rapidly as the recessions unfold.

Using YFR_t to measure credit market sentiment, I present four empirical findings consistent with the predictions of the theoretical model outlined above. First, YFR_t is a strong predictor of returns to credit risk in the cross-section of corporate bonds. I measure returns to credit risk in the cross-section of corporate bonds as the return spread between the bonds of the 20% riskiest firms in the economy and the bonds of 20% safest firms. The risk of a firm is measured by the firm's distance-to-default, so the 20% riskiest firms are the 20% of firms with the lowest distance-to-default at a given point in time. By regressing this portfolio return spread on YFR_t, I find that a one standard deviation decrease in YFR_t lowers the expected return of the riskiest bonds by 0.15% relative to the safest bonds over the following month. The result substantiates the view that YFR_t captures credit market sentiment as implied by the model. Further, consistent with the model's predictions, the returns to credit risk in the cross-section of equities are also strongly predicted by the level of YFR_t. Specifically, a one standard deviation decrease in YFR_t lowers expected returns of the 20% riskiest equities over the 20% safest equities by a sizeable 0.76% over the following month. The predictability grows substantially with the prediction horizon to 1.6% for the bond portfolio and 7.5% for the equity portfolio at the 12-month prediction horizon.

I show that the bond and stock predictability captured by YFR_t are not subsumed by standard credit spreads or other known measures of credit market sentiment. Specifically, I run a horse race regression of portfolio returns on YFR_t including the "excess bond premium" of Gilchrist and Zakrajšek (2012), the high-yield share of Greenwood and Hanson (2013), the VIX, and average credit spread of BAA rated bonds as controls, and find that YFR_t maintains its economic and statistical significance. I further run a series of robustness tests to show that the predictive relationship between YFR_t and the portfolio returns is not an artifact of the specific portfolio construction, nor the product of small-sample biases such as the Stambaugh (1999) bias.

Second, I show that periods of low YFR_t predict significantly lower returns to the riskiest bonds and stocks relative to the safest bonds and stocks. While the first finding outlined above implies that a low YFR_t is associated with a low risk compensation in the cross-section of bonds and stocks, documenting that this risk compensation is in fact *negative* is key to distinguishing rational risk aversion from diagnostic expectations in my model. I find that when YFR_t is in the lowest quartile of its full sample distribution, the average return of the riskiest 20% of bonds is significantly below that of the safest bonds by 0.8% over the following twelve months, that is, an inversion of the risk-return relationship. As the model predicts, the result is even starker for equities, where the 20% riskiest stocks underperform the safest stocks by 7.3% over the following twelve months, when YFR_t is in its lowest quartile. The results are robust to changing both the portfolio construction and to changing the thresholds for what is defined as a "low yield-for-risk period".

Third, I show that YFR_t is a strong predictor of credit risk in the time series, measured as the excess return on the aggregate bond market. I control for changes in the term structure of Treasury yields to show that the predictability is driven by changes in the price of credit risk. The predictive power of YFR_t on returns to credit risk in the cross-section thus carries over to the returns of the aggregate bond market, where the price of credit risk is an important component. I again run a horse race of YFR_t against alternative predictors found in the literature, and find that YFR_t does not loose predictive power from the inclusion of alternative predictors. This naturally does not rule out the importance of other measures of market sentiment, but merely underlines the novelty and strength of YFR_t as a measure of credit market sentiment.

Fourth, I show that firms increase their net debt issuance following periods of low YFR_t. In particular, a one standard deviation fall in YFR_t is associated with an increase in net debt issuance over the following quarter of 0.26% relative to total assets. I show that this dynamic is driven by the behavior of the riskiest issuers. In particular, while the safest 20% of firms on average issue more debt than the riskiest 20%, the safest 20% do not change their net debt issuance when YFR_t is in its lowest quartile, relative to when it is not. In contrast, the riskiest 20% of issuers increase their debt issuance from roughly zero to 0.64% of total assets, when YFR_t enters its lowest quartile.

Beyond the literature mentioned above, my paper relates to the body of work decomposing corporate bond yields with measures of credit risk (Huang and Huang, 2012; Collin-Dufresne et al., 2001; Elton et al., 2010; Feldhütter and Schaefer, 2018).[3] Notably, Gilchrist and Zakrajšek (2012) extracts the excess bond premium (EBP), which captures the time-varying level of credit spreads after accounting for the risk in economy. The EBP is therefore highly correlated with the time-varying intercept in my cross-sectional regression. Yield-for-risk, in contrast, measures the time-varying slope of the cross-sectional relationship between risk and credit spreads, as opposed to the overall level of credit spreads. I contribute to the literature on credit spread decompositions by showing that the compensation for risk in the cross-section of bonds fluctuates dramatically, and that investors, at times, are almost completely insensitive to risk.

Further, my paper relates to the large literature documenting that credit growth and sentiment predicts output growth, financial crises and expected returns (Borio and Drehmann (2009), Schularick and Taylor (2012), Mian et al. (2017), López-Salido et al. (2017), Krishnamurthy and Muir (2020), Greenwood et al. (2021), Saunders et al. (2021)). In particular, Greenwood and Hanson (2013) show that deteriorating quality of corporate bond issuers predicts low corporate bond returns moving forward. Further, Baron and Xiong (2017) and Fahlenbrach, Prilmeier, and Stulz (2018) find that bank equity investors neglect risks and realize negative returns following periods of rapid bank credit growth. I complement these findings by using yield-for-risk to identify periods of risk neglect in the cross-section of both corporate bonds and equities.

In summary, I contribute to the literature by deriving a new, intuitive measure of credit market sentiment from the cross-section of bond yields. I name this measure yield-for-risk (YFR_t) and estimate it in a panel of investment-grade corporate bonds going back to 1976. I document that YFR_t is a strong predictor of returns to credit risk in the cross-section of corporate bonds and stocks, returns to credit risk in the time-series of the aggregate bond market, and of net debt issuance, particularly by the riskiest firms. I further show that YFR_t predicts an inversion in the risk-return relationship in both corporate bonds and stocks, where the riskiest assets have lower expected returns than the safest assets. I consider a model with a risk-inverse investor, and

[3] Other risk factors have been linked with the yields of corporate bonds. A non-exhaustive list includes: (1) liquidity risk (Longstaff et al., 2005; Giesecke et al., 2011; Bao et al., 2011; Dick-Nielsen et al., 2012; Chen et al., 2018), (2) idiosyncratic volatility (Campbell and Taksler, 2003), (3) inflation risk (Kang and Pflueger, 2015).

show that the results documented empirically are consistent with theories of extrapolative beliefs.

The remainder of the paper is structured as follows. Section 2 lays out my theoretical findings. Section 3 contains my data sources. Section 4 describes my empirical measure of credit market sentiment, *yield-for-risk*, and Section 5 presents the empirical results. Section 6 concludes. The appendix contains all proofs as well as additional empirical results and robustness tests.

2 Theory

2.1 Model

I consider an economy with an infinite number of firms financed by debt and equity. The economy has two periods, $t \in \{0, T\}$. At time 0, a representative investor maximizes the expected utility of his consumption by constructing a portfolio from the assets issued by the firms. At time T, the value of the firms is returned to the investor through the bonds and stocks issued. The investor's portfolio choice is a result of both risk aversion and extrapolative beliefs, and I show how each affects asset prices in equilibrium.

Firms and Assets. The (log) payoff of firm i's underlying assets, V_i, is given as the sum of three variables:

$$\log V_i = \delta + \epsilon_C + \epsilon_i$$

Here, δ is a parameter common to all firms reflecting news about the economy, ϵ_C is a common shock affecting all firms equally, and ϵ_i is an idiosyncratic shock specific to firm i. The common shock and the idiosyncratic shocks are all independent, normally distributed with mean zero and variances of σ_C^2 and σ_I^2, respectively, which I write as $\epsilon_C \sim N(0, \sigma_C^2)$ and $\epsilon_i \sim N(0, \sigma_I^2)$ for all i. Further, all idiosyncratic shocks in the economy are mutually independent. The news parameter δ determines the expected (log) payoff of the firms. If the news is good ($\delta > 0$) firms in the economy become more profitable, and if the news is bad ($\delta < 0$) firms become less profitable. We can think of δ as news about GDP growth, unemployment, or other macroeconomic variables, which influence the earnings potential of all firms in the economy.

Each firm has a supply of shares normalized to one and a supply of bonds expiring at time T, which is also normalized to one. The face value of the bonds issued by firm i is denoted by K_i, and is the key feature which distinguishes firm i from the other firms in the economy at time 0. The time-T payoffs of firm i's bonds, D_i, and stocks, E_i, are:

$$D_i = \min\{V_i, K_i\} \tag{1.1}$$

$$E_i = \max\{V_i - K_i, 0\} \tag{1.2}$$

In case of default, $V_i < K_i$, the equity holders are wiped out, and the remaining value of the firm falls to the bond holders. If a firm does not default, bond holders are paid in full, and equity investors receive the residual claim on the firm's underlying assets.

The market payoff $V_{Mkt.}$ is the sum of the payoffs of the assets issued by the firms in the economy. Using the law of large numbers, the total payoff of the market (i.e. all assets in the economy) is:

$$V_{Mkt.} = \int_{\mathcal{A}} V_i d\mu_i = \exp\{\delta + \frac{1}{2}\sigma_I^2 + \epsilon_C\} \tag{1.3}$$

where $\mathcal{A}$ denotes the set of firms in the economy which have a mass of one, and μ is the measure which assigns weights to the firms.[4] Finally, a risk-free asset which promises a payoff of one at time T is available in zero net supply.

Representative Investor. A representative investor seeks to maximize his expected utility of consumption over the model's two periods by choosing the amount of risk-free asset, π^{rf}, as well as the number of bonds, π_i^D, and stocks, π_i^E, from each firm i to include in his portfolio. The investor's utility function, u, formalizes his constant relative risk aversion:

$$u(c) = \frac{c^{1-\gamma}}{1-\gamma} \tag{1.4}$$

where γ is the relative risk aversion parameter. The investor is initially endowed with all assets in the economy, as well as some amount of non-financial wealth W_0. At time 0, the investors consumption, C_0, thus equals his initial endowment (non-financial wealth plus assets) minus the cost of his portfolio. At time T, the investors consumption, C_T, equals the payoff of his portfolio. The investor's maximization problem is:[5]

$$\max_{\pi_i^D, \pi_i^E, \pi^{rf}} \quad u(C_0) + E^\theta[u(C_T)]$$

$$\begin{aligned} \text{s.t.} \qquad C_0 &= W_0 - \int_{\mathcal{A}} (\pi_i^E - 1) P_i^E d\mu_i - \int_{\mathcal{A}} (\pi_i^D - 1) P_i^D d\mu_i - \pi^{rf} \exp\{-y^f\} \\ C_T &= \int_{\mathcal{A}} \pi_i^E E_i + d\mu_i + \int_{\mathcal{A}} \pi_i^D D_i d\mu_i + \pi^{rf} \end{aligned} \tag{1.5}$$

where P_i^D denotes the price of firm i's bonds, P_i^E denotes the price of firm i's equity, and y^f denotes the risk-free (log) bond yield.

The superscript θ in the expectation in equation (1.5) indicates that the investor has diagnostic expectations (Bordalo, Gennaioli, and Shleifer, 2018), which is a formalization of the Kahneman and Tversky (1972) representativeness heuristic. I use the superscript θ throughout the paper to indicate densities and expectations formed under the diagnostic measure. Diagnostic expectations depart from rational expectations by embedding extrapolation in the investor's belief formation. Specifically, the investor overestimates the likelihood of states which become objectively more likely given the news parameter δ, and underestimate the likelihood of states which become objectively less likely given δ. The investor evaluates the news relative to his prior, which I assume is $\delta = 0$, meaning good news ($\delta > 0$) acts as a positive shock while bad news ($\delta < 0$) is a negative shock to the investor. The representativeness of a given realization of the firm's value V_i is defined as the ratio between the objective likelihood of V_i occurring given the news δ, and the investor's prior belief about the likelihood of V_i occurring: $\frac{f(V_i|\delta)}{f(V_i|\delta=0)}$.

Formally, under diagnostic expectations, the investor evaluates expectations using a distorted density function $f^\theta(V_i|\delta)$, which combines the true density function of a firm's payoffs, $f(V_i|\delta)$, with the representa-

[4]Applying the law of large numbers to get to the aggregate market payoff requires a particular structure on the set of firms in the economy, $\mathcal{A}$. I take the structure as given here and refer to Constantinides and Duffie (1996) p. 226-227 for a technical discussion.

[5]To limit notation, I assume the investor has no preference regarding the timing of his consumption.

tiveness, $\frac{f(V_i|\delta)}{f(V_i|\delta=0)}$, of the firm's payoffs:

$$f^{\theta}(V_i|\delta) = f(V_i|\delta)\left(\frac{f(V_i|\delta)}{f(V_i|\delta=0)}\right)^{\theta} \times C \tag{1.6}$$

Here, $\theta \geq 0$ governs how distorted the investor's beliefs are, and $C = \exp\left\{\frac{-\delta^2\theta(1+\theta)}{2\sigma^2}\right\}$ is a constant that ensures that f^{θ} integrates to one.

Extrapolation occurs as the investor observes news δ, and overestimates how good or bad the news actually is by assigning too high probabilities to states of the world that become objectively more likely given the news $\frac{f(V_i|\delta)}{f(V_i|\delta=0)} > 1$, i.e., states which are representative, and too low probabilities to states of the world which become objectively less likely $\frac{f(V_i|\delta)}{f(V_i|\delta=0)} < 1$.[6] Risk neglect occurs following good news as the investor underestimates the probability if low realizations of firm value V_i, which have become less likely given the good news.

A convenient feature of coupling diagnostic expectations with lognormally distributed payoffs is that investors still perceive a firm's payoff as being lognormally distributed, but with a biased location parameter, as I show next.[7]

Lemma 1. *An investor with diagnostic expectations perceives the underlying value of the firm as being lognormally distributed with a biased location parameter. Specifically, the investor perceives the distribution of firm i's payoff to be lognormally distributed with the biased location parameter $\delta(1+\theta)$, and shape parameter equal to the true shape parameter: $\sqrt{\sigma_I^2 + \sigma_C^2}$.*

Equilibrium. In equilibrium the representative investor's demand for stocks and bonds equals the supply, $\pi_i^E = \pi_i^D = 1$, for all i, and the demand for the risk-free asset equals zero, $\pi^{rf} = 0$. As a consequence, the investor consumes his full initial non-financial wealth endowment at time 0, $C_0 = W_0$, and the aggregate payoff of the market at time T, $C_T = V_{Mkt.}$. Without loss of generality, I normalize the initial wealth of the investor to 1.

2.2 Theoretical results

By combining the equilibrium relation with the investor's first-order conditions, I can define a stochastic discount factor, m, which prices all assets in the economy.

Proposition 1 (Stochastic Discount Factor). *A unique equilibrium exists where the price of any time-T payoff X can be written as $P = E^{\theta}[mX]$, where the stochastic discount factor, m, is given by:*

$$m = \exp\{-\gamma[\delta + \frac{1}{2}\sigma_I^2 + \epsilon_C]\}$$

and E^{θ} denotes the expectation formed under the diagnostic measure given in equation (1.6).

Having defined the stochastic discount factor m, the equilibrium risk-free bond yield is given from the representative investor's expectation of m.

[6] To be exact, it is the states of the world which are *sufficiently* representative, $\left(\frac{f(V_i|\delta)}{f(V_i|\delta=0)}\right)^{\theta} \times C > 1$, that are overweighted under diagnostic expectations. This small correction stems from the normalization constant C.

[7] Lemma 1 echoes findings of Maxted (2020) and Bordalo, Gennaioli, Shleifer, and Terry (2021) who study real business cycle models with diagnostic expectations.

Corollary 1. *The equilibrium risk-free (log) bond yield is:*

$$y^f = \gamma[\delta(1+\theta) + \frac{1}{2}\sigma_I^2] - \frac{1}{2}\gamma^2\sigma_C^2$$

The risk-free bond yield increases with the expected (log) payoff of the market ($\delta(1+\theta) + \frac{1}{2}\sigma_I^2$) as the investor becomes wealthier and requires a higher risk-free bond yield to postpone consumption. Diagnostic expectations affects the risk-free bond yield by amplifying the effect of the news, δ, about the market's future payoff. For example, if the investor receives good news, $\delta > 0$, extrapolation means the investor overestimates the future payoff of the market and thus his future consumption, and sets the risk-free bond yield too high. Conversely, if the investor receives bad news he becomes too pessimistic about the future economy and the risk-free bond yield drops. Market volatility, σ_C, lowers the risk-free bond yield as the investor seeks to hedge against uncertainty by saving in the risk-free asset.

Expected Returns. To understand how risk aversion and beliefs interact to form expected returns, it is useful to first look at the expected return of a given firm's total assets. Let $R_i = \frac{E[V_i]}{P_i^V}$ be the gross return on firm i's total assets, where $P_i^V = E^\theta[mV_i]$ is the time 0 price of firm i's assets, and $E[V_i]$ is the rational expected payoff of firm i's assets.

Proposition 2 (**Expected Return on Firm**)**.** *The (log) expected excess return on firm i's assets is:*

$$\log E[R_i] - y^f = \gamma\sigma_C^2 - \delta\theta$$

Note that the expected excess return differs from the investor's required excess return (i.e. the investor's expectation of the return), which simply equals the risk premium $\gamma\sigma_C^2$. The investor is thus not aware of his bias, $\delta\theta$, which affects the asset's expected return as the investor misprices the firm as a consequence of extrapolative beliefs. In particular, if the investor's beliefs are sufficiently biased, and he receives good news $\delta > 0$, the expected excess return of the firm's underlying assets becomes negative. I define such a situation as a "bubble".

Definition 1. *I define a bubble as a situation where positive news, $\delta > 0$, and biased beliefs, $\theta > \theta^* = \frac{\gamma\sigma_C^2}{\delta}$, make expected excess returns on the firm's underlying assets negative.*

As such, bubbles are periods where beliefs are sufficiently distorted to dominate risk premia and lead to expected negative excess returns.

To calculate expected returns of bonds and stocks in the economy, as well as credit spreads, I introduce distance-to-default, DD_i, as the measure of a firm's credit risk. Distance-to-default measures how far a firm is from default in terms of asset volatility:

$$DD_i = \frac{\delta - \log(K_i)}{\sigma_V} \tag{1.7}$$

where $\sigma_V = \sqrt{\sigma_I^2 + \sigma_C^2}$ is the volatility of the firms assets, and $\delta - \log(K_i)$ is the distance between the firm's expected log payoff, δ, and its (log) default barrier, $\log K_i$. The (log) credit spread on firm i's bond is the difference between the bond's (log) yield, $y_i = \log\left(\frac{K_i}{P_i^D}\right)$, and the (log) risk-free bond yield, y^f. Here, $P_i^D = E^\theta[mD_i]$ is the price of firm i's bond. The (log) credit spreads is the difference between the (log) yield of firm i's bond and the risk-free bond yield: $cs_i = y_i - y^f$.

Proposition 3 (**Credit Spread**). *The (log) credit spread on firm i's bond is:*

$$cs_i = -\log\left(\frac{P_i^V}{\exp\{-y^f\}K_i}\Phi\left(-DD_i - \sigma_V - \frac{\theta\delta}{\sigma_V} + \gamma\frac{\sigma_C^2}{\sigma_V}\right) + \Phi\left(DD_i + \frac{\theta\delta}{\sigma_V} - \frac{\gamma\sigma_C^2}{\sigma_V}\right)\right) \tag{1.8}$$

where Φ is the cumulative density function of a standard normal distribution.

We see that a bond's credit spread is driven by the model's three components:

1. Credit risk from the firm's capital structure: DD_i
2. Bias in the investor's expectations: $\delta\theta$
3. Risk aversion from the investor's preferences: $\gamma\sigma_C^2$

In the special case of a rational, risk neutral investor ($\gamma = \theta = 0$) the credit spread of a bond is approximately equal to the expected loss on the bond:

$$cs_i = -\log(1 - EL_i) \approx EL_i \tag{1.9}$$

where EL_i is the (rational) expected loss on the bond issued by firm i measured as a fraction of the notional:

$$\begin{aligned} EL_i &= E[1_{\{V_i<K_i\}}\frac{K_i - V_i}{K_i}] \\ &= \Phi(-DD_i) - \frac{E[V_i]}{K_i}\Phi(-DD_i - \sigma_V) \end{aligned} \tag{1.10}$$

If the investor has diagnostic expectations, $\theta > 0$, we can replace the true distance to default, DD_i, with the investor's perceived distance to default, $DD_i^\theta = DD_i + \frac{\delta\theta}{\sigma_V}$, and the true expected firm value, $E[V_i]$, with the investor's expectation about the firm value $E^\theta[V_i]$ to get the investor's expected loss:

$$EL_i^\theta = \Phi(-DD_i^\theta) - \frac{E^\theta[V_i]}{K_i}\Phi(-DD_i^\theta - \sigma_V) \tag{1.11}$$

We can see that because the investor overestimates the firm payoff V_i when $\delta > 0$ and thus the firm's distance to default, the investor underestimates the expected loss on the bond, $EL_i^\theta < EL_i$, and therefore requires a too low credit spread on the firm's bond.

The expected returns on a firm's bond and stock are simple functions of the bond's expected loss and yield, as well as the firm's leverage. Let $R_i^D = \frac{D_i}{P_i^D}$ denote the gross return on firm i's bond, and $R_i^E = \frac{E_i}{P_i^E}$ denote the gross return on the firm i's equity, where P_i^E is the price of firm i's equity at time 0. Further, let $L_i = \frac{P_i^D}{P_i^E}$ be the market leverage of the firm at time 0.

Proposition 4 (**Expected Returns on Assets**).

1. *The (log) expected excess return on firm i's bond is approximately the difference between the log credit spread and the expected loss on the bond:*

$$\log E[R_i^D] - y^f = cs_i + \log(1 - EL_i) \approx cs_i - EL_i$$

2. *The (log) expected excess return on firm i's equity is the (log) expected excess return on firm i's assets amplified by the firm's leverage:*

$$\log E[R_i^E] - y^f = \log E[R_i] - y^f + \log\left(1 + L_i\left(\frac{E[R_i] - E[R_i^D]}{E[R_i]}\right)\right)$$

Proposition 4.2 is a restatement of Modigliani and Miller (1958) Proposition 2. From Proposition 4 we can prove that in the cross-section of firms, the expected returns on a firm's equities are more sensitive to changes in the firm's capital structure than the expected returns on a firm's bonds:

Proposition 5 (**Risk Sensitivity**). *For low enough K_i, the expected return on equities is more sensitive to changes in risk than the expected returns on bonds:*

$$\left|\frac{\partial}{\partial K_i} E[R_i^E]\right| \geq \left|\frac{\partial}{\partial K_i} E[R_i^D]\right| \geq 0$$

Note that it is only in the special case, where the investor is effectively risk-neutral, $\theta = \theta^*$, that the inequalities of Proposition 5 are not strict.

Further, Proposition 4 makes it is clear that a low credit spread implies a low expected return. In fact, in a bubble, the expected excess return on a firm's bonds and stocks turn negative as prices become too elevated. This effect is strongest for the riskiest firms, i.e. the firms with the highest leverage, leading to an inversion in the risk-return relationship:

Proposition 6 (**Risk-Return Inversion**). *The relationship between risk and expected return inverts when news is good $\delta > 0$, and the investor's beliefs are sufficiently biased $\theta > \theta^*$:*

$$\frac{\partial}{\partial K_i} E[R_i^E] < 0$$
$$\frac{\partial}{\partial K_i} E[R_i^D] < 0$$

Figure 2 illustrates the relationship between risk, measured by a firm's outstanding debt K_i, and the expected returns on a firm's assets, both in a "normal" economy, and a bubble economy. We can see that the Modigliani and Miller (1958) propositions hold both in and out of a bubble, as it is the fundamental value of the firm, which the investor gets wrong, not the value of one particular asset. We see that the expected return on a firm's bond naturally approaches the risk-free bond yield as the firm's leverage, measured by the face value of the firm's debt, approaches zero. As leverage increases, the expected return on the firm's bond approaches the expected return on a firm's total assets. By definition, the expected return on the firm's underlying assets is below the risk-free bond yield in a bubble, and, as consequence, the expected return on the firm's debt is decreasing with the firm's leverage. Similarly, for an all-equity financed firm, the expected return on a firm's equity is equal to the expected return on the firm's assets. As the firm increases its leverage, the expected return on the firm's equity either increases (no bubble) or decreases (bubble), because the equity is just a levered bet on the firm's assets. In normal times (i.e. outside of a bubble) the expected return on a firm's assets is above the expected return on a firm's debt, and the expected return on a firm's equity therefore increases with leverage. In a bubble, the expected return on a firm's assets is less that then expected return on a firm's debt, and the expected return on a firm's equity therefore decreases with leverage.

Figure 2 depicts this inversion in the risk-return relationship for both the expected returns on bonds and stocks in a bubble.

Testable Predictions. In summary, the theory leads to the following testable predictions for the cross-section of returns on bonds and stocks:

1. The expected return on risky bonds over safe bonds is predicted by the difference in credit spreads between the bonds, relative to the difference in their expected losses.

2. Similarly, the difference in credit spreads between the risky and safe bonds relative to the difference in their expected losses predicts the expected return on risky equities over safe equities.

3. In a bubble, $\theta > \theta^*$, the expected returns on both risky bonds over safe bonds, and the expected returns of risky equities over safe equities, is negative, with the equity portfolio carrying the most negative expected return. Empirically, this means that risk neglect is easier to detect in the cross-section of stock returns than in the cross-section of bond returns.

3 Data

I construct a panel of corporate bond returns and yields using information from three databases. The first database is the Lehman/Warga database, which provides monthly information – including yields, returns, maturities, and ratings – on the publicly traded, nonconvertible bonds in the Lehman Brothers Bond Indices from January 1973 to March 1997. Returns are calculated from lot bid prices, which are based on either actual dealer quotes or "matrix prices" calculated from the dealer quotes on resembling bonds. I include only bonds with yields and returns based on actual dealer quotes in my sample.[8]

The second bond database is the ICE Fixed Income platform, which provides daily data on the constituents on the ICE Bank of America Fixed Income Indices (formerly known as the Bank of America-Merrill Lynch Global Research FICC index platform) starting in December 1996. The database includes information on returns, yields, and bond-level characteristics such as duration and ratings. The third database is the WRDS Corporate Bond Panel, which compiles information from the TRACE Standard database and the TRACE enhanced database to construct a monthly panel of returns, yields, and bond characteristics for all corporate bonds traded since July 2002.[9]

To estimate the credit spread of each bond in the panel, I subtract the yield of a synthetic zero-coupon Treasury bond with duration equal to that of the corporate bond. I obtain data on the U.S. Treasury yield curve from The Federal Reserve Board (Gürkaynak, Sack, and Wright, 2007) and estimate the yield of the synthetic Treasury bond using linear interpolation.[10]

I retrieve information on quarterly accounts from CompuStat, and information on monthly equity returns and market capitalizations from CRSP. Given that book data is not reported at a monthly frequency, I

[8]See Gebhardt, Hvidkjaer, and Swaminathan (2005) and Hong and Warga (2000) for more details on this database.

[9]See https://wrds-www.wharton.upenn.edu for more information.

[10]For a given maturity m^* the synthetic Treasury yield $y^f_{m^*}$ is found as:

$$y^f_{m^*} = y_{\underline{m}} + \frac{y^f_{\overline{m}} - y^f_{\underline{m}}}{\overline{m} - \underline{m}}(m^* - \underline{m})$$

where $\underline{m}$ is the longest duration less that m^* for which we have data on Treasury yields. Similarly, $\overline{m}$ is the shortest duration greater than m^* for which we have data on Treasury yields.

include the most recently available book data within a year. I further add information from Mergent FISD on special bond characteristics such as callability, convertability, and sinking-fund provisions, when these are not provided by the databases listed above.

I merge the three corporate bond databases to construct a monthly panel of bond yields and returns along with the firm level characteristics from 1502 different firms starting in January 1976 and ending in February 2019.[11] My sample consists of senior investment-grade bonds (BAA3 and higher on Moody's rating scale) from the Lehman/Warga database (January 1976 to December 1996), the ICE Bank of America Fixed Income Indices (January 1997 to June 2002), and the WRDS (TRACE) Corporate Bond Panel (July 2002 to February 2019). I include bonds with time to maturity greater than 2 years issued by non-financial firms with a market capitalization of more than \$50 million in 2016 real terms.[12] I exclude speculative-grade bonds to keep the composition of my sample as homogeneous as possible over time, such that my results are not affected by, e.g., the growth in speculative-grade bonds experienced during the 1980's. Further, by looking only at investment-grade bonds, I minimize potential obfuscation stemming from differences in liquidity, which is known to be an important determinant of credit spreads among speculative-grade bonds, but much less so among investment-grade bonds.[13] It is further plausible that risk neglect is strongest among bonds with an external endorsement in the form of an investment-grade credit rating. Finally, I exclude all convertible and putable bonds along with bonds with sinking fund provisions in order to better identify the relationship between credit risk and credit spreads.

Returns, yields, and firm characteristics such as distance-to-default are all winsorized at the 1% level to mitigate worries that outliers might be driving the results. I keep the data at bond-level, which means I allow firms to enter the panel with multiple bonds. I do this to better correct for bond characteristics such as duration and callability. An alternative approach is to aggregate returns and yields to firm level, effectively creating one hybrid bond for each firm. There is precedent for both approaches in the literature (Bessembinder et al., 2009), but my results are not sensitive to the approach used. Summary statistics for my sample can be found in Table I.

4 Measuring Sentiment: Yield-for-Risk

I define a novel measure of credit market sentiment, which captures how much credit spreads fluctuate with credit risk in the cross-section of bonds at a given point in time. Specifically, I measure the additional yield required by investors when a firm moves one standard deviation closer to default. I name this measure yield-for-risk (YFR_t), and I estimate it by regressing credit spreads on distance-to-default at each point in time:

$$y_{ijt} - y^f_{jt} = \alpha_t + YFR_t \times (-\widetilde{DD}_{it}) + \gamma_t' Z_{ijt} + \epsilon_{ijt} \tag{1.12}$$

Here, y_{ijt} is the time-t yield of bond j issued by firm i, and y^f_{jt} is the yield of a zero-coupon Treasury bond with maturity equal to the duration of bond j. Subtracting the Treasury yield ensures that YFR_t is measuring compensation for risk and is not contaminated by the term structure of risk-free rates. Following the model

[11] While the Lehman/Warga database starts in 1973 there are very few actual quotes before 1976, which is the reason my sample starts here.

[12] Non-financial firms are defined as firm's with SIC codes outside the range 6000-6799.

[13] Feldhütter and Schaefer (2018) find no relation between liquidity and bond yields among investment-grade bonds from 1987-2012. Similarly, Dick-Nielsen et al. (2012) finds liquidity to have little effect on investment-grade bond yields outside the 2008 financial crises.

in Section 2, risk is measured by a firm's distance-to-default and is estimated following the methodology of Bharath and Shumway (2008):

$$\widetilde{DD}_{it} = \frac{\log\left((ME_{it} + F_{it})\right) + r_{it-1} - 0.5\sigma_{it}^2 - \log(F_{it})}{\sigma_{it}} \tag{1.13}$$

Here, ME_{it} is the market value of the firm's equity, F_{it} is the face value of the firm's debt, r_{it-1} is the return on the firm's stock over the past year, and σ_{it} is the volatility of the firm's assets.[14] The tilde is added to distinguish the empirical measure of distance-to-default, $\widetilde{DD}_{it}$, from the theoretical distance-to-default, DD_i, defined in equation (1.7). To see that the empirical measure of distance-to-default, $\widetilde{DD}_{it}$, approximates the theoretical distance-to-default, note that the first three terms in the numerator of equation (1.13) approximates the expected (log) value of the firm i one year from now, assuming the value of the firm follows a geometric Brownian motion with drift set to last years equity return r_{it-1}. As in the model, a high $\widetilde{DD}_{it}$ means a firm is safe, as it has low leverage relative to the volatility of its underlying assets and therefore little risk of default. Vice versa, a low $\widetilde{DD}_{it}$ means the firm is relatively close to its default barrier, F_{it}, and thus risky. The vector Z_{ijt} contains the control variables: the (log) duration of the bond, the size of the issuer, the age of the bond, and an indicator variable that equals one if bond j is callable.[15] I include duration to account for the term structure of credit spreads, while issuer size is included to mitigate the potential differences in liquidity between bonds issued by larger firms and bonds issued by smaller firms. Similarly, bond age is included as a control variable to account for potential differences in liquidity between newly issued bonds and seasoned bonds. Lastly, I control for callability to account for the time-varying value of the option to redeem the bond early.[16]

Figure 1 presents the time-series plot of YFR_t. A strength of YFR_t as a measure of sentiment is that it easily identifies periods where investors are insensitive to risk. For example, in May of 2007, immediately prior to the financial crisis, YFR_t reaches levels as low as 0.01%, which means the investors require just 1 basis point more in yield for holding a bond that is one standard deviation closer to default. Given that the cross-sectional standard deviation in distance-to-default is 6.3 in May, 2007, a YFR_t of 0.01% corresponds to investors requiring just 0.15% more in yield when distance-to-default falls by two standard deviations. In contrast, during the Global Financial Crisis in March, 2009, YFR_t reaches 0.29%, meaning investors on average require 29 basis points in additional yield when a bond moves a standard deviation closer to default. Given that the cross-sectional standard deviation in distance-to-default is 3.3 in March 2009, a YFR_t of 0.29% corresponds to investors requiring 1.9 percentage points more in yield when distance-to-default falls by two standard deviations.

Episodes of low YFR_t are particularly interesting given that the credit spread of a bond must at least compensate the investor for the bond's expected loss, as seen in the model of Section 2. This means that in May of 2007, investors expect losses to increase by at most 0.01% when a bond moves one standard deviation closer to default. To be clear, this may be rational, and YFR_t cannot ex ante reject that investors are correctly assessing the risk of the bond market. YFR_t simply provides a bound on the beliefs investors must have about the relationship between risk and expected losses in the cross-section of corporate bonds.

[14] The face value of debt is approximated by a firm's current liabilities plus one-half the firm's long-term liabilities (`dlcq`+0.5×`dlttq`). The volatility of the firm's assets is estimated as $\sigma_{it} = E_{it}/(E_{it}+F_{it})\sigma_{it}^E + F_{it}/(E_{it}+F_{it})(0.05+0.25\sigma_{it}^E)$, where σ_{it}^E is the annualized volatility of the firm's monthly stock return over the past year.

[15] Issuer size is defined as the log of total assets (`atq`), and bond age is defined as the (log) number of years the bond has been in my panel.

[16] For example, Duffee (1998) documents the time-varying value of the option embedded in a callable bond.

To understand what characterizes periods of high and low yield-for-risk, I regress YFR_t on four variables, which capture the state of the economy and the current sentiment in the market. The first variable is the issuer-weighted default rate of corporations obtained from Moody's Investors Service in a given year, the second is the net fraction of banks reporting tighter lending standard minus the fraction of banks report looser lending standards in the the Federal Reserve's Senior Loan Officer Opinion Survey in a given quarter, the third is the excess return on the corporate bond market over the past three years (annualized), and the fourth is the excess return on the stock market over the past three years (annualized). Table II presents the results. Yield-for-risk is scaled to basis points (bp) in the regressions such that a coefficient of 2.2 in Column 1 means that a 1% lower default rate in a given year is associated with a 2.2 bp lower YFR_t by the end of the year. Similarly, a quarter where the fraction of banks reporting tightening lending standards minus the fraction of banks reporting loosening lending standard falls by 1% is succeeded by a 0.15 bp lower YFR_t at the end of the quarter. Lastly, a 1% higher annual excess bond market return over the past three years, or a 1% higher annual excess stock market return over the past three years is followed by a 0.15 bp, and 0.38 bp, lower YFR_t, respectively. In summary, we see that low YFR_t is preceeded by low default rates among corporates, loosening lending standards, and high returns in both the bond and stock markets. The results are consistent with the notion that periods of low yield-for-risk are periods where investors regard the bond market as being fairly safe based on the past performance of bonds and the markets in general.

Given that the theoretical relationship between distance-to-default and credit spreads is non-linear, as seen in Proposition 3, I conduct a final exercise to assess the ability of YFR_t to describe the cross-sectional distribution of credit spreads. First, Figure 3 plots the relationship at two dates to show that the explanatory power of YFR_t varies substantially over time, but that the linear specification is a natural first approximation to describing the cross-sectional relationship between risk and credit spread. In fact, excluding $\widetilde{DD}_{it}$ from the regression equation (1.12) reduces the (within) R^2 dramatically from 36% to 19%.[17] In contrast, adding the squared of distance-to-default, $\widetilde{DD}_{it}^2$, to catch potential non-linearities, only increases the R^2 by a further 5%. In addition, the squared distance-to-default contributes with almost no explanatory power for the periods we are particularly interested in identifying, namely when YFR_t is low.[18] Adding the squared distance-to-default as a control variable to the estimation of the YFR_t parameter does not change the basic dynamics of YFR_t, nor its ability to predict returns in the cross-section and the time-series of corporate bonds and equities. It does however ruin the interpretability of YFR_t, and is therefore left out. Finally, it should be noted that the objective of YFR_t is not to obtain the best cross-sectional mapping from distance-to-default to credit spreads, but instead to extract a single, intuitive metric, which captures the sentiment of bond market investors.

5 Empirical Implementation and Results

5.1 Predicting Returns to Credit Risk in the Cross-Section

If YFR_t captures sentiment, either in the form of time-varying risk aversion or diagnostic expectations, it also predicts returns, as shown in Proposition 4. In particular, it should predict the returns of the riskiest bonds over the safest bonds, and the riskiest equities over the safest equities. To test the hypothesis that YFR_t predicts the cross-section of bond returns, I construct a self-financing portfolio with monthly rebalancing,

[17]Within R^2 measures the how much of the variation in credit spreads the regression model explains after accounting for the variation explained by the date fixed effect, a_t, and the fixed effect accounting for callable bonds.

[18]For example, when YFR_t is in its lowest quartile, adding $\widetilde{DD}_{it}^2$ to the estimation increases (within) R^2 by less than 2%.

which is long the bonds of the riskiest firms at time t (i.e. the firms with the lowest distance-to-default), and short the bonds of the safest firms (i.e. the firms with the highest distance-to-default). Formally, let k_t denote the number of bonds in my panel at time t and define the h-month return to the $n\%$ riskiest bonds as:

$$r_{t+h}^{n\%\ riskiest} = \sum_{j=1}^{k_t} w_{jt} r_{ijt+h} 1_{\{\widetilde{DD}_{it} < n^{th} \text{ percentile}\}} \tag{1.14}$$

Here, r_{ijt+h} is the h-month return on the bond j issued by firm i from time t to time $t+h$, $1_{\{\widetilde{DD}_{it} < n^{th} \text{ percentile}\}}$ is an indicator variable, which equals one if firm i is among the $n\%$ riskiest firms at time t, meaning it has a distance-to-default which is below the n'th percentile at time t. w_{jt} is the portfolio weight of bond j, i.e. the fraction of the portfolio invested in bond j. Similarly, I define the return to the $n\%$ safest bonds as:

$$r_{t+h}^{n\%\ safest} = \sum_{j=1}^{k_t} w_{jt} r_{ijt+h} 1_{\{\widetilde{DD}_{it} > (100 - n^{th}) \text{ percentile}\}} \tag{1.15}$$

For my baseline analysis, I use equal-weighted returns $w_{jt} = (\sum_{h=1}^{k_t} 1_{\{\widetilde{DD}_{ht} < n^{th} \text{ percentile}\}})^{-1}$, and include the 20% riskiest firms in the high-risk portfolio and the 20% safest firms in the low-risk portfolio ($n = 20$).[19] I then estimate the forecasting model:

$$r_{t+h}^{20\%\ riskiest} - r_{t+h}^{20\%\ safest} = \alpha + \beta \times YFR_t + \zeta^T X_{t+h} + \epsilon_{t+h} \tag{1.16}$$

where $r_{t+h}^{20\%\ riskiest} - r_{t+h}^{20\%\ safest}$ is the h-month return to the 20% riskiest corporate bonds over the 20% safest corporate bonds, and YFR_t is the yield-for-risk parameter estimated from equation (1.12) normalized by its standard deviation. The vector X_{t+h} contains the change in the level of the 10-year Treasury yield, and the change in the slope of the Treasury yield curve, measured as the difference between the 10-year and the 1-year Treasury yield, as control variables. The changes in the level and slope of the Treasury yield curve are measured contemporaneously with the returns of the long-short bond portfolio, and are included to ensure that any predictability detected stems for the repricing of credit risk, and not changes in the risk-free rate, which is the other key determinant of bond returns.

Panel A of Table III presents the results of predicting returns to credit risk in the cross-section of corporate bonds at the 1-, 6- and 12-month horizon. We see that YFR_t significantly predicts returns to the cross-section of bonds consistent with the interpretation of YFR_t as a measure of bond market sentiment: when YFR_t is high the expected return on risky bonds over safe bonds is high and positive, and when YFR_t is low, the expected return on risky bonds over safe bonds is low. The effect is statistically and economically significant, and grows substantially with the prediction horizon. A one standard deviation increase in yield-for-risk leads to a 15 basis point increase in the average returns of the riskiest bonds over the safest bonds over the following month, a 1.0% increase in average returns over the following 6-months, and 1.6% increase over the following 12-months. The predictability remains significant and virtually unchanged in magnitude when controlling for contemporaneous changes in the level and slope of the Treasury yield curve, which indicates that YFR_t is in fact predicting changes in the price of credit risk. In order to account for autocorrelation and

[19] In the robustness analysis below I show that my results are robust to different specifications of weights w_{jt} and portfolio inclusion criteria n.

heteroskedasticity in the regression residuals, I use Newey and West (1987) standard errors with 0, 9 and 18 monthly lags at the 1-, 6- and 12-month prediction horizon, respectively, to assess the statistical significance of the regression coefficients. I calculate p-values using "fixed-b" asymptotics of Kiefer and Vogelsang (2005) to tackle the well-known issue that t-statistics based on Newey and West (1987) standard errors tend to over-reject in finite samples.

Panel B of Table III repeats the prediction exercise outlined above, but with equity returns replacing bond returns. That is, I construct a self-financing portfolio with monthly rebalancing which is long equities from riskiest quintile of firms, and short equities from the safest quintile of firms. In accordance with Proposition 5, Table III shows that YFR_t also predicts returns to credit risk in the cross-section of equities, and that the returns are more sensitive to fluctuations in sentiment than bond returns. Specifically, a one standard deviation increase in YFR_t leads to a 76 basis point increase in the average returns of the riskiest equities over the safest equities over the following month, a 4.5% increase in average returns over the following 6-months, and 7.5% increase over the following 12-months. Once again we see that controlling for changes in the level and slope of the Treasury yield curve does not materially alter the results.

I test the novelty of YFR_t as a measure of credit risk sentiment by running a horse race of YFR_t as a predictive variable against other well-known measures of credit market sentiment; Excess Bond Premium (EBP) of Gilchrist and Zakrajšek (2012), the *High Yield Share* (HYS) of Greenwood and Hanson (2013), and the CBOE VIX index. The EBP is designed to capture the risk premium in corporate bonds, i.e. the compensation for *"... bearing exposure to US corporate credit risk, above and beyond the compensation for expected defaults."*, while the HYS measures the fraction of newly issued bonds issued by firms with a non-investment grade credit rating. The VIX is constructed to measure 30-day expected volatility from call options on the S&P500 index. Further, I test that the predictability reported in Table III is not subsumed by a standard credit spread such as the average difference in yields between BAA rated bonds and 10-year Treasury bonds. Table IV shows that YFR_t maintains its predictive power in light of the inclusion of any of the other sentiment measures.[20] Further, none of the other known measures of sentiment predict returns to the cross-section of bonds and stocks with any significance, when YFR_t is included in the regression. Note that the HYS is measured only at a quarterly frequency, while the VIX is only available from January 1990. I therefore loose some observations when including these two as controls.

Robustness

I perform a series of additional test to alleviate concerns about the robustness of the predictability documented above. First, I show that my results are not sensitive to the specification of the portfolios. Specifically, I reestimate the forecasting regression (1.16) across a range of different inclusion criteria: $n \in \{15, 20, 25, 30, 35\}$. That is, I predict the returns of the 15% riskiest bonds (and stocks) over the return of the 15% safest bonds (and stocks), the returns of the 20% riskiest bonds (and stocks) over the return of the 20% safest bonds (and stocks), and so forth. Further, in my baseline specification, I calculate portfolio returns with equal weight on every bond in the portfolio. As a consequence, my results might be driven by the smallest bonds and stocks and thus not representative of the market. I redo the prediction exercise (1.16), but weight each bond

[20] The predictive results are only reported on a 12-month basis for brevity, but are similar at 1-month and 6-month prediction horizons. Further, the predictability survives the inclusion of a range of alternative sentiment measures such as the TED Spread (the spread between 3-month USD LIBOR and the 3-month Treasury Bill), the GZ Spread (the average credit spread of Gilchrist and Zakrajšek (2012)), and measures of expected stock market returns like the CAY measure of Lettau and Ludvigson (2001) and cyclically-adjusted price-earnings ratio (CAPE) of Shiller (2000).

by the amount outstanding to address this concern. Similarly, for equity returns, I weight each stock by the market capitalization of the firm.[21] Table V presents the results, showing that as I raise the criteria for entering the portfolio (lower n) the magnitude of the predictive coefficient naturally increases. E.g. if YFR_t falls by one standard deviation, the 12-month returns of the 15% riskiest bonds falls by 1.76% relative to the 15% safest (Panel A, line 1, second last column). In contrast, the returns of the 35% riskiest bonds falls by 1.19% relative to the 35% safest (Panel A, line 5, second last column). This pattern is true across prediction horizons, and is unaffected by changing the portfolio weights to reflect the amount outstanding. The same is true for the predictability of returns to the riskiest equities over the safest equities, as evident from Panel B. The shaded cells of the table indicate the baseline specifications presented in Table III.

Another concern is that the duration of the portfolio changes over time, making the contemporaneous term structure controls included in regression (1.16) invalid. To address this issue, I construct a hedged bond return by measuring the return of each bond in my panel in excess of the return on a synthetic Treasury bond with equal duration:

$$r^{bond,hedged}_{ijt+h} = r^{bond}_{ijt+h} - r^{f}_{t+h} \tag{1.17}$$

where r^{bond}_{ijt+h} is the return from t to $t+h$ on the bond j issued by firm i, and r^{f}_{t+h} is the return on a risk-free Treasury bond of equal duration to bond j from over the same period.

Table V, Panel A presents the results of performing the forecasting regression (1.16) with standard bond returns replaced by the hedged bond returns defined in (1.17). We see that the predictive power of YFR_t on future bond returns is unaffected by the change in dependent variable, indicating that time-varying duration of the long-short portfolio is not driving the predictive relationship.

For equity returns there is not an obvious way to hedge against changes in the risk-free rate, since we do not know the duration of equities. Instead, I use a 36-month rolling window regression to estimate the sensitivity of the one-month equity return of each firm to the one-month return on a 10-year Treasury bond. That is, for each stock i at each date, $\bar{t}$, I regress the one-month equity return r^{stock}_{it+1} on the one-month return of a 10-year Treasury bond using data from $\bar{t}-36$ to $\bar{t}$ only:

$$r^{equity}_{it+1} = a + b_{i\bar{t}}\ r^{f}_{t+1} + e_t \quad \text{for } t \in [\bar{t}-36, \bar{t}] \tag{1.18}$$

I then calculate the h-month interest-rate hedged equity return of firm i, $r^{equity,hedged}_{it+h}$, as equity return of firm i, r^{equity}_{it+h}, minus the sensitivity of firm i's equity returns to Treasury returns, b_{it}, times the h-month return to the 10-year Treasury bond, r^{f}_{t+h}:

$$r^{equity,hedged}_{it+h} = r^{equity}_{it+h} - b_{it} r^{f}_{t+h} \tag{1.19}$$

Table V Panel B presents the results of the forecasting regression (1.16) with hedged equity returns as the dependent variable. We again see that the predictive power of YFR_t on future returns is unaffected by controlling for the changes in risk-free interest rates.

As a final robustness test, I address the concern that finite sample statistical issues may lead me to

[21] Formally, for bonds I let the weight parameter be: $w_{jt} = \frac{Amount\ Outstanding_{jt}}{\sum_h Amount\ Outstanding_{ht}}$, and for equities I let the weighing be $w_{it} = \frac{Market\ Capitalization_{it}}{\sum_h Market\ Capitalization_{ht}}$. I limit weights to be at most 20% such that no single firm or bond dominates the portfolios.

overstate the economic magnitudes of the predictability of returns due to Stambaugh (1999) bias, and the statistical significance of my results due to the tendency of asymptotic standard errors to over-reject in finite samples. The latter concern should be mitigated by the use of Kiefer and Vogelsang (2005) p-values throughout the paper, which are designed to handle this issue. As an additional robustness test, I use the stationary moving blocks bootstrap technique of Politis and Romano (1994) to construct 100,000 pseudo samples, and apply a bootstrap-t procedure to obtain a non-parametric estimate of the p-values.[22] The success parameter applied in creating the pseudo samples is 1/12, meaning that average block length is 12 months, but the result is not sensitive to this specification. Table X presents a comparison of the p-values obtained using regular asymptotic theory and Newey and West (1987) standard errors, using the Kiefer and Vogelsang (2005) adjusted p-values, and finally the p-values obtained from the bootstrap-t procedure. I find virtually no difference in p-values between the methods indicating that finite sample bias is not obfuscating the statistical inference.

Further, Table X reports the standard bootstrap bias estimator, i.e. the difference between the coefficient estimate obtained in my original sample, and the average coefficient estimate of the 100,000 bootstrapped pseudo samples, and shows that bias in the coefficient estimates is negligible. To bolster this conclusion, I also present an analytical estimate of the Stambaugh (1999) bias using the method of Boudoukh et al. (2020) who develop a framework for calculating this bias in overlapping, long-horizon regression. The bias estimated from this analytical approach does not materially differ from the bias estimated using the bootstrap procedure, and I conclude that my results are not driven by small-sample biases.

5.2 Predicting Risk-Return inversion

Panel A and B of Table III both report statistically significant, negative intercepts across all specifications. This implies that the returns on the riskiest bonds and stocks underperforms the returns of the safest bonds and stocks significantly, as sentiment increases and YFR_t approaches zero in accordance with Proposition 6. To formally test if low YFR_t predicts negative returns to risk, I split my time series into four equal-sized periods based on the value of YFR_t. That is, I calculate the empirical distribution of YFR_t based on my full sample and assign all dates at which YFR_t is below the 25^{th} percentile to one group, all dates at which YFR_t is between its 25^{th} and 50^{th} percentile to the next group, and so on. For each of these four groups, I then calculate the average 1-year return to the long-short bond and equity portfolios presented above. Figure 4 presents the results with confidence bands calculated using Newey and West (1987) standard errors with 18 lags and Kiefer and Vogelsang (2005) "fixed-b" asymptotics. We see that when YFR_t is in its lowest quartile, the risk-return relationship has significantly inverted as the riskiest bonds underperform the safest bonds by 0.8% (t-statistic = -3.0) over the following year. Further, the same result holds true in the equity market, where the riskiest equities underperform the safest equities by 7.3% (t-statistic = -4.0) over the following year. In contrast, when YFR_t is in its highest quartile, the riskiest bonds outperform the safest bonds by 2.6% (t-statistic = 2.9) over the following year, and the riskiest equities outperform the safest equities by 10.2% (t-statistic = 3.3) over the following 12 months, consistent with the idea that investors require a premium for holding riskier bonds and stocks. The inversion of the risk return relationship in periods of low YFR_t is consistent with Proposition 6, and evidence that investors neglect the risks embedded in firms' capital

[22] Greenwood, Hanson, Shleifer, and Sørensen (2021) applies the same non-parametric block bootstrap technique and provides a detailed description of the approach in Section D of their Internet Appendix. I refer to their paper for a more detailed description of the method applied here.

structures.

To show that the risk-return inversion documented in Figure 4 is not an artifact of the specification, I change both the criteria for entering the high- and low-risk portfolios, and the periods we consider as periods of high and low yield-for-risk, and redo the analysis above. Specifically, let $r_{t+12}^{n\%\ riskiest}$ be the average 12-month portfolio return on assets issued by firms with distance-to-default below the n'th percentile, and $r_{t+12}^{n\%\ safest}$ be the average 12-month returns on assets issued by firms with distance-to-default above the $(100-n)$'th percentile as defined in (1.14) and (1.15). Further, let $1_{\{YFR_t \leq m\text{'th percentile}\}}$, $1_{\{YFR_t > m\text{'th percentile}\}}$ and $1_{\{m\text{'th percentile} < YFR_t \leq (100-m)\text{'th percentile}\}}$ denote indicator variables that switch on if YFR_t is below its m'th percentile, above its $(100-m)$'th percentile, or in between its m'th and $(100-m)$'th percentile, respectively. I then estimate the regression model:

$$\begin{aligned} r_{t+12}^{n\%\ riskiest} - r_{t+12}^{n\%\ safest} =& \lambda^{Low} \times 1_{\{YFR_t \leq m\text{'th percentile}\}} + \\ & \lambda^{Mid} \times 1_{\{m\text{'th percentile} < YFR_t \leq (100-m)\text{'th percentile}\}} + \\ & \lambda^{High} \times 1_{\{YFR_t > (100-m)\text{'th percentile}\}} + \epsilon_{t+12} \end{aligned}$$

for $n \in \{15, 20, 25, 30, 35\}$ and $m \in \{20, 25, 30, 35\}$. Table VI presents the coefficient estimates and t-statistics for the different specifications for both corporate bonds (Panel A) and equities (Panel B). For both asset classes and all specifications, we see an inversion of the risk-return relationship when YFR_t is low. The inversion is statistically significant across all specifications, except when applying the loosest portfolio criteria (n=35) to the bond market portfolios. As expected, raising the criteria for portfolio inclusion (i.e. lowering n) decreases the β^{low} estimates, and increases β^{high} estimates, as the differences in risk between the high-risk and the low-risk portfolio increases. Likewise, as we sharpen the criteria for what constitutes periods of high and low YFR_t, the coefficient estimates increase (in absolute sense) as the indicator variables capture periods of more pronounced sentiment.

In addition to the robustness tests above, I estimate the potential influence of finite sample bias using the block-bootstrap methodology described in Section 5.1. Table X presents estimates of p-values and biases in coefficient estimates from the bootstrap procedure. We see that finite sample biases do not seem to be driving the risk-return inversion. For example, the bootstrap bias estimate of my baseline coefficient estimate λ^{Low} for corporate bond returns is -0.06% compared to a coefficient estimate of -0.84%. Similarly, for equity returns the bootstrap bias estimate of λ^{Low} is -0.61% relative to a coefficient estimate of -7.78% in my original regression. Further, the results of the bootstrap-t procedure shows us that the statistical significance remains.

5.3 Predicting Aggregate Bond Market Returns

Sentiment should predict not only the returns to credit risk in the cross-section as documented above, but also the time-series as measured by returns to the aggregate bond market. To test this hypothesis, I measure the h-month excess return of the aggregate bond market as the difference between the average h-month return of all bonds in my panel (including non-investment grade bonds) and the h-month risk-free Treasury yield. I regress the excess return of the bond market on YFR_t as in Section 5.1:

$$r_{t+h}^{mkt} - y_t^{f,h} = \alpha + \beta \times YFR_t + \zeta^T X_{t+h} + \delta^T Z_t + \epsilon_{t+h} \tag{1.20}$$

where r^{mkt}_{t+h} is the return on the aggregate bond market from time t to $t+h$ and $y^{f,h}_t$ is the h-month Treasury yield at time t. The yield-for-risk parameter, YFR_t, is normalized by its standard deviation, and X_{t+h} is a vector of control variables which contains the change in the level of the 10-year Treasury yield, and the change in the slope of the Treasury yield curve as in regression (1.16). The vector Z_t contains a series of alternative measures of bond market sentiment; the Excess Bond Premium (Gilchrist and Zakrajšek, 2012), the High Yield Share (Greenwood and Hanson, 2013), the CBOE VIX, and the BAA Spread.

Table VII presents the results. Panel A shows that yield-for-risk is a strong predictor of aggregate excess bond market returns with a one standard deviation increase in YFR_t increasing excess aggregate bond market returns by .23% over the following month, 1.24% over the following 6 months, and 2.05% over the following 12 months. Controlling for contemporaneous changes in Treasury yields does not alter the predictive power of YFR_t, indicating that it is indeed fluctuations in the price of credit risk that YFR_t predicts.

I again test the strength and novelty of YFR_t as a predictive variable by including the known measures of sentiment listed in the vector Z_t in the predictive regression. Table VII, Panel B presents the results at the 12-month prediction horizon, and we see that YFR_t maintains its predictive power despite the inclusion of alternative predictors. I control for changes in the term structure of risk-free rates by including changes in the level and slope of Treasury yields in the regression as above.[23]

The strong predictability of bond market returns, raises the question if the return on the equity market is also predicted by YFR_t. According to the model of Section 2, the determinants of the returns to the aggregate bond market and the aggregate equity market should be the same, and we therefore expect to see the same predictive power for aggregate equity market returns as for aggregate bond market returns. I rerun regression (1.20) with the excess aggregate equity market return as the dependent variable, and while there is a positive relationship between YFR_t and future excess equity market returns, the relationship is not statistically significant.[24]

5.4 Predicting Debt Issuance

It is well-known that firms adjust their capital structure in response to the valuations of their assets (Baker and Wurgler, 2000; Ma, 2019). To see how firm behavior relates to YFR_t, I run a panel regression of net debt issuance on YFR_t using quarterly book data from Compustat. Table VIII presents the results of the forecasting regression:

$$Issuance_{it+3} = \alpha_i + \beta \times YFR_t + \delta^T Z_{it} + \epsilon_{it+3} \tag{1.21}$$

where $Issuance_{it+3}$ is the net debt issuance measured as the difference between long-term debt issuance (`dltis`) and long-term debt reduction (`dltr`) over the quarter from t to $t+3$. Yield-for-risk, YFR_t, is the parameter estimate from equation (1.12) normalized by its standard deviation, and Z_{it} is a vector of control variables which contains measures of balance sheet strength, the 10-year US Treasury yield as well as 4 quarterly lags of the dependent variable. I include lags of the dependent variable to control for trends in firm debt issuances, as well as potential omitted variables, while the 10-year Treasury yield is included to control

[23] In untabulated tests, I rerun the analysis using the adjusted bond returns described in the robustness tests of Section 5.1 with no consequence to the results.

[24] I obtain the value-weighted equity market return of all US firms listed on NYSE, AMEX, or NASDAQ that have a CRSP share code of 10 or 11 from Ken French's website: mba.tuck.dartmouth.edu/pages/faculty/ken.french, and use this as my measure of the aggregate equity market return.

for the level of interest rates broadly. To control for balance sheet strength, I include the firm's cash holdings and short-term investments (`cheq`), as well as net income (`niq`) and earnings (`ebitda`) over the previous quarter. All balance sheet variables are normalized by the lag total assets of the firm (`atq`). I include all non-financial firms in Compustat and not just the firms present in my bond panel.[25]

Table VIII shows that a one standard deviation decrease in YFR_t is associated with an average increase in debt issuance of 0.29% over the following quarter measured as a percentage of firm assets. From Table VIII, Column 2 we see that YFR_t retains its predictive power when including the control variables, though the parameter estimate falls a bit to -0.24%. As an additional robustness test, Column 3 of Table VIII presents the results of the regression model with firm fixed effects as an alternative to the inclusion of lagged dependent variables. The firm fixed effects specification has the advantage that it controls for any time-invariant, firm-specific omitted variable which could influence my result due the changing composition of my panel. We see that the change in specification causes only a small decrease in the predictive power of YFR_t.

Compustat only reports long-term debt issuance (and reduction) beginning in 1984 and so the prediction exercise using net debt issuance as the dependent variable does not span the full time-series for which YFR_t is available. I therefore rerun the forecasting regression in equation (1.21), but replace net debt issuance with the change in total liabilities as the dependent variable. I measure total liabilities as the difference between a firm's total assets (`atq`) and book equity.[26] The change in total liabilities is a broader measure of a firm's leverage than net debt issuance as it includes all firm liabilities and not just long-term debt. Column 4 of Table VIII presents the results of regression (1.21) with the change in total liabilities as dependent variable, and shows us that a one standard deviation decrease in YFR_t is an even stronger predictor of the change in total liabilities ($\beta = -0.47\%$) than of the net debt issuance. Overall, the results tell us that periods of low YFR_t are periods where firms increase their leverage by increasing both their long-term debt issuance and by increasing other liabilities.

The unbalanced nature of my panel may mean my results are driven primarily by the dates with relatively more observations. To mitigate this concern, I collapse my panel into a single time-series by measuring the average net debt issuance, and the average change in total liabilities, at each date, and regress these averages on YFR_t, the 1-year Treasury yield and four quarterly lags of the dependent variable. Columns 5 and 6 of Table VIII presents the results. I find that YFR_t still predicts net debt issuance and change in total liabilities in the collapsed time-series setting.

Having documented that firms on average increase their debt issuance when YFR_t is low, I now test whether it is the riskiest firms who are most sensitive to sentiment. I measure the relative riskiness of each firm i at each date t as the fraction of firms which are safer that firm i at time t:

$$Risk_{it} = \frac{1}{k_t - 1} \sum_{j=1}^{k_t} 1_{\{\widetilde{DD}_{jt} > \widetilde{DD}_{it}\}} \tag{1.22}$$

Here, k_t is the number of firms in the panel at time t, and $1_{\{\widetilde{DD}_{jt} > \widetilde{DD}_{it}\}}$ is an indicator variable that switches on if firm j has a higher distance-to-default than firm i at time j. The construction of the variable ensures

[25] My results do not change materially, if I restrict my sample to include only firms with bonds in my panel, though the statistical significance is somewhat dampened due to the lower number of observations. As with the bond panel, I restrict the sample to only include firms with a market capitalization above \$50 m. in 2016 inflation-adjusted terms.

[26] Book equity is defined as in Fama and French (1993) as stockholders' equity (`seqq`) plus deferred taxes and investment tax credit (`txditcq`) minus preferred stock (`pstkq`). Deferred taxes, investment tax credit and preferred stock are accounted for when provided and otherwise set to zero.

that the riskiest firm at a given point in time has $Risk_{it} = 1$ while the safest firm has $Risk_{it} = 0$. Table IX presents the results of the regression:

$$Issuance_{it+3} = \alpha_i + \beta \times YFR_t + \chi \times Risk_{it} + \xi \times YFR_t \times Risk_{it} + \delta^T Z_{it} + \epsilon_{it+3} \tag{1.23}$$

where Z_{it} includes the same control variables as in regression specification (1.21). Table IX shows that the main effect of the risk variable is between -0.6% and -1% depending on the specification. This means the riskiest firm in the cross section on average issues less debt as a percentage of total assets than the safest. This is not surprising as safe firms have a higher debt capacity, and thus can issue more debt at lower rates. The more interesting part of the analysis is the negative interaction effect between the cross-sectional risk measure and YFR_t. For example, Column 1 of Table IX shows that the main effect of YFR_t is -0.16%, while the interaction effect between YFR_t and the risk percentile is -0.19%, meaning the riskiest firm in the cross-section is more than twice as sensitive to YFR_t than the safest firm in the cross-section. Columns 2 and 3 show that the result is robust to the inclusion of lagged dependent variables and controls for balance sheet strength. Further, the result holds when changing the dependent variable to changes in total liabilities as shown in Column 4.

The periods of low YFR_t are of special interest in my analysis as they are periods of potential risk neglect. I take a closer look at these periods by testing if it is the riskiest firms that increase their debt, and by how much, in periods of low YFR_t, as we would expect given the results in Table IX. To do so, I estimate the regression:

$$\begin{aligned} Issuance_{it+3} = &\sum_{k=1}^{5} \chi_k 1_{\{\widetilde{DD}_{it} \text{ in k'th Quintile}\}} \\ &+ \sum_{k=1}^{5} \xi_k \left(1_{\{\widetilde{DD}_{it} \text{ in k'th Quintile}\}} \times 1_{\{\text{Low } YFR_t\}}\right) + \delta^T Z_{it} + \epsilon_{it+3} \end{aligned} \tag{1.24}$$

where Z_{it} contains the same control variables as in regression (1.21), i.e., the 10-year US Treasury yield, four lags of the dependent variable, as well as the firm's cash holdings and short-term investments (`cheq`), net income (`niq`), and earnings (`ebitda`) over the previous quarter, normalized by the lag total assets of the firm (`atq`). $1_{\{\widetilde{DD}_{it} \text{ in k'th Quintile}\}}$ is an indicator variable that switches on if $\widetilde{DD}_{it}$ is in the k'th quintile at time t. For example, for the indicator variable $1_{\{\widetilde{DD}_{it} \text{ in } 1^{st} \text{ Quintile}\}}$ takes the value of one if the firm i is among the 20% riskiest firms at time t. The indicator variable $1_{\{YFR_t < 25^{\text{th}} \text{ pct.}\}}$ switches on if YFR_t is below its 25^{th} percentile. The average issuance of firms in the k'th risk quintile when YFR_t is high (i.e. not in its lowest quartile), is thus measured by χ_k, while ξ_k measures the difference in debt issuance by firms in the k'th risk quintile between periods where YFR_t is in its lowest quartile, and periods when it is not. For example, χ_1 measures the average net debt issuance by 20% riskiest firms when YFR_t is the top 75% of its full sample distribution, and ξ_1 measures the additional debt issuance by the riskiest firms when YFR_t enters its lowest quartile. This means that $\chi_1 + \xi_1$ measures the total net debt issuance of the riskiest firms when YFR_t is in its lowest quartile. I dub ξ_i the additional net debt issuance. Figure 5 Panel A presents a plot of the average debt issuance (χ_k) of firms by risk group. Consistent with Table IX, it is the safest firms which issue most debt when YFR_t is high. Figure 5 Panel B plots the additional net debt issuance (ξ_i) by firms in each of the risk groups when YFR_t is in its lowest quartile, and shows that it is the riskiest firms which increase their debt issuance when YFR_t is low. In contrast, the safest firms do not adjust their issuance between periods of low YFR_t and high YFR_t. The increase in debt issuance by the riskiest firms is substantial relative to their issuance outside the period of low YFR_t, where their net debt issuance is not significantly different from 0. Specifically, the riskiest 20% of firms increase their net debt issuance by a statistically significant 0.78% of total assets when YFR_t is in its lowest quartile relative to other periods. In contrast, the safest 20% of firm do not change their issuance between periods of low YFR_t and high YFR_t. The coefficients presented in Figure 5 are estimated controlling for the level of the 10-year Treasury yield, four lags of the dependent variable, and the strength of the firms' balance sheets. Table AI in the Appendix presents the table version of the regression illustrated in Figure 5 in column 5, and further shows that the result is not sensitive to the choice of control variables.

The result suggests that credit cycles may be driven, in large part, by the net debt issuance of the riskiest firms in the economy, who take advantage of the low compensation for risk required by investors. The result is consistent with Greenwood and Hanson (2013) who show that the composition of debt issuers is a strong predictor of returns to the aggregate bond market. In Table AII of the appendix, I further show that low YFR_t is associated with an increase in net equity purchases and a decrease in cash holdings by the largest firms in the economy. Further, all firms, small and large, increase their capital expenditure when YFR_t is low. The results suggests that low YFR_t is associated with both an increase in investments, and with cross-market arbitrage (Ma, 2019) as firms substitute debt for equity.

6 Conclusion

I consider an equilibrium asset pricing model of corporate bonds and stocks, which includes both rational risk aversion and extrapolative beliefs embedded via diagnostic expectations. I test the predictions generated by the model's two mechanisms by introducing a new measure of credit market sentiment named yield-for-risk. Using yield-for-risk, I document periods of almost complete disconnect between credit spreads and risk in the cross-section of bonds, and find that these periods are associated with low past defaults, loose lending standards and high past returns on both the bond and the stock market. I further document that periods of low yield-for-risk coincide with an inversion in the risk-return relationship in both the bond market and the stock market. That is, when yield-for-risk is low, the expected returns of high-risk bonds and stocks are significantly lower than the expected returns of low-risk bonds and stocks. I further find that yield-for-risk is a strong predictor of the aggregate returns to the bond market, as well as the net debt issuance. In particular, it is the net debt issuance by the riskiest firms, which is sensitive to the level of yield-for-risk.

The evidence is consistent with the model's predictions, that investors, at times, overestimate the fundamental value of risky firms relative to safe firms, and overpay for the riskiest firms' bonds and stocks. The findings indicate that extrapolative beliefs are a central driver of credit prices and credit growth, and support the boom-bust hypothesis of credit cycles proposed by Kindleberger (1978) and Minsky (1977). As such, yield-for-risk provides a novel and useful tool for policy makers to assess the level of optimism in the bond market. As yield-for-risk is derived from price and book data, a natural extension of this paper would be to combine yield-for-risk with measures of economic fragility, such as credit growth, and see if the combination increases the predictive power of yield-for-risk on both returns and economic outcomes. I leave this question for future research.

Table I. Summary Statistics.

This table presents summary statistics for my sample of monthly returns, yields and characteristics of senior unsecured bonds issued by non-financial firms from January 1976 to February 2019. The sample includes information of 1,502 individual firms and 10,189 individual bonds. The panel is constructed using information from the Lehman/Warga database (January 1976-December 1996), the ICE Bank of America Fixed Income Indices (January 1997-June 2002) and WRDS Corporate Bond Panel (TRACE) (July 2002-February 2019).

				Percentile				
	N	Mean	SD	1st	25th	50th	75th	99th
Bond Level Variables								
Yield: y_{ijt} (%)	646,715	4.9	2.3	1.0	3.2	4.6	6.3	12.1
Credit Spread: (%)	646,715	1.5	1.0	0.2	0.8	1.3	1.9	5.3
Duration (years)	646,715	7.2	4.0	1.9	3.9	6.3	10.4	16.9
Time to Maturity (years)	646,715	11.4	8.7	2.1	4.5	7.9	18.6	29.7
Monthly Bond Return (%)	646,715	0.6	2.6	−6.3	−0.4	0.5	1.6	7.8
Rating Number	646,715	7.3	2.1	1.0	6.0	8.0	9.0	10.0
Firm Level Variables								
Distance-to-default: $\widetilde{DD}_{it}$	152,268	9.1	5.6	0.4	5.2	8.2	11.9	27.3
Number of Bonds per Firm	152,268	9.0	12.5	1.0	2	4	11	60.0
Monthly Equity Return (%)	152,268	1.0	8.1	−21.1	−3.4	1.1	5.4	22.1
Macro Variables								
Yield for Risk: YFR_t (bp)	516	6.7	4.5	0.3	3.6	5.7	8.7	23.2
Excess Bond Market Return (%)	516	0.3	1.7	−3.9	−0.5	0.4	1.2	4.2
Excess Equity Market Return (%)	516	0.6	4.4	−10.7	−1.9	1.0	3.4	10.3

Table II. Yield-for-Risk and the State of the Market

This table presents the results of the regression:

$$YFR_t = \alpha + \beta \times X_t + \epsilon_t$$

where YFR_t is yield-for-risk (measured in basis points), and X_t represents a range of explanatory variables capturing the state of the economy. The explanatory variables are: (1) "Past defaults" which measures the issuer-weighted default rate for all corporates over the past year (available annually, source: Moody's Investors Service), (2) "Tightening lending standards" which is the net fraction of banks that have reported tightened lending standards minus the fraction banks that have reported loosening lending standards over the past quarter (available quarterly, source: The Federal Reserve's Senior Loan Officer Opinion Survey), (3) "Bond market return" which is the excess return of the bond market over the previous three years (available monthly, source: Own bond panel), and (4) "The equity market returns" which is the excess return on the equity market over the previous three years (available monthly, source: Ken R. French's data library). t-statistics are reported in the brackets and based on Newey and West (1987) standard errors with 5 lags. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively, using Kiefer and Vogelsang (2005) corrected p-values. The table shows that low levels of YFR_t are associated with low past defaults, loose lending standards, and high bond and equity market returns.

	Yield-for-Risk			
	(1)	(2)	(3)	(4)
Past defaults	2.20**			
	[2.93]			
Tightening lending standards		0.15***		
		[6.08]		
Bond market return			−0.15**	
			[−2.24]	
Equity market return				−0.38***
				[−4.90]
Constant	4.18***	5.98***	7.18***	10.05***
	[2.95]	[12.01]	[12.33]	[10.57]
Observations	42	115	480	480
R^2	0.24	0.50	0.02	0.30

Table III. Predicting Returns to Credit Risk in the Cross-Section

This table presents the results of the return forecasting regression:

$$r^{20\%\ riskiest}_{t+h} - r^{20\%\ safest}_{t+h} = \alpha + \beta \times YFR_t + \zeta^T X_{t+h} + \epsilon_{t+h}$$

where $r^{20\%\ riskiest}_{t+h}$ is the average h-month return of assets issued by 20% riskiest firms at time t as measured by distance-to-default, while $r^{20\%\ safest}_{t+h}$ is the average h-month return of the assets issued by the 20% safest firms at time t. Panel A presents the results when measuring the corporate bond returns of the riskiest over the safest firms. Panel B repeats the analysis using the equity returns of the riskiest over the safest firms. The regressors are yield-for-risk, YFR_t, as estimated from equation (1.12) and normalized by its standard deviation, the change in the 10-year Treasury yield, $\Delta_h y^{10}_{t+h}$, from year t to $t+h$, and the change in the slope of the Treasury yield curve, $\Delta_h(y^{10}_{t+h} - y^{1}_{t+h})$, from year t to $t+h$. The slope of the Treasury yield curve is measured as the difference between the 10-year and 1-year Treasury yield. t-statistics are reported in the brackets and based on Newey and West (1987) standard errors with lags of 0, 9, 18 months for prediction horizons 1, 6 and 12 months, respectively. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively, using Kiefer and Vogelsang (2005) corrected p-values. The table shows that yield-for-risk strongly predicts returns to credit risk in the cross-section of both corporate bonds and equities.

Panel A: *Predicting returns to credit risk in the cross-section: Corporate Bonds*

	Horizon (h)					
	1-month returns		6-month returns		12-month returns	
	(1)	(2)	(3)	(4)	(5)	(6)
YFR_t	0.15**	0.13**	0.97***	0.90***	1.64***	1.57***
	[2.48]	[2.41]	[4.14]	[3.81]	[4.38]	[4.44]
$\Delta_h y^{10}_{t+h}$		0.23***		0.62***		0.91***
		[6.75]		[3.20]		[3.82]
$\Delta_h(y^{10}_{t+h} - y^{1}_{t+h})$		0.10**		0.05		−0.11
		[2.48]		[0.43]		[−0.55]
Constant	−0.22***	−0.19***	−1.35***	−1.21***	−2.04***	−1.83***
	[−3.02]	[−2.79]	[−4.01]	[−3.57]	[−3.77]	[−3.43]
Observations	516	516	516	516	516	516
Adjusted R^2	0.03	0.14	0.17	0.25	0.26	0.36

Table III: Predicting Returns to Credit Risk in the Cross-Section ***(Continued)***

Panel B: *Predicting returns to credit risk in the cross-section: Equities*

	Horizon (h)					
	1-month returns		6-month returns		12-month returns	
	(1)	(2)	(3)	(4)	(5)	(6)
YFR_t	0.76***	0.70**	4.45***	4.07***	7.51***	7.27***
	[2.64]	[2.55]	[5.23]	[4.71]	[6.69]	[6.17]
$\Delta_h y^{10}_{t+h}$		0.37**		1.28*		2.07*
		[2.05]		[1.86]		[2.04]
$\Delta_h(y^{10}_{t+h} - y^{1}_{t+h})$		0.61***		1.39*		0.21
		[2.93]		[1.85]		[0.19]
Constant	−1.16***	−1.04***	−6.25***	−5.55***	−9.82***	−9.23***
	[−2.90]	[−2.75]	[−4.77]	[−4.08]	[−4.90]	[−4.38]
Observations	516	516	516	516	516	516
Adjusted R^2	0.04	0.07	0.21	0.24	0.27	0.29

Table IV. Yield-for-risk vs. Alternative Measures of Sentiment

This table presents the results of the return forecasting regression:

$$r^{20\%\ riskiest}_{t+12} - r^{20\%\ safest}_{t+12} = \alpha + \beta \times YFR_t + \delta^T Z_t + \epsilon_{t+h}$$

For columns (1)-(5), $r^{20\%\ riskiest}_{t+12} - r^{20\%\ safest}_{t+12}$ is the average 12-month return of the bonds issued by the 20% riskiest firms over the average 12-month return of the bonds issued by the 20% safest firms. For columns (6)-(10), $r^{20\%\ riskiest}_{t+12} - r^{20\%\ safest}_{t+12}$ is the 12-month returns of the 20% safest equities over the 20% riskiest equities. The yield-for-risk parameter YFR_t is estimated from equation (1.12). The vector Z_t contains the alternative return predictors: the excess bond premium (Gilchrist and Zakrajšek (2012)), the high yield share (Greenwood and Hanson (2013)), the VIX, and the average spread between BAA rated bonds and 10-year Treasury yield. All regressors are normalized by their standard deviation. t-statistics are reported in the brackets and based on Newey and West (1987) standard errors with 18 months lags for prediction. Regressions with HYS as regressor are quarterly and include 6 quarterly lags. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively, using Kiefer and Vogelsang (2005) corrected p-values. The table shows that the predictive power of yield-for-risk on returns to credit risk is not subsumed by other known measures of credit market sentiment.

	12-month bond portfolio returns					12-month equity portfolio returns				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
YFR_t	1.60***	1.70***	1.92***	1.48***	1.61**	7.37***	8.31***	7.02***	7.26***	8.71***
	[5.05]	[4.45]	[4.17]	[3.94]	[2.91]	[5.06]	[9.07]	[5.99]	[5.72]	[6.16]
Excess Bond Premium	0.08				0.21	0.24				2.51
	[0.22]				[0.47]	[0.16]				[1.72]
High Yield Share		0.44			0.72		0.20			2.37*
		[1.76]			[1.82]		[0.23]			[1.67]
VIX			−0.42		−0.75			1.04		−0.83
			[−0.85]		[−1.83]			[0.82]		[−0.62]
BAA spread				0.35	0.93				0.54	−1.96
				[0.92]	[1.70]				[0.34]	[−1.27]
Constant	−1.98***	−3.38***	−1.72	−2.73***	−4.75*	−9.63***	−10.75***	−12.35***	−10.91***	−8.30**
	[−3.76]	[−3.26]	[−1.39]	[−2.95]	[−2.22]	[−3.85]	[−4.24]	[−3.61]	[−2.75]	[−2.24]
Observations	516	131	350	516	105	516	131	350	516	105
Adjusted R^2	0.26	0.22	0.27	0.27	0.26	0.27	0.37	0.38	0.27	0.40

Table V. Robustness of Return Predictability to Specification

This table presents the results of different specifications of the regression model:

$$r_{t+12}^{n\%\ riskiest} - r_{t+12}^{n\%\ safest} = \alpha + \beta \times YFR_t + \epsilon_{t+h}$$

where $r_{t+12}^{n\%\ riskiest}$ is the average 12-month return of all firms with distance-to-default below the n'th percentile, and $r_{t+12}^{n\%\ safest}$ is the average 12-month return of all firms with distance-to-default above the $(100 - n)$'th percentile. The table presents results for three alternative portfolio methodologies: (1) Equal-weighted returns, (2) Value-weighted returns, and (3) Equal-weighted returns hedged against changes in the Treasury yield. Panel A presents results for bond portfolios. Panel B presents results for equity portfolios. t-statistics are based on Newey and West (1987) standard errors with 0, 9 and 18 lags for forecasting horizons of 1 month, 6 months and 12 months, respectively. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively, using Kiefer and Vogelsang (2005) corrected p-values. The table shows that the predictive power of YFR_t on credit risk in the cross-section of bonds and stocks is robust to alternative specifications of the forecasting regression model.

Panel A: *Predicting returns to credit risk: Corporate Bonds*

	Equal-weighted returns					
	1-month		6-month		12-month	
Portfolio threshold (n)	β	t-statistic	β	t-statistic	β	t-statistic
0.15	0.16	2.3**	1.06	4.2***	1.76	4.2***
0.20	**0.15**	**2.5****	**0.97**	**4.1*****	**1.64**	**4.4*****
0.25	0.12	2.3**	0.84	3.9***	1.44	4.2***
0.30	0.12	2.4**	0.77	3.9***	1.31	4.4***
0.35	0.10	2.3**	0.70	4.0***	1.19	4.2***

	Value-weighted returns					
	1-month		6-month		12-month	
Portfolio threshold (n)	β	t-statistic	β	t-statistic	β	t-statistic
0.15	0.15	2.2**	1.03	4.2***	1.75	4.4***
0.20	0.16	2.5**	1.00	4.4***	1.72	4.7***
0.25	0.14	2.4**	0.89	4.2***	1.54	4.6***
0.30	0.13	2.4**	0.84	4.2***	1.43	4.7***
0.35	0.11	2.4**	0.78	4.2***	1.31	4.5***

	Returns hedged against changes in risk-free rate					
	1-month		6-month		12-month	
Portfolio threshold (n)	β	t-statistic	β	t-statistic	β	t-statistic
0.15	0.15	2.3**	0.96	3.6***	1.67	3.6***
0.20	0.14	2.5**	0.87	3.4***	1.50	3.6***
0.25	0.11	2.3**	0.77	3.3***	1.34	3.5***
0.30	0.11	2.3**	0.71	3.4***	1.23	3.7***
0.35	0.09	2.3**	0.64	3.3***	1.11	3.6***

Table V: Robustness of Return Predictability to Specification (Continued)

Panel B: *Predicting returns to credit risk: Equities*

	Equal-weighted returns					
	1-month		6-month		12-month	
Portfolio threshold (n)	β	t-statistic	β	t-statistic	β	t-statistic
0.15	0.86	2.7***	5.02	4.8***	8.68	6.0***
0.20	**0.76**	**2.6***	**4.45**	**5.2***	**7.51**	**6.7***
0.25	0.69	2.6***	4.13	5.7***	7.01	7.4***
0.30	0.66	2.9***	3.94	6.0***	6.70	7.7***
0.35	0.58	2.8***	3.60	6.0***	6.24	7.9***

	Value-weighted returns					
	1-month		6-month		12-month	
Portfolio threshold (n)	β	t-statistic	β	t-statistic	β	t-statistic
0.15	0.79	2.4**	4.63	4.4***	7.62	4.3***
0.20	0.63	2.1**	4.05	4.2***	6.44	4.1***
0.25	0.58	2.1**	3.68	4.4***	5.90	4.2***
0.30	0.53	2.1**	3.38	4.4***	5.39	4.3***
0.35	0.48	2.1**	2.86	4.1***	4.43	3.8***

	Returns hedged against changes in risk-free rate					
	1-month		6-month		12-month	
Portfolio threshold (n)	β	t-statistic	β	t-statistic	β	t-statistic
0.15	0.94	3.3***	5.86	7.1***	8.91	6.2***
0.20	0.81	3.1***	5.22	8.2***	7.75	7.1***
0.25	0.72	3.0***	4.80	8.8***	7.11	7.9***
0.30	0.69	3.2***	4.53	9.3***	6.71	8.0***
0.35	0.61	3.1***	4.12	8.9***	6.19	7.8***

Table VI. Robustness of Thresholds for Risk-Return Inversion

This table presents the results of different specifications of the regression model:

$$\begin{aligned} r_{t+12}^{n\%\ riskiest} - r_{t+12}^{n\%\ safest} = & \lambda^{Low} \times 1_{\{YFR_t \leq m\text{'}th\ percentile\}} + \\ & \lambda^{Mid} \times 1_{\{m\text{'}th\ percentile < YFR_t \leq (100-m)\text{'}th\ percentile\}} + \\ & \lambda^{High} \times 1_{\{YFR_t > (100-m)\text{'}th\ percentile\}} + \epsilon_{t+12} \end{aligned}$$

where $r_{t+12}^{n\%\ riskiest}$ is the average 12-month return of all firms with distance-to-default below the n'th percentile, and $r_{t+12}^{n\%\ safest}$ is the average 12-month return of all firms with distance-to-default above the $(100 - n)$'th percentile. $1_{\{YFR_t \leq m\text{'}th\ percentile\}}$, $1_{\{YFR_t > m\text{'}th\ percentile\}}$ and $1_{\{m\text{'}th\ percentile < YFR_t \leq (100-m)\text{'}th\ percentile\}}$ are indicator variables that switch on if YFR_t is below its m'th, above its $(100 - m)$'th or in between its m'th and $(100 - m)$'th percentile, respectively. t-statistics are based on Newey and West (1987) standard errors with 18 lags. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively, using Kiefer and Vogelsang (2005) corrected p-values. The table shows that risk-return inversion is robust for both asset classes across specifications.

Panel A: *Risk-Return Inversion: Corporate Bonds*

	YFR_t indicator threshold (m)							
	0.20	0.25	0.30	0.35	0.20	0.25	0.30	0.35
Portfolio threshold (n)	λ^{Low}				$t(\lambda^{Low})$			
0.15	-1.0	-0.9	-0.8	-0.8	-2.5**	-2.6**	-2.5**	-2.4**
0.20	-0.9	**-0.8**	-0.7	-0.7	-2.8***	**-3.0*****	-2.7**	-2.5**
0.25	-0.7	-0.6	-0.6	-0.5	-2.3**	-2.5**	-2.3**	-2.1**
0.30	-0.6	-0.6	-0.5	-0.5	-2.0*	-2.2**	-2.1**	-1.8*
0.35	-0.5	-0.5	-0.4	-0.4	-1.6	-1.8*	-1.8*	-1.6
	λ^{Mid}				$t(\lambda^{Mid})$			
0.15	0.0	-0.1	-0.1	-0.2	0.0	-0.1	-0.3	-0.3
0.20	0.1	0.0	-0.1	-0.1	0.2	0.0	-0.2	-0.3
0.25	0.0	0.0	-0.1	-0.1	0.1	0.0	-0.2	-0.2
0.30	0.1	0.1	0.0	0.0	0.4	0.2	0.1	0.1
0.35	0.2	0.1	0.1	0.1	0.6	0.5	0.3	0.2
	λ^{High}				$t(\lambda^{High})$			
0.15	3.1	2.7	2.4	2.1	2.4**	2.7**	2.8***	2.9***
0.20	2.9	**2.6**	2.3	2.1	2.5**	**2.9*****	3.0***	3.1***
0.25	2.7	2.4	2.1	1.8	2.6**	2.9***	3.0***	3.0***
0.30	2.5	2.2	2.0	1.7	2.8***	3.1***	3.2***	3.2***
0.35	2.3	2.1	1.8	1.6	2.7***	3.1***	3.2***	3.3***

Table VI: Robustness of Thresholds for Risk-Return Inversion (Continued)

Panel B: *Risk-Return Inversion: Equities*

	YFR_t indicator threshold (m)							
	0.20	0.25	0.30	0.35	0.20	0.25	0.30	0.35
Portfolio threshold (n)	λ^{Low}				$t(\lambda^{Low})$			
0.15	-8.9	-8.1	-7.6	-6.4	-3.3***	-3.5***	-3.7***	-3.2***
0.20	-8.3	**-7.3**	-6.7	-5.6	-3.9***	**-4.0***	-4.1***	-3.4***
0.25	-8.0	-7.0	-6.5	-5.4	-4.4***	-4.5***	-4.5***	-3.8***
0.30	-8.0	-7.2	-6.5	-5.6	-4.4***	-4.6***	-4.5***	-4.0***
0.35	-7.4	-6.6	-6.1	-5.3	-4.3***	-4.4***	-4.5***	-4.0***
	λ^{Mid}				$t(\lambda^{Mid})$			
0.15	1.4	1.9	2.1	1.2	0.8	1.1	1.2	0.6
0.20	1.3	1.6	1.6	0.7	0.9	1.0	1.1	0.4
0.25	1.6	1.8	1.9	1.0	1.2	1.3	1.3	0.7
0.30	1.2	1.3	1.2	0.4	0.9	1.0	0.9	0.3
0.35	1.0	1.1	1.1	0.3	0.8	0.9	0.8	0.2
	λ^{High}				$t(\lambda^{High})$			
0.15	13.9	11.6	10.9	10.5	3.3***	3.2***	3.5***	3.8***
0.20	12.0	**10.2**	9.7	9.3	3.5***	**3.3***	3.6***	3.9***
0.25	11.1	9.8	9.3	9.1	3.7***	3.6***	4.0***	4.3***
0.30	10.0	9.0	8.6	8.4	3.6***	3.7***	4.1***	4.4***
0.35	9.1	8.3	7.9	7.8	3.6***	3.8***	4.2***	4.5***

Table VII. Predicting Returns to the Aggregate Bond Market

This table presents the results of the forecasting regression:

$$r^{mkt}_{t+h} - y^{f,h}_t = \alpha + \beta \times YFR_t + \zeta^T X_{t+h} + \delta^T Z_t + \epsilon_{t+h} \tag{1.25}$$

where r^{mkt}_{t+h} is the return on the aggregate bond market from time t to $t+h$, $y^{f,h}_t$ is the h-month Treasury yield at time t, YFR_t is yield-for-risk (normalized), X_{t+h} contains the change in the 10-year Treasury yield, and the change in the difference between the 10-year and the 1-year Treasury yield. Z_t contains the Excess Bond Premium (Gilchrist and Zakrajšek, 2012), the High Yield Share (Greenwood and Hanson, 2013), the CBOE VIX, and the BAA Spread. t-statistics are reported in the brackets and based on Newey and West (1987) standard errors with lags of 0, 9, 18 months for prediction horizons 1, 6 and 12 months, respectively. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively, using Kiefer and Vogelsang (2005) corrected p-values. The table shows that yield-for-risk is a strong predictor of the aggregate bond market.

Panel A: *Predicting returns to the aggregate corporate bond market*

	Horizon					
	1-month returns		6-month returns		12-month returns	
	(1)	(2)	(3)	(4)	(5)	(6)
YFR_t	0.23***	0.25***	1.24***	1.55***	2.05***	2.64***
	[3.43]	[4.30]	[3.26]	[4.80]	[2.93]	[4.90]
$\Delta_h y^{10}_{t+h}$		−1.23***		−3.15***		−4.86***
		[−26.02]		[−15.74]		[−12.57]
$\Delta_h(y^{10}_{t+h} - y^{1}_{t+h})$		0.13**		−0.15		−0.62
		[2.22]		[−0.86]		[−1.39]
Constant	0.01	−0.06	−0.06	−0.76	0.31	−1.12
	[0.05]	[−0.78]	[−0.09]	[−1.55]	[0.26]	[−1.23]
Observations	516	516	516	516	516	516
Adjusted R^2	0.02	0.68	0.08	0.68	0.09	0.69

Table VII: Predicting Returns to the Aggregate Bond Market (Continued)

Panel B: *Robustness of bond market return predictability*

	12-month bond market returns				
	(1)	(2)	(3)	(4)	(5)
YFR_t	1.77***	2.86***	2.88***	1.51***	2.42***
	[4.77]	[4.84]	[5.90]	[4.03]	[4.65]
Excess Bond Premium	1.61***				0.05
	[3.44]				[0.06]
High Yield Share		−0.38			−0.64
		[−1.18]			[−0.86]
VIX			0.52		−0.44
			[0.64]		[−0.72]
BAA spread				2.44***	1.38
				[5.69]	[1.17]
Constant	0.001	0.001	−2.25	−6.04***	−1.64
	[0.002]	[0.0005]	[−1.23]	[−4.81]	[−0.45]
Treasury term structure controls	Y	Y	Y	Y	Y
Observations	516	131	350	516	105
Adjusted R^2	0.72	0.59	0.58	0.76	0.56

Table VIII. Average Issuance and Yield-for-Risk

This table presents the results of the regression model:

$$Issuance_{it+3} = \alpha_i + \beta \times YFR_t + \delta^T Z_{it} + \epsilon_{it+3} \tag{1.26}$$

where $Issuance_{it+3}$ is the 3-month net debt issuance by company i from t to $t+3$, and YFR_t is yield-for-risk at time t normalized by its standard deviation. Z_{it} is a vector of control variables which include the firm's cash, net income and EBITDA, as well as 4 lags of the dependent variable or a company fixed effect. The right-hand panel runs an alternative OLS specification with average issuance as dependent variable. t-statistics are reported in the brackets based on Driscoll and Kraay (1998) standard errors for panel regressions and Newey and West (1987) standard errors for OLS with 4 lags. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively, using Kiefer and Vogelsang (2005) corrected p-values. The table shows that yield-for-risk predicts net debt issuance.

	Panel				OLS	
	Net Issuance$_{t+3}$			ΔTotal Liab.	Net Issuance$_{t+3}$	ΔTotal Liab.
	(1)	(2)	(3)	(4)	(5)	(6)
YFR_t	-0.29^{***}	-0.24^{***}	-0.20^{***}	-0.47^{***}	-0.16^{***}	-0.25^{***}
	[−5.73]	[−6.49]	[−5.41]	[−5.46]	[−6.31]	[−4.33]
Risk free rate		0.05^{**}	0.07^{***}	0.08^{*}	−0.01	0.01
		[1.97]	[3.11]	[1.82]	[−0.56]	[0.98]
Cash and Short-term Investments		-0.01^{***}	-0.01^{***}	−0.001		
		[−3.98]	[−4.77]	[−0.27]		
Net Income		−0.002	0.02^{***}	0.02		
		[−0.29]	[2.88]	[1.50]		
EBITDA		-0.02^{***}	-0.02^{***}	-0.04^{***}		
		[−5.81]	[−3.35]	[−8.10]		
Lags of dependent variable	0	4	0	4	4	4
Fixed Effects			Firm			
R2	0.00	0.01	0.00	0.02	0.49	0.50
Observations	97,720	97,720	97,720	117,061	137	171

Table IX. Issuance by Risky Firms

This table presents the results of the regression model:

$$Issuance_{it+3} = \alpha_i + \beta \times YFR_t + \chi \times Risk_{it} + \xi \times YFR_t \times Risk_{it} + \delta^T Z_{it} + \epsilon_{it+3} \qquad (1.27)$$

where $Issuance_{it+3}$ is the 3-month net debt issuance by company i from t to $t+3$, YFR_t is yield-for-risk at time t (normalized), and Z_{it} is the same vector of control variables as in Table VIII. $Risk_{it}$ is measures the fraction of firm's safer than firm i at time t. t-statistics are reported in the brackets based on Driscoll and Kraay (1998) standard errors with 4 lags. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively, using Kiefer and Vogelsang (2005) corrected p-values. The table shows that the net debt issuance of the riskiest firms is more sensitive yield-for-risk than the net debt issuance of the safest firms.

	Net Issuance$_{t+3}$			ΔTotal Liab.
	(1)	(2)	(3)	(4)
YFR_t	-0.17^{***}	-0.17^{***}	-0.17^{***}	-0.42^{***}
	[−4.21]	[−4.27]	[−4.11]	[−5.55]
$Risk_{it}$	-0.66^{***}	-0.71^{***}	-1.07^{***}	-2.24^{***}
	[−4.66]	[−5.76]	[−9.27]	[−11.70]
$YFR_t \times Risk_{it}$	-0.23^{**}	-0.23^{**}	-0.24^{**}	-0.22^{**}
	[−2.23]	[−2.33]	[−2.45]	[−2.16]
Cash and Short-term Investments			-0.02^{***}	-0.01^{***}
			[−6.82]	[−4.03]
Net Income			-0.02^{***}	−0.02
			[−3.10]	[−1.25]
EBITDA			-0.03^{***}	-0.05^{***}
			[−6.39]	[−8.99]
Lags of dependent variable	0	4	4	4
R2	0.00	0.01	0.01	0.03
Observations	97,720	97,720	97,720	117,061

Table X. Using Bootstrap to Calculate p-values and Finite Sample Biases

This table presents p-values and biases for the coefficient estimates from my main linear return prediction model:

$$r_{t+h}^{High\ Risk} - r_{t+h}^{Low\ Risk} = \alpha + \beta^{(h)} \times YFR_t + \zeta^T X_{t+h} + \epsilon_{t+h}$$

and the test for average 12-month returns by yield-for-risk quartile from Figure 4:

$$r_{t+12}^{High\ Risk} - r_{t+12}^{Low\ Risk} = \sum_{i=1}^{4} \lambda_i 1_{\{YFR_t \text{ in } i\text{'th quartile}\}} + \epsilon_{t+h}$$

The table presents the p-values calculated using standard asymptotics, "fixed-b" asymptotics as in Kiefer and Vogelsang (2005), and p-values calculated using the block bootstrap method described in the main text with 100,000 samples, and block sizes being drawn from a geometric distribution with success probability 1/12. t-statistics are calculated using Newey and West (1987) standard errors with 0, 9 and 18 lags for 1-, 6-, and 12-month forecasting horizon. The table also presents the bootstrap bias estimates for all regression coefficients, and the Boudoukh, Israel, and Richardson (2020) (BIR2020) estimate of the Stambaugh (1999) bias for the univariate linear regressions. Panel A and B present the results for bond returns and equity returns, respectively. The table shows that finite sample biases such as Stambaugh (1999) are not driving the predictive power of yield-for-risk or the risk-return inversion.

Panel A: *Return of riskiest bonds over safest bonds*

	Linear Regression			Regression on YFR_t quartile			
	1-month	6-month	12-month	12-month			
	$\beta^{(1)}$	$\beta^{(6)}$	$\beta^{(12)}$	λ_1	λ_2	λ_3	λ_4
Coefficient estimate	0.15	0.97	1.64	-0.84	-0.36	0.36	2.53
t-statistic	[2.5]	[4.1]	[4.4]	[-3.0]	[-0.7]	[0.9]	[2.9]
$P(>\|t\|)$ asymptotic	(0.014)	(0.000)	(0.000)	(0.004)	(0.512)	(0.369)	(0.005)
$P(>\|t\|)$ fixed-b	(0.013)	(0.000)	(0.000)	(0.006)	(0.623)	(0.432)	(0.007)
$P(>\|t\|)$ bootstrap	(0.011)	(0.009)	(0.003)	(0.013)	(0.670)	(0.578)	(0.031)
Bias (bootstrap)	0.00	0.01	0.01	-0.06	0.08	-0.02	0.01
Bias (BIR2020)	0.01	0.05	0.08				

Panel B: *Return of riskiest equities over safest equities*

	Linear Regression			Regression on YFR_t quartile			
	1-month	6-month	12-month	12-month			
	$\beta^{(1)}$	$\beta^{(6)}$	$\beta^{(12)}$	λ_1	λ_2	λ_3	λ_4
Coefficient estimate	0.76	4.45	7.51	-7.78	-0.26	3.50	10.22
t-statistic	[2.6]	[5.2]	[6.7]	[-4.0]	[-0.2]	[1.7]	[3.3]
$P(>\|t\|)$ asymptotic	(0.008)	(0.000)	(0.000)	(0.000)	(0.874)	(0.081)	(0.001)
$P(>\|t\|)$ fixed-b	(0.008)	(0.000)	(0.000)	(0.000)	(0.842)	(0.106)	(0.002)
$P(>\|t\|)$ bootstrap	(0.000)	(0.000)	(0.000)	(0.001)	(0.948)	(0.101)	(0.006)
Bias (bootstrap)	0.01	0.07	0.07	-0.61	0.49	0.38	-0.20
Bias (BIR2020)	0.01	0.04	0.08				

Figure 1. Yield-for-Risk.

This figure presents the time-variation in my measure of credit market sentiment, yield-for-risk (YFR_t). YFR_t is estimated from a cross-sectional regression of the time-t credit spread, $y_{ijt} - y_{jt}^f$, of the bond j issued by firm i on firm i's distance-to-default, $\widetilde{DD}_{it}$, at time t:

$$y_{ijt} - y_{jt}^f = \alpha_t + YFR_t \times (-\widetilde{DD}_{it}) + \delta_t^T Z_{ijt} + \epsilon_{ijt}$$

where Z_{ijt} contains the control variables bond duration, bond age and firm size (all in logs). The credit spread of bond j is defined as the yield of bond j minus the yield of a US Treasury bond with duration equal to that of bond j, and the firm's distance-to-default is calculated following the methodology of Bharath and Shumway (2008). The shaded areas mark NBER economic recessions.

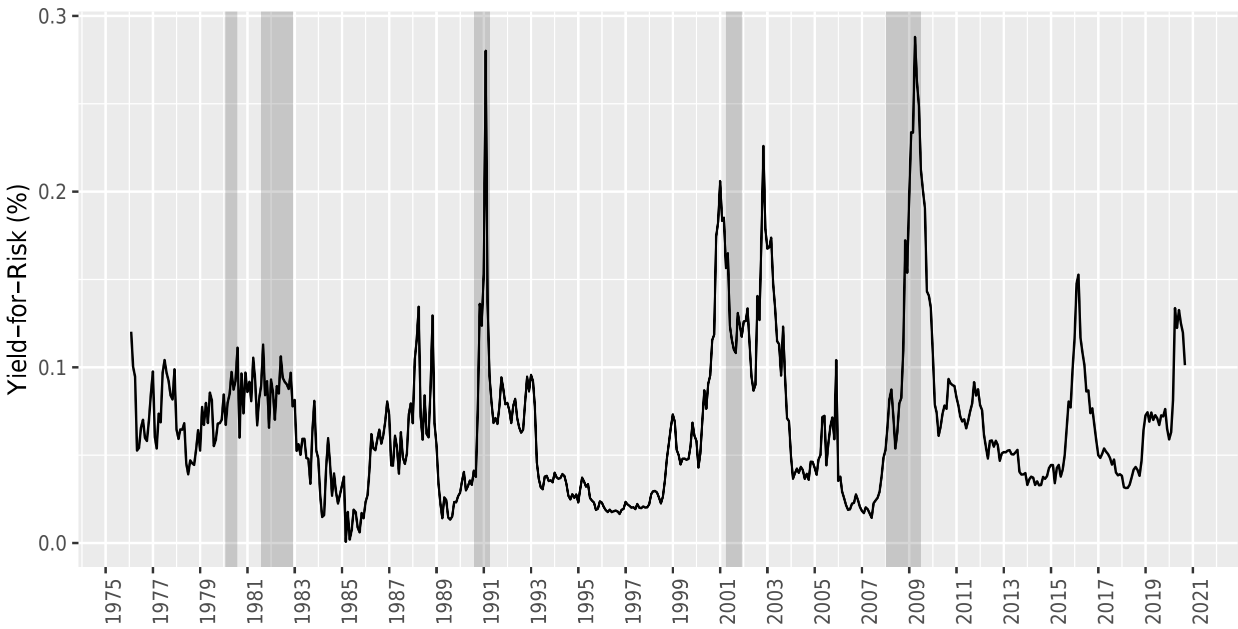


Figure 2. Expected Returns and Capital Structure.

This figure illustrates the theoretical relationship between a firm's outstanding debt (K_i) and the expected returns on a firm's total assets ($\log E[R_{iT}]$), bonds ($\log E[R^D_{iT}]$), equity ($\log E[R^E_{iT}]$), and the risk-free bond yield (y^f). The left-hand panel presents a no-bubble economy ($\theta = 0.9$), and the right-hand panel presents a bubble economy ($\theta = 1.1$). The remaining parameters are: $\delta = 0.01$, $\gamma = 1$, $\sigma_I = 0.4$, $\sigma_C = 0.1$.

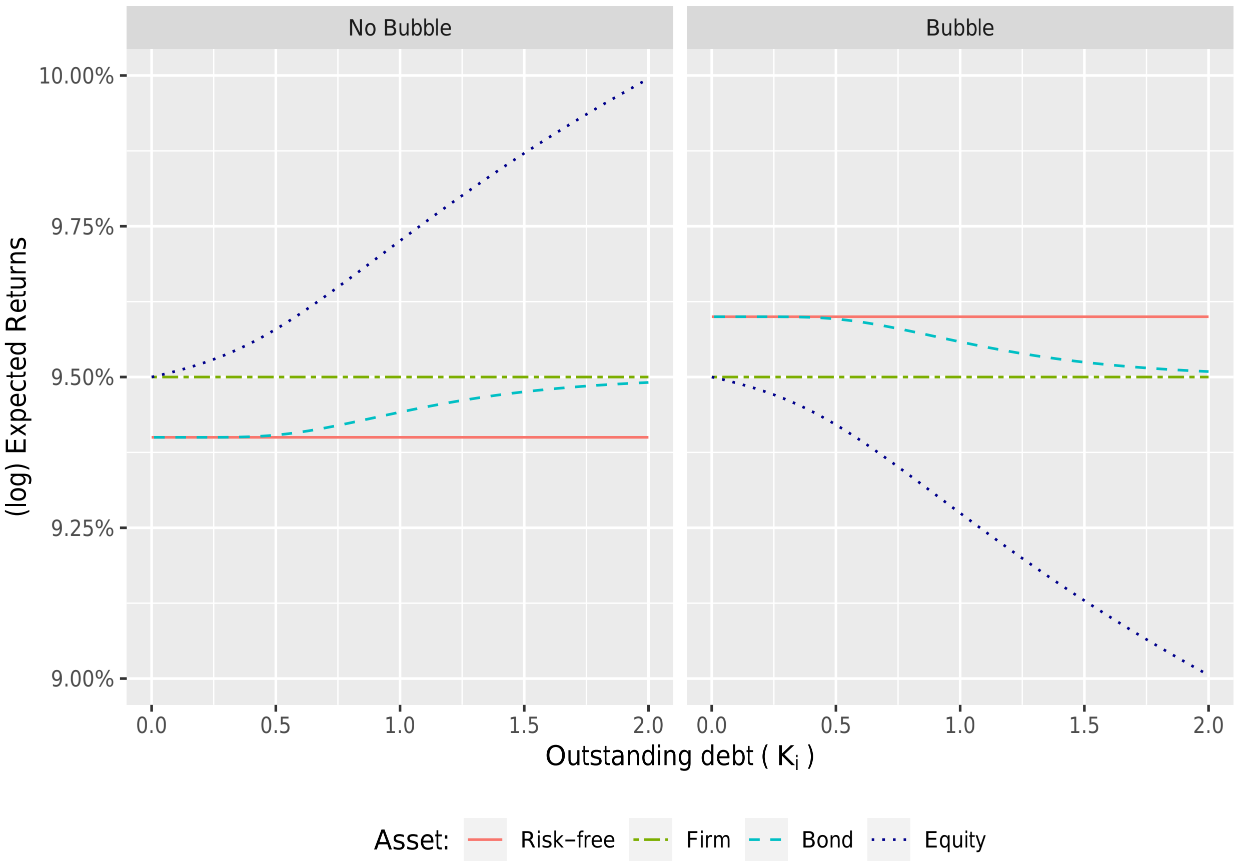


Figure 3. Cross-section of Credit Spreads and Risk.

This figure presents a scatter plot of credit spreads and the distance-to-default on, respectively, May 31st, 2007 and March 31st, 2009. The dashed lines illustrate the fit of credit spreads regressed on distance-to-default at each date:

$$y_{ijt} - y^f_{jt} = a - b \times \widetilde{DD}_{it} + e_{it}$$

where $y_{ijt} - y^f_{jt}$ is the credit spread of bond j at time t issued by firm i over the yield of a US Treasury bond with duration equal to that of of bond j, $\widetilde{DD}_{it}$ is the firm's distance-to-default. The figure shows a low estimate of b (i.e. a low yield-for-risk) in May 2007 immediately prior to the Global Financial Crisis (GFC), and a high estimate of b (i.e. a high yield-for-risk) during the GFC in March 2009.

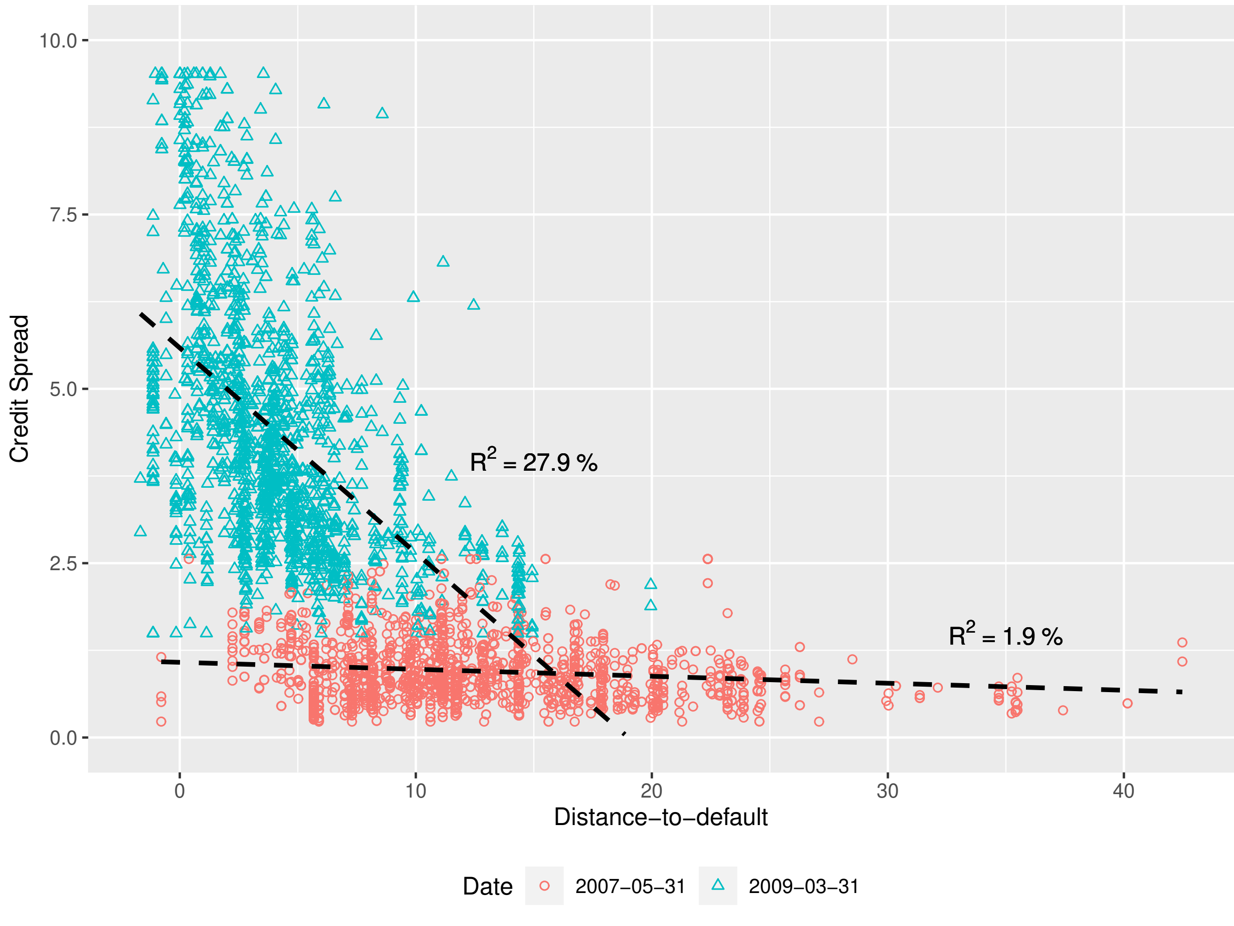
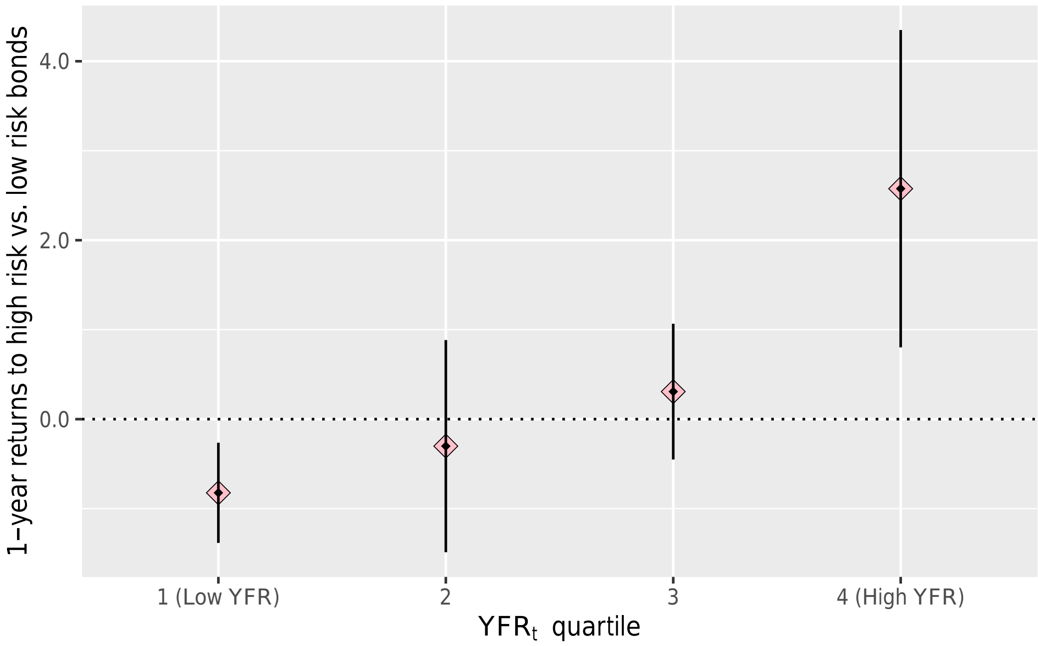


Figure 4. Risk-Return Inversion

Panel A plots the average one-year return of a portfolio which is long the 20% riskiest bond and short the 20% safest bonds following periods of low and high yield-for-risk (YFR_t). "Low YFR_t" is defined as dates where YFR_t is below its 25$^{\text{th}}$ percentile and "high YFR_t" is defined as dates where YFR_t is above its 75$^{\text{th}}$ percentile. The figure also presents average returns to the portfolio strategy when YFR_t is in its second and third quartile. Panel B presents a similar figure, but with average returns to equities instead. The bars illustrate the 95% confidence interval calculated with Newey and West (1987) standard errors with 18 lags and Kiefer and Vogelsang (2005) "fixed-b" asymptotics. The figure shows that high-risk assets significantly underperform low-risk assets following periods of low yield-for-risk.

Panel A: 1-year average returns of high-risk vs low-risk portfolio: *Corporate Bonds*



Panel A: 1-year average returns of high-risk vs low-risk portfolio: *Equities*

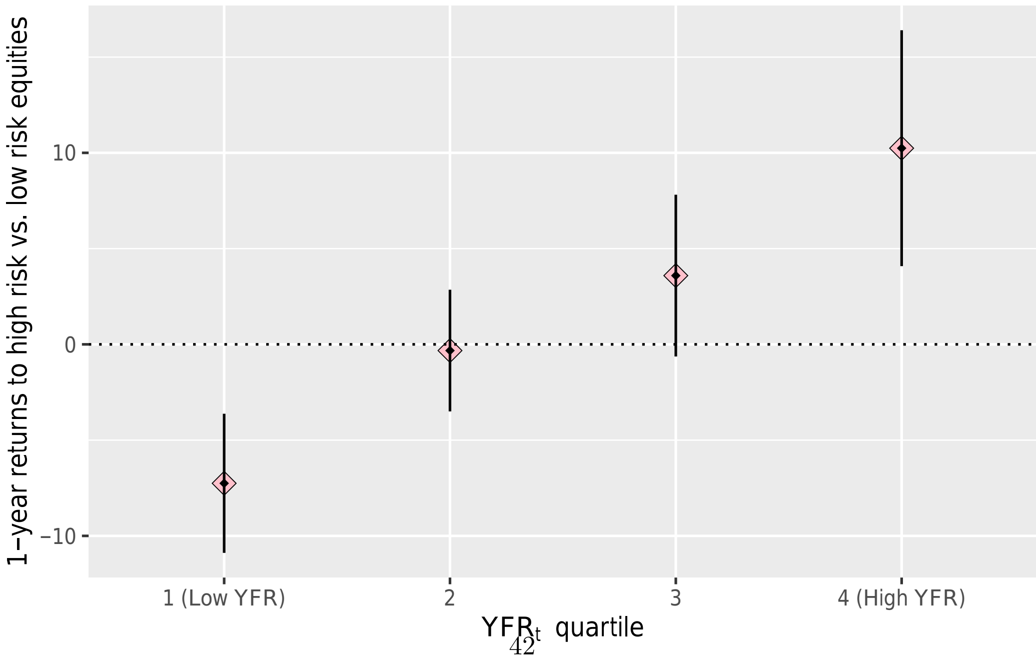


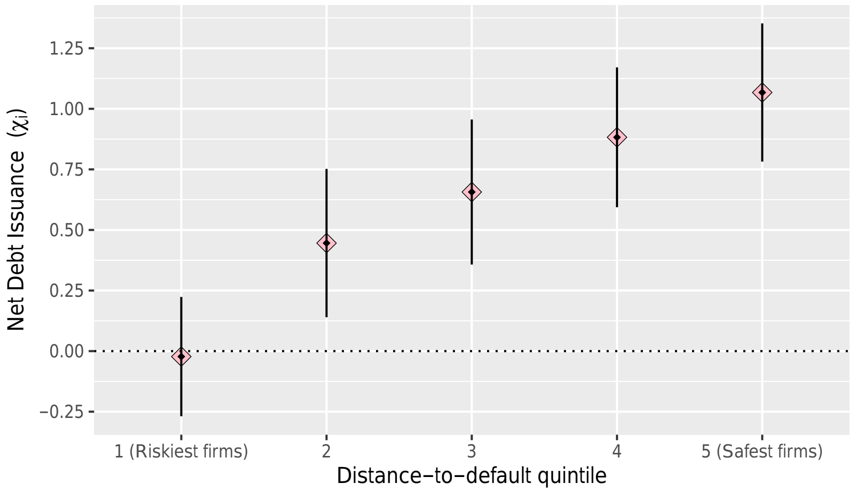
Figure 5. Excess Debt Issuance.

Panel A presents the average quarterly net debt issuance (χ_k) when yield-for-risk (YFR_t) is high (above its 25[th] percentile), and Panel B presents the additional average quarterly net debt issuance (ξ_k) when yield-for-risk is low (below its 25[th] percentile). Firms are split into five groups from the riskiest to the safest, depending on their distance-to-default. Average and additional issuance is measured for each group from the regression:

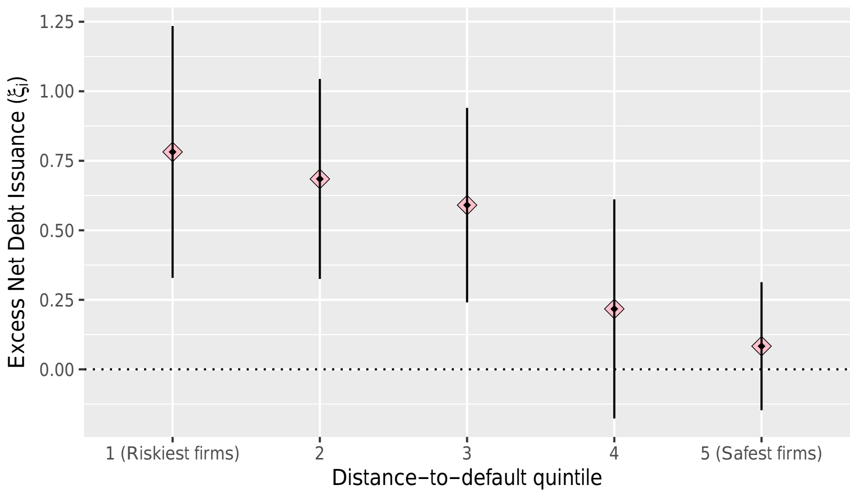
$$Issuance_{it+3} = \sum_{k=1}^{5} (\chi_k + \xi_k \times 1_{\{\text{Low } YFR_t\}}) \times 1_{\{\widetilde{DD}_{it} \textit{ in k'th Quintile}\}} + \delta^T Z_{it} + \epsilon_{it+3}$$

where Z_{it} contains control variables, consisting of the ten-year Treasury bill rate, four lags of the dependent variable, and controls for the strength of the firms balance sheet (cash, net income and EBITDA). The bars illustrate the 95% confidence interval calculated with Driscoll and Kraay (1998) standard errors using 4 lags and Kiefer and Vogelsang (2005) "fixed-b" asymptotics. The figure shows that high-risk firms increase their debt issuance when yield-for-risk is low, while low-risk firms do not change their issuance.

Panel A: *Average net debt issuance: dates with high YFR_t*



Panel B: *Additional net debt issuance: dates with low YFR_t*



7 Appendix: Proofs

Proof of Lemma 1

Let

$$f(x|\mu,\sigma) = \frac{1}{x\sigma\sqrt{2\pi}} \exp\left\{-\frac{1}{2}\frac{(\log x - \mu)^2}{\sigma^2}\right\}$$

denote the density function for lognormally distributed variable, x, with log expectation μ and log standard deviation σ. We see that:

$$f(x|\mu+\Delta,\sigma) \times \left(\frac{f(x|\mu+\Delta,\sigma)}{f(x|\mu,\sigma)}\right)^{\theta} = f(x|\mu+\Delta(1+\theta),\sigma) \times \left(\frac{\Delta^2\theta(1+\theta)}{2\sigma^2}\right)$$

$\square$

Proof of Proposition 1

The first order condition to the investor's maximization problem (1.5) wrt. π_i^E is:

$$\frac{\partial}{\partial \pi_i^E}\{u(W_0 - \int_{\mathcal{A}}(\pi_i^E - 1)P_i^E d\mu_i - \int_{\mathcal{A}}(\pi_i^D - 1)P_i^D d\mu_i) \\ + E^{\theta}[u(\int_{\mathcal{A}}\pi_i^E(V_i - K_i)^+ d\mu_i + \int_{\mathcal{A}}\pi_i^D \min\{V_i, K_i\}d\mu_i)]\} = 0$$

Therefore,

$$P_i^E = E^{\theta}[\frac{u'(\int_{\mathcal{A}}\pi_i^E(V_i - K_i)^+ d\mu_i + \int_{\mathcal{A}}\pi_i^D \min\{V_i, K_i\}d\mu_i)}{u'(W_0 - \int_{\mathcal{A}}(\pi_i^E - 1)P_i^E d\mu_i - \int_{\mathcal{A}}(\pi_i^D - 1)P_i^D d\mu_i)}(V_i - K_i)^+]$$

Next, set initial wealth $W_0 = 1$ and invoke the equilibrium condition $\pi_i^E = \pi_i^D = 1$ for all i. Note that $u'(x) = x^{-\gamma}$, and that the aggregate payoff of the market can be found by LLN as shown in (1.3). We then have that:

$$\begin{aligned} P_i^E &= E^{\theta}[\left(\int_{\mathcal{A}} V_i d\mu_i\right)^{-\gamma}(V_i - K_i)^+] \\ &= E^{\theta}[m(V_i - K_i)^+] \end{aligned}$$

where $m = \exp\{-\gamma(\pi + \frac{1}{2}\sigma_I^2 + \epsilon_C)\}$. It is straightforward to show that the stochastic discount factor, m, can be used to price any payoff function dependent on the underlying value of the firm's assets: $f(V_i)$ such that $P_i^{f(V_i)} = E^{\theta}[mf(V_i)]$.

Proof of Corollary 1 and Proposition 2

The distribution of stochastic discount factor, m, and the distribution of the firm's underlying assets are:

$$\begin{aligned} \log m &\sim N(-\gamma[\Delta + \frac{1}{2}\sigma_I^2], \gamma^2\sigma_C^2) \\ \log V_i &\sim N(\Delta, \sigma_I^2 + \sigma_C^2) \\ \Rightarrow \log m + \log V_i &\sim N(\Delta(1-\gamma) - \gamma\frac{1}{2}\sigma_I^2, \sigma_I^2 + (1-\gamma)^2\sigma_C^2) \end{aligned}$$

Further, the price and the (rational) expected payoff of the firm's assets are:

$$\begin{aligned} P_i^V &= E^\theta[mV_i] \\ &= \exp\left\{\Delta(1-\gamma)(1+\theta) + \frac{1}{2}\sigma_I^2(1-\gamma) + \frac{1}{2}(1-\gamma)^2\sigma_C^2\right\} \\ &= \exp\left\{-y^f + \delta\theta - \gamma\sigma_C^2\right\} E[V_i] \\ E[V_i] &= \exp\left\{\Delta + \frac{1}{2}\sigma_I^2 + \frac{1}{2}\sigma_C^2\right\} \end{aligned}$$

Corollary 1 and Proposition 2 follow by applying Lemma 1:

$$\begin{aligned} r^f &= -\log\left(E^\theta[m]\right) \\ &= \gamma[\Delta(1+\theta) + \frac{1}{2}\sigma_I^2] - \gamma^2\frac{1}{2}\sigma_C^2 \\ \log E[V_i]/P_i^V - r^f &= \gamma\sigma_C^2 - \Delta\theta \end{aligned}$$

Proof of Proposition 3 and 4

The price of firm i's equity, P_i^E, and bond, P_i^D, are:

$$\begin{aligned} P_i^E &= E^\theta[m(V_i - K_i)^+] \\ &= E^\theta[mV_i 1_{\{V_i > K_i\}}] - K_i E[m 1_{\{V_i > K_i\}}] \\ &= P_i^V \Phi\left(DD_i + \frac{\theta\delta}{\sigma_V} - \frac{\gamma\sigma_C^2}{\sigma_V} + \sigma_V\right) - \exp\{-r^f\}K_i\Phi\left(DD_i + \frac{\theta\delta}{\sigma_V} - \frac{\gamma\sigma_C^2}{\sigma_V}\right) \quad (1.28) \\ P_i^D &= P_i^V - P_i^E \\ &= P_i^V\left(1 - \Phi\left(DD_i + \frac{\theta\delta}{\sigma_V} - \frac{\gamma\sigma_C^2}{\sigma_V} + \sigma_V\right)\right) + K/R^f\Phi\left(DD_i + \frac{\theta\delta}{\sigma_V} - \frac{\gamma\sigma_C^2}{\sigma_V}\right) \quad (1.29) \end{aligned}$$

Note that the Modigliani and Miller (1958) propositions hold in my model as the value of the firm is independent of the firm's capital structure. With prices of debt and equity in hand Proposition 3 and 4 follows from the definitions of yields and expected returns.

To prove (1.28), first write the total payoff of firm i's assets as:

$$\log V_i = \delta + u_i \quad (1.30)$$

where $u_i = \epsilon_C + \epsilon_i \sim N(0, \sigma_V^2)$ and $\sigma_V^2 = \sigma_C^2 + \sigma_I^2$. Next, look at the first term in (1.28):

$$\begin{aligned}
&E^\theta[mV_i 1_{\{V_i > K_i\}}] \\
&\quad = E^\theta[E^\theta[m|V_i]V_i 1_{\{V_i > K_i\}}] \\
&\quad = P_i^V \exp\left\{-\frac{1}{2}\left(\sigma_V - \frac{\gamma\sigma_C^2}{\sigma_V}\right)^2\right\} E^\theta[\exp\left\{\left(\sigma_V - \frac{\gamma\sigma_C^2}{\sigma_V}\right)\frac{u_i}{\sigma_V}\right\} 1_{\{V_i > K_i\}}] && (1.31) \\
&\quad = P_i^V \Phi\left(DD_i + \frac{\theta\delta}{\sigma_V} - \frac{\gamma\sigma_C^2}{\sigma_V} + \sigma_V\right) && (1.32)
\end{aligned}$$

To get from the first to the second equation we use that:

$$m|V_i \sim \log N\left(-\gamma[\delta + \frac{1}{2}\sigma_I^2] - \frac{\gamma\sigma_C^2}{\sigma_V^2}u_i, \gamma^2\frac{\sigma_C^2\sigma_I^2}{\sigma_V^2}\right) \tag{1.33}$$

To get from (1.31) to (1.32) note that u_i/σ_V is a standard normal variable such that:

$$\begin{aligned}
&E^\theta[\exp\left\{\left(\sigma_V - \frac{\gamma\sigma_C^2}{\sigma_V}\right)\frac{u_i}{\sigma_V}\right\} 1_{\{V_i > K_i\}}] \\
&\quad = \int_{V_i^\theta = K_i}^\infty \exp\left\{\left(\sigma_V - \frac{\gamma\sigma_C^2}{\sigma_V}\right)\frac{u_i}{\sigma_V}\right\} df\left(\frac{u_i}{\sigma_V}\right) \\
&\quad = \frac{1}{\sqrt{2\pi}}\int_{V_i^\theta = K_i}^\infty \exp\left\{\left(\sigma_V - \frac{\gamma\sigma_C^2}{\sigma_V}\right)\frac{u_i}{\sigma_V} - \frac{1}{2}\left(\frac{u_i}{\sigma_V}\right)^2\right\} d\left(\frac{u_i}{\sigma_V}\right) \\
&\quad = \frac{1}{\sqrt{2\pi}}\int_{\frac{\log K_i - \delta(1+\theta)}{\sigma_V}}^\infty \exp\left\{-\frac{1}{2}\left(\frac{u_i}{\sigma_V} - \left(\sigma_V - \frac{\gamma\sigma_C^2}{\sigma_V}\right)\right)^2\right\} d\left(\frac{u_i}{\sigma_V}\right) \exp\left\{\frac{1}{2}\left(\sigma_V - \frac{\gamma\sigma_C^2}{\sigma_V}\right)^2\right\} \\
&\quad = \Phi\left(\left(\sigma_V - \frac{\gamma\sigma_C^2}{\sigma_V}\right) - \frac{\log K_i - \delta(1+\theta)}{\sigma_V}\right) \exp\left\{\frac{1}{2}\left(\sigma_V - \frac{\gamma\sigma_C^2}{\sigma_V}\right)^2\right\} \\
&\quad = \Phi\left(DD_i + \frac{\theta\delta}{\sigma_V} - \frac{\gamma\sigma_C^2}{\sigma_V} + \sigma_V\right) \exp\left\{\frac{1}{2}\left(\sigma_V - \frac{\gamma\sigma_C^2}{\sigma_V}\right)^2\right\} && (1.34)
\end{aligned}$$

Note that V_i^θ is the payoff the investor believes the firm will generate:

$$V_i^\theta = \exp\{\delta(1+\theta) + u_i\} \tag{1.35}$$

The second term in (1.28) is derived in much the same way as the first term and only the main steps are presented here:

$$\begin{aligned}
&K_i E^\theta[m 1_{\{V_i > K_i\}}] \\
&\quad = K_i E^\theta[E^\theta[m|V_i] 1_{\{V_i > K_i\}}] \\
&\quad = K_i/R^f \exp\left\{-\frac{1}{2}\left(\frac{\gamma\sigma_C^2}{\sigma_V}\right)^2\right\} E^\theta[\exp\left\{\frac{\gamma\sigma_C^2}{\sigma_V}\frac{u_i}{\sigma_V}\right\} 1_{\{V_i > K_i\}}] \\
&\quad = K_i/R^f \Phi\left(DD_i + \frac{\theta\delta}{\sigma_V} - \frac{\gamma\sigma_C^2}{\sigma_V}\right) && (1.36)
\end{aligned}$$

Proof of Proposition 5

To prove Proposition 5 it is sufficient to show that:

$$\left|\lim_{K_i\to 0}\frac{\partial}{\partial K_i}E[R_i^E]\right| > \left|\lim_{K_i\to 0}\frac{\partial}{\partial K_i}E[R_i^D]\right| \geq 0$$

for $\theta \neq \theta^*$. To ease notation let $D_i = \min(V_i, K_i)$ be the time T payoff of the firm's bond, $E_i = \max(V_i - K_i, 0)$ be the time T payoff of the firm's equity, $P_i^D = E^\theta[m\min(V_i, K_i)]$ be the price of the firm's bond, and $P_i^E = E^\theta[m\max(V_i - K_i, 0)]$ be the price of the firm's equity. Finally, define the constant $\psi = \frac{\theta\Delta - \gamma\sigma_C^2}{\sigma_V}$. We have that:

$$\begin{aligned}
\lim_{K_i\to 0}\frac{\partial}{\partial K_i}R_i^E &= \lim_{K_i\to 0}\frac{1}{E_i}\left(\frac{E[R_i^E]}{R^f}\Phi(d_2) - \Phi(DD_i)\right)\\
&= \frac{1}{P_i^V}\left(\frac{E[R_i^V]}{R^f} - 1\right)\\
&= \frac{1}{P_i^V}\left(\exp\{\gamma\sigma_V^2 - \theta\Delta\} - 1\right)\begin{cases} < 0 & \text{for } \theta > \theta^* \wedge \Delta > 0\\ = 0 & \text{for } \theta = \theta^*\\ > 0 & \text{otherwise}\end{cases}
\end{aligned} \tag{1.37}$$

Next, we look at the sensitivity of expected bond returns in the limit:

$$\begin{aligned}
\lim_{K_i\to 0}\frac{\partial}{\partial K_i}R_i^D &= \lim_{K_i\to 0}\frac{1}{D_i^2}\left(D_i\Phi(DD_i) - \frac{E[D_i]}{R^f}\Phi(DD_i + \psi)\right)\\
&= \lim_{K_i\to 0}\frac{1}{\frac{\partial^2}{\partial K_i^2}D_i^2}\left(\frac{\partial^2}{\partial K_i^2}\left\{D_i\Phi(DD_i) - \frac{E[D_i]}{R^f}\Phi(DD_i+\psi)\right\}\right) && (1.38)\\
&= \frac{0}{2(R^f)^{-2}} && (1.39)\\
&= 0 && (1.40)
\end{aligned}$$

To get from (1.38) to (1.39) I introduce a useful Lemma:

Lemma 2. *Let ϕ be the density function of a standard normal distribution, then:*

$$f(x) = a\exp\{bx + c\}\phi(x + d) \to 0 \qquad \textit{for } x \to \pm\infty$$

where a, b, c, d, $x \in \mathbb{R}$.

Proof.

$$\begin{aligned}
f(x) &= a\exp\{bx + c\}\phi(x + d)\\
&= \frac{a}{\sqrt{2\pi}}\exp\{-\frac{1}{2}(x+d)^2 + bx + d\}\\
&= \frac{1}{\sqrt{2\pi}}\exp\{-\frac{1}{2}x^2 + (b-d)x + (c - \frac{1}{2}d^2)\}
\end{aligned}$$

□

Next, see that:

$$
\begin{aligned}
&\frac{\partial^2}{\partial K_i^2}\left\{D_i\Phi(DD_i) - \frac{E[D_i]}{R^f}\Phi(DD_i+\psi)\right\} \\
&= \frac{\partial}{\partial K_i}\left\{\frac{E[D_i]}{R^f}\frac{1}{\sigma_V}\frac{1}{K_i}\Phi(DD_i+\psi) - P_i^D\frac{1}{\sigma_V}\frac{1}{K_i}\phi(DD_i+\psi)\right\} \\
&= \frac{\Phi(DD_i)}{R^f}\frac{1}{\sigma_V}\frac{1}{K_i}\phi(DD_i+\psi) - \frac{E[D_i]}{R^f}\frac{1}{\sigma_V}\frac{1}{K_i^2}\phi(DD_i+\psi) - \frac{E[D_i]}{R^f}\frac{1}{\sigma_V^2}\frac{1}{K_i^2}\phi'(DD_i+\psi) \\
&\quad - \Phi(DD_i+\psi)\frac{1}{R^f}\frac{1}{\sigma_V}\frac{1}{K_i}\phi(DD_i) + P_i^D\frac{1}{\sigma_V}\frac{1}{K_i^2}\phi(DD_i) + P_i^D\frac{1}{\sigma_V^2}\frac{1}{K_i^2}\phi'(DD_i) \qquad (1.41)
\end{aligned}
$$

and note that all the terms of (1.41) equal 0 for $K_i \to 0$. E.g. see that

$$\lim_{K_i\to 0}\frac{\phi'(DD_i)}{K_i^2} = \lim_{K_i\to 0}\frac{\phi(DD_i)}{\frac{1}{3}K_i^3} = 0$$

Where the first equality stems from L'Hôpital's Rule and the second equality uses Lemma 2.

□

Proof of Proposition 6

To prove Proposition 6 note that the expected return on debt, $E[R_i^D] = \frac{E[\min\{K_i,V_i\}]}{P_i^D}$, has the following limits:

$$\lim_{K_i\to 0} E[R_i^D] \to R^f \qquad (1.42)$$

$$\lim_{K_i\to \infty} E[R_i^D] \to E[R_i^V] \qquad (1.43)$$

where $E[R_i^V] = \frac{E[V_i]}{P_i^V}$ is the expected return on the firms total assets and R^f is the (gross) risk-free rate.

Proof. By L'Hôpital's Rule:

$$
\begin{aligned}
\lim_{K_i\to 0} R_i^D &= \lim_{K_i\to 0}\frac{E[D_i]}{P_i^D} \\
&= \lim_{K_i\to 0}\frac{\frac{\partial}{\partial K_i}E[D_i]}{\frac{\partial}{\partial K_i}P_i^D} \\
&= \lim_{K_i\to 0}\frac{\Phi(DD_i)}{\Phi(d_{i2})/R^f} \\
&= R^f
\end{aligned}
$$

Oppositely for $K_i \to \infty \Rightarrow \min\{K_i, V_i\} \to V_i \to V_i \Rightarrow R_i^D \to R_i^V$. □

Given that expected return on debt is monotonic in K_i we get:

$$\theta > \theta^* \wedge \Delta > 0 \Rightarrow R^f > E[R_i^V] \Rightarrow \frac{\partial}{\partial K_i}E[R_i^D] < 0$$

where $\theta^* \equiv \frac{\gamma\sigma_C^2}{\Delta}$.

To prove that the expected return on equity, $\frac{\partial}{\partial K_i}E[R_i^E] < 0$ for $\theta > \theta^* \wedge \Delta > 0$ rewrite the expected return on equity:

$$E[R^E] = E[R_i^V] + L_i\left(E[R_i^V] - E[R_i^D]\right)$$

where $L = \frac{P_i^D}{P_i^E}$ is the leverage of the firm. Given the limits for the expected return on debt (1.42) and (1.43), and the assumption that expected returns on debt is monotonic in K_i, we have that:

$$\theta > \theta^* \wedge \Delta > 0 \Rightarrow E[R_i^V] - E[R_i^D] < 0$$

It is straightforward to prove that K_i, $\frac{\partial}{\partial K_i}L > 0$, is increasing in K_i, making the expected return on equity decreasing in K_i.

8 Appendix: Additional Empirical Results

Table AI. Excess Debt Issuance.

This table presents alternative specifications of the regression model used to generate Figure 5:

$$Issuance_{it+3} = \sum_{k=1}^{5}(\chi_k + \xi_k \times 1_{\{\text{Low } YFR_t\}}) \times 1_{\{\widetilde{DD}_{it} \text{ } in\ k\text{'}th\ Quintile\}} + \delta^T Z_{it} + \epsilon_{it+3}$$

where Z_{it} contains control variables, consisting of the 10-year Treasury yield, four lags of the dependent variable, and controls for the strength of the firms balance sheet (cash, net income and EBITDA). $1_{\{\text{Low } YFR_t\}}$ is an indicator variable, which takes the value of one if YFR_t is in its lowest quartile. $1_{\{\widetilde{DD}_{it} \text{ } in\ k\text{'}th\ Quintile\}}$ is an indicator variable that switches on if $\widetilde{DD}_{it}$ is in the k'th quintile at time t. t-statistics are reported in the brackets and based on Driscoll and Kraay (1998) standard errors using 4 lags and Kiefer and Vogelsang (2005) "fixed-b" asymptotics.

	Net Debt Issuance$_{t+3}$				
	(1)	(2)	(3)	(4)	(5)
Risk Quintile 1	-0.03	-0.17	-0.20	0.01	-0.02
	[-0.31]	[-1.38]	[-1.63]	[0.06]	[-0.18]
Risk Quintile 2	0.35***	0.21	0.20	0.46***	0.45***
	[2.75]	[1.45]	[1.39]	[2.92]	[2.90]
Risk Quintile 3	0.50***	0.36***	0.36***	0.67***	0.66***
	[4.28]	[2.68]	[2.64]	[4.39]	[4.36]
Risk Quintile 4	0.66***	0.53***	0.52***	0.89***	0.88***
	[7.14]	[3.92]	[3.92]	[6.12]	[6.09]
Risk Quintile 5	0.73***	0.59***	0.59***	1.07***	1.07***
	[9.20]	[4.34]	[4.46]	[7.44]	[7.45]
Risk Quintile 1×Low YFR_t	0.92***	0.76***	0.76***	0.78***	0.78***
	[3.21]	[3.13]	[3.28]	[3.25]	[3.41]
Risk Quintile 2×Low YFR_t	0.82***	0.66***	0.66***	0.68***	0.68***
	[3.76]	[3.40]	[3.54]	[3.62]	[3.77]
Risk Quintile 3×Low YFR_t	0.72***	0.56***	0.58***	0.58***	0.59***
	[3.32]	[3.12]	[3.25]	[3.22]	[3.35]
Risk Quintile 4×Low YFR_t	0.35	0.18	0.20	0.21	0.22
	[1.56]	[0.91]	[0.97]	[1.04]	[1.09]
Risk Quintile 5×Low YFR_t	0.25**	0.09	0.10	0.08	0.08
	[2.28]	[0.75]	[0.83]	[0.65]	[0.72]
Balance Sheet Controls	F	F	F	T	T
Risk-free rate control	F	T	T	T	T
Lags of dependent variable	0	0	4	0	4
Observations	97,720	97,720	97,720	97,720	97,720
R^2	0.01	0.01	0.02	0.02	0.02

Table AII. Stock Repurchases, Investments, Cash holdings and Yield-for-Risk

This table presents the results of the regression model:

$$y_{it+3} = \beta \times YFR_t + \gamma' Z_{it} + \epsilon_{it+3}$$

where $y_{it+3} \in \{\text{Net Equity Purchase}_{it+3}, \text{CAPX}_{it+3}, \text{Cash}_{it+3}\}$. Here, Net Equity Purchase_{it+3} is the 3-month net equity purchase by company i from t to $t+3$, CAPX_{it+3} is the 3-month increase in capital expenditures by company i from t to $t+3$, and Cash_{it+3} is the increase in cash and short-term investments from t to $t+3$. The regressor YFR_t is yield-for-risk at time t, and Z_{it} is a vector of control variables which include the firm's net income and EBITDA, as well as 4 lags of the dependent variable. t-statistics are reported in the brackets based on Driscoll and Kraay (1998) standard errors for panel regressions and Newey and West (1987) standard errors for OLS with 4 lags. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively, using Kiefer and Vogelsang (2005) corrected p-values.

	Large firms (Total Assets > 1bn. USD)						Small firms (Total Assets ≤ 1bn. USD)					
	Net Eq. Purch.$_{t+3}$		CAPX$_{t+3}$		Cash$_{t+3}$		Net Eq. Purch.$_{t+3}$		CAPX$_{t+3}$		Cash$_{t+3}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
YFR_t	−0.10***	−0.10***	−0.11***	−0.08***	0.13***	0.17***	0.04	0.01	−0.19***	−0.06**	0.08	0.11
	[−4.26]	[−4.91]	[−3.39]	[−3.97]	[3.24]	[4.01]	[0.68]	[0.12]	[−3.82]	[−2.17]	[0.84]	[1.16]
Risk free rate		−0.04***		−0.0003		0.03		−0.06		0.01		0.04
		[−2.74]		[−0.03]		[1.41]		[−1.27]		[0.68]		[0.57]
Net Income		0.08***		0.04***		0.03***		0.19***		0.04***		0.01
		[5.03]		[5.62]		[2.77]		[6.05]		[8.21]		[0.23]
EBITDA		−0.01*		−0.03***		0.03***		0.04***		−0.03***		0.04**
		[−1.76]		[−7.28]		[4.43]		[2.79]		[−7.69]		[2.45]
Lags of dependent variable	0	4	0	4	0	4	0	4	0	4	0	4
R2	0.00	0.07	0.00	0.65	0.00	0.04	0.00	0.06	0.01	0.40	0.00	0.01
Observations	32,392	32,392	37,212	37,212	37,493	37,493	49,286	49,286	59,474	59,474	60,200	60,200

Chapter 2

Predictable Financial Crises

with Robin Greenwood, Samuel G. Hanson, and Andrei Shleifer.

Abstract

Using historical data on postwar financial crises around the world, we show that the combination of rapid credit and asset price growth over the prior three years, whether in the nonfinancial business or the household sector, is associated with a 40% probability of entering a financial crisis within the next three years. This compares with a roughly 7% probability in normal times, when neither credit nor asset price growth is elevated. Our evidence challenges the view that financial crises are unpredictable "bolts from the sky" and supports the Kindleberger-Minsky view that crises are the byproduct of predictable, boom-bust credit cycles. This predictability favors policies that lean against incipient credit-market booms.

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A central issue in the study of macroeconomic stability is the predictability of financial crises. An important line of thought holds that crises are largely unpredictable. For example, each of the three principal policymakers in the 2008 U.S. financial crisis, Hank Paulson, Tim Geithner, and Ben Bernanke, has taken this position.[1] Similarly, Gorton (2012, p. 42) argues that "crises are sudden, unpredictable events." This view is supported by theories that see crises as due to sunspot equilibria (Cole and Kehoe (2000), Chari and Kehoe (2003)), and by early evidence showing that, while crises are often preceded by weak economic fundamentals, the degree of predictability is low (Kaminsky and Reinhart (1999)).

An alternative view sees financial crises as largely predictable byproducts of rapid credit expansions accompanied by asset price booms (Minsky (1977, 1986), Kindleberger (1978)). Borio and Lowe (2002) show that rapid credit growth and asset price growth predict banking crises in 34 countries between 1970 and 1999, spurring an extensive literature on so-called "early warning indicators." More recently, Schularick and Taylor (2012) show that credit expansions, growth of risky credit as a share of total credit, and narrow credit spreads all predict financial fragility and deteriorating macroeconomic outcomes (see also Greenwood and Hanson (2013), Baron and Xiong (2017), López-Salido, Stein, and Zakrajšek (2017), Mian, Sufi, and Verner (2017), Krishnamurthy and Muir (2020)). Kirti (2020) and Richter, Schularick, and Wachtel (2021) explore factors that can help separate good and bad credit booms. Notwithstanding this evidence, however, precise estimates of the probability of a financial crisis following credit and asset price booms remain unavailable. More importantly, how high the probability of a crisis should be permitted to climb before prompting preemptive policy action remains an open question.

In this paper, we estimate the probability of financial crises as a function of past credit and asset price growth. Such an estimate has been facilitated by the development of historical chronologies of financial crises by Reinhart and Rogoff (2011), Jordà, Taylor, and Schularick (2017), and Baron, Verner, and Xiong (2021, BVX). BVX use hand-collected historical data on bank stock returns to improve existing crisis chronologies, which to date have been based on narrative accounts. We rely on BVX's chronology to construct an indicator variable for the onset of a financial crisis. We then combine historical data on the growth of outstanding credit to nonfinancial businesses and households with data on the growth of equity and home prices to estimate the future probability of a financial crisis in a panel of 42 countries over the period 1950 to 2016.

We present six findings. First, consistent with Schularick and Taylor (2012), we show that crises can be predicted using past credit growth in simple linear forecasting regressions. In particular, we show that both nonfinancial business and household credit growth forecast the onset of a future crisis. However, the degree of predictability is modest, even at horizons of up to five years. Schularick and Taylor (2012) find that a one-standard-deviation increase in real one-year credit growth leads to a 2.8 percentage point increase in the probability of a crisis over the next five years. Repeating their analysis on our sample with BVX's crisis chronology, we obtain virtually the same result.

Second, we show that the degree of predictability rises substantially when we focus on large credit expansions that are accompanied by asset price booms. When nonfinancial business credit growth is high and stock market valuations have risen sharply, or when household credit growth is high and home prices have risen sharply, the probability of a subsequent crisis is substantially higher. The combination of rapid credit growth

[1] According to former U.S. Secretary of the Treasury Tim Geithner, "Financial crises cannot be reliably anticipated or preempted" (see Geithner (2014)). According to former U.S. Secretary of the Treasury Hank Paulson, "My strong belief is that these crises are unpredictable in terms of cause, timing, or the severity when they hit" (see https://www.brookings.edu/wp-content/uploads/2018/09/ es_20180912_financial_crisis_day2_transcript.pdf). According to Federal Reserve Chairman Ben Bernanke, "This crisis involved a 21st century electronic panic by institutions. It was an oldfashioned run in new clothes" (see https://www8.gsb.columbia.edu/articles/chazen-global-insights/ financial-system-will-survive-says-ben-bernanke.)

and asset price growth in a given sector signals an outward shift in the supply of credit, which sows the seeds of its own destruction (Borio and Drehmann (2009), Greenwood and Hanson (2013), Jordà, Schularick, and Taylor (2015), Baron and Xiong (2017), López-Salido, Stein, and Zakrajšek (2017), Kirti (2020)). We do not use data on credit spreads, which would likely increase the predictability of crises, because the scarcity of such data would substantially reduce our sample.

To establish these results, we construct a simple "Red-Zone" indicator, *R-zone* for short, that identifies periods of potential credit-market overheating. Specifically, we classify a country as in the business *R-zone* if nonfinancial business credit growth over the past three years is in the top quintile of the full-sample distribution and stock market returns over the same window are in the top tercile. The probability of a crisis at a one-year horizon is 13% if a country is in the business *R-zone*, a substantial increase over the unconditional probability of 4%. The comparable probability is 14% if a country is in the household *R-zone* — that is, if household credit growth and home price growth are both elevated. Crucially, the degree of predictability increases dramatically with horizon: the probability of experiencing a financial crisis within the next three years is 45% for countries in the business *R-zone* and 37% for countries in the household *R-zone*. Put differently, even after entering the *R-zone*, crises are often slow to develop, suggesting that policymakers have time to act based on early warning signs. For instance, the United States was in the household *R-zone* from 2002 to 2006 ahead of the financial crisis that arrived in 2007.

The interaction effect between credit growth and asset price growth is empirically quite robust. Specifically, our forecasting results are not sensitive to the specific thresholds used to classify past credit and asset price growth as "high." For instance, we obtain similar results if, instead of the full sample, we use a backward-looking expanding sample to compute the cutoffs underlying *R-zone*. The results are also similar if we consider different historical crisis chronologies such as those in Reinhart and Rogoff (2011) and Jordà, Taylor, and Schularick (2017) or if we exclude developing countries from the sample. Finally, the results continue to hold if we end the analysis before the 2008 Global Financial Crisis (GFC), suggesting that in the pre-GFC period economists and policymakers could have better understood that credit-market overheating poses significant risks if they had asked the right questions.

Third, we show that overheating in the business and household credit markets are separate phenomena that independently predict the arrival of future crises. Specifically, 64% of the crises in our sample were preceded by either a household or a business *R-zone* event within the prior three years. These two forms of overheating are particularly dangerous, however, in the rare instances in which they occur in tandem (e.g., Japan in 1988).

Fourth, we show that overheating in credit markets has a global component and is correlated across countries. We construct global business and global household *R-zone* variables to capture the fraction of countries in our sample that are in the *R-zone* each year. We find that including these global variables in our forecasting regressions substantially increases the predictability of crises. For example, in 2007 while Germany was nowhere near the *R-zone*, 33% of sample countries were in the business *R-zone* and 36% were in the household *R-zone*. As a result, in 2007 the predicted probability of Germany experiencing a crisis within three years was 37%, and, Germany did indeed experience a crisis in 2008. When we account for these global variables, we estimate that the probability of a subsequent crisis in the United States rose from 31% in 2002 when the United States first entered the household *R-zone* to 51% in 2006.

Fifth, we show that *R-zone* events predict future contractions in real gross domestic product (GDP). López-Salido, Stein, and Zakrajšek (2017) show that periods of credit-market overheating predict lower real GDP growth at a horizon of two years. Mian, Sufi, and Verner (2020) demonstrate that rapid credit growth—especially household credit growth—forecasts low real GDP growth over the medium run. Adrian, Grinberg, Liang, and Malik (2018) find that financial stability measures—which include credit growth—predict higher downside risks to GDP growth. We show that the business and household *R-zones* also reliably predict GDP contractions, which we define as a 2% decline in real GDP in a given year. This result is only partially driven by the well-known fact that financial crises themselves are associated with GDP contractions (Reinhart and Rogoff (2009)).

In the final section of the paper, we turn to the question motivating our analysis: How high should the probability of a financial crisis be allowed to climb before prompting preemptive action on the part of policymakers? The answer to this question depends on the statistical trade-off between false positive and false negative classification errors. As we increase the credit and asset price growth thresholds for assigning country-years to the *R-zone*, we increase the likelihood that a given *R-zone* event is followed by a financial crisis. At the same time, using more stringent assignment thresholds raises the likelihood that a given crisis is not preceded by an *R-zone* event. We illustrate this trade-off with a downward-sloping "policy possibility frontier" that plots the true negative rate (TNR; the percentage of noncrisis years not preceded by an *R-zone* event) against the true positive rate (TPR; the percentage of crises preceded by an *R-zone* event). The question then is what point on this frontier should a policymaker tasked with promoting financial stability choose. We show that financial crises are sufficiently predictable that policymakers should adopt a do-nothing strategy—that is, never take preventative action even when concerns about credit-market overheating become acute—only if they think that the costs of false alarms are extremely large, perhaps implausibly so, relative to those of false negatives.

Prior studies show that several early warning signals, particularly rapid growth in aggregate credit, help predict the arrival of financial crises.[2] We make several contributions to this literature. First, we document the strength of the interaction effect between credit growth and asset price growth using a simple and transparent methodology. Second, we uncover a higher degree of crisis predictability than has been documented in prior studies. Finally, we calibrate a simple model of macroprudential policymaking under uncertainty, highlighting the trade-off between the costs of acting on false alarms and the costs of failing to act when action would be beneficial.

Our findings favor the Kindleberger-Minsky view of credit cycles and financial crises, formalized in recent theoretical models such as Bordalo et al. (2018), Shleifer and Gennaioli (2018), Greenwood et al. (2019), Maxted (2020), and Krishnamurthy and Li (2020). These models share the common premise that expectations errors (typically due to overextrapolation) lead to excessive borrowing and investment during credit booms. Since these overly optimistic beliefs are disappointed on average, they predictably give rise to credit busts and financial crises. In this way, the Kindleberger-Minsky view provides a foundation for the "credit supply shocks" often used as a starting point for modeling economic busts (Hall (1988), Eggertsson and Krugman (2012), Korinek and Simsek (2016), Guerrieri and Lorenzoni (2017), and Bordalo et al. (2021)).

Our findings also have implications for macrofinancial policy. Adherents of the "bolt from the sky" view of crises often advocate a wait-and-see attitude to policy interventions as credit expands rapidly. Under this view, policymakers should not try to be policemen ex ante but rather should only fight fires ex post.

[2]For example, Borio and Lowe (2002), Borio and Drehmann (2009), Schularick and Taylor (2012), Drehmann and Juselius (2014), and Aldasoro et al. (2018) each examine the impact of aggregate credit growth. Borio and Drehmann (2009), Jordà, Schularick, and Taylor (2015), Aldasoro, Borio, and Drehmann (2018), and Krishnamurthy and Muir (2020) also consider the interaction between credit and asset price growth.

In contrast, the Kindleberger-Minsky view that our evidence favors argues for more proactive measures to lean against incipient credit booms. When an economy is heading toward the *R-zone*, a government might consider tightening monetary policy, increasing bank equity capital ratios, or adopting other countercyclical macroprudential policies. Stein (2013, 2014) and Borio (2014) advocate prophylactic measures of this sort, which inevitably involve taking away the punch bowl when the party starts to get out of hand. Indeed, the post GFC era has witnessed the advent of several macroprudential tools that have been used in precisely this manner. When a policymaker faces a greater than 40% probability of a financial crisis over the near term and a comparable probability of a recession, a wait-and-see attitude appears to be ill-advised.

1 Predicting Financial Crises

1.1 Data

Our data consist of indicator variables for financial crises merged with annual data on household and nonfinancial business credit growth, home prices, and equity prices, which we collect for 42 countries from 1950 through 2016. As we describe below, some data on financial crises reach back earlier than 1950, but the availability of data on household and business credit constrains our sample to the postwar period. Furthermore, since we would like to speak to the current debate about optimal macrofinancial policy, it seems natural to restrict attention to this modern, postwar period.

The key dependent variables in most of our analysis are binary indicators for the onset of a financial crisis, which have been painstakingly constructed in several papers. Traditional chronologies of financial crises rely solely on narrative accounts of bank runs, failures, or bailouts. (Reinhart and Rogoff, 2011, RR) construct a list of financial crises covering 70 countries from 1800 to 2010 based on these narrative criteria. Jordà, Taylor, and Schularick (2017, JST) combine crisis indicators from several narrative chronologies and consult country experts to construct a list of financial crises, which covers 17 countries from 1870 to 2016.

BVX identify several shortcomings of existing crisis chronologies. Defining a banking crisis as "an episode in which the aggregate banking sector's ability to intermediate funds is severely impaired," BVX argue that a large decline in the market value of banks' equity is necessary, but not sufficient, for the arrival of a crisis. They also argue that a bout of widespread bank failures or of severe short-term funding withdrawals—a banking panic—is sufficient, but not necessary, for the arrival of a crisis.[3]

To operationalize their definition of banking crises, BVX assemble data for 46 countries from 1870 to 2016 on (i) bank equity prices, (ii) narrative accounts of widespread bank failures, and (iii) narrative accounts of severe bank panics. Using these data, BVX define two broad types of banking crises. The first type, which BVX call "bank equity crises," are events whereby bank stocks decline by more than 30% from their previous peak and there is narrative evidence of widespread bank failures. The second type, which BVX call "banking panic crises," are events whereby there is narrative evidence of severe withdrawals of short-term funding from banks. A given crisis in BVX's composite chronology may be a bank equity crisis, a banking panic, or both.[4]

[3]While not strictly a necessary condition, most episodes with widespread bank failures or pan- ics also feature a bank stock price decline of 30% or more. In our sample, BVX record 112 episodes in which bank stock prices fell more than 30%, 47 episodes featuring widespread bank failures, and 39 banking panics. Of the 47 episodes with widespread failures, 41 saw a drop in bank stocks of more than 30%. Similarly, of the 39 panic episodes, 34 saw a drop in bank stocks of more than 30%. In the six episodes in which widespread failures or panics were not associated with a 30% drop in bank stocks, bank stocks fell by at least 16% and 22% on average.

[4]In BVX's chronology, a crisis begins in the first year in which bank stocks first fall by 30% from their prior peak or in which

While most of the crises in the resulting chronology are identified in existing chronologies, BVX uncover several previously overlooked crises, remove a number of spurious episodes, and exclude a handful of minor episodes that had smaller effects on the banking system.

Table I compares the BVX, RR, and JST financial crisis indicator variables for the country-years in our sample. Based on the BVX indicator, the unconditional probability of a crisis onset in any given country-year is 4.0%. This compares to an unconditional probability of 2.6% based on the JST indicator and 3.6% based on the RR indicator.[5] Some of the differences reflect discrepancies in when these chronologies date the onset of a crisis. For instance, according to BVX, the United Kingdom suffered financial crises beginning in 1973, 1991, and 2008, whereas the JST database lists these same crises as beginning in 1974, 1991, and 2007. However, these are not the only differences. For instance, RR indicate that the United Kingdom suffered two additional crises in 1984 and 1995. The chronologies also sometimes disagree about whether an extended episode of banking distress should be treated as a single crisis or as a sequence of crises. For example, JST treat the 2008 GFC and the 2010 to 2011 Eurozone crisis as a single crisis for European countries whereas BVX treat them as separate crisis episodes.

The International Monetary Fund's (IMF) Global Debt Database (Mbaye, Moreno-Badia, and Chae (2018)) provides data on total credit outstanding— including both loans and debt securities—to nonfinancial businesses and households. The IMF data cover 190 countries going back to 1950, with 84 countries reporting outstanding credit separately for nonfinancial businesses and households. We supplement the IMF credit data using information from the JST and Jordà, Schularick, and Taylor (2015) MacroHistory databases, which contains annual information on outstanding loans to nonfinancial businesses and households in 17 countries. We collect credit data for Thailand from the Bank of International Settlements' (BIS) Total Credit Statistics, which provides total outstanding loans and debt securities to nonfinancial businesses and households. [6]

Data on equity price indices come primarily from Global Financial Data (GFD). Where suitable data are not available from GFD, we obtain equity price data from the IMF's International Financial Statistics database or the JST MacroHistory database as augmented by Jordà et al. (2019). Using data on nominal price inflation from the World Bank's World Development Indicators and the MacroHistory database, we compute the inflation-adjusted change in equity prices. We obtain inflation-adjusted home price indices from the BIS Residential Property Price database, which we use to compute real home price growth. We again supplement the BIS data on real home prices with data from the JST MacroHistory database and the Organization for Economic Cooperation and Development (OECD)'s Housing Prices database.[7]

Finally, we obtain nominal and real GDP from the World Bank's World Development Indicators and the MacroHistory database.

Our data on credit growth and asset prices are summarized in the bottom panel of Table I, with Tables IAI, IAII, and IAIII in the Internet Appendix providing further details on the sources for the individual country series. Our baseline sample includes every country-year observation beginning in 1950 and ending

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there is a banking panic. Even when a crisis eventually culminates in a panic, BVX show that the panic is typically preceded by a large decline in the value of bank equity.

[5]If we restrict attention to the 858 country-years for which all three indicators are defined, the unconditional probability of crisis onset is 3.5%, 2.8%, and 3.0% according to BVX, JST, and RR, respectively.

[6]When merging credit data from different sources for a country, we calculate three-year changes in outstanding credit separately using each data source and then merge the resulting three-year changes. Since outstanding debt securities are generally quite small for those country-years where we have JST loan data but not IMF credit data, this procedure yields smooth series for three-year cumulative credit growth.

[7]For more information on the BIS Residential Property Price database, see http://www.bis.org/statistics/pp.htm. For more on the OECD's Housing Prices database, see https://data.oecd.org/price/housing-prices.htm.

in 2016 for which we have data on either (i) past three-year nonfinancial business credit growth and equity price growth or (ii) past three-year household credit growth and home price growth, as well as the BVX crisis indicator in the following four years. The result is an unbalanced panel data set that covers 42 countries.

1.2 Predicting Financial Crises with Past Credit Growth

Schularick and Taylor (2012) show that financial crises can be predicted by elevated bank loan growth over the previous five years. We start by presenting linear forecasting regressions that revisit these results, but with two small changes. First, we expand the sample to include the additional crises identified by BVX. Second, motivated by recent work suggesting different roles for household and business credit (Mian, Sufi, and Verner (2017)), we separately examine how well these two forms of credit growth predict future financial crises. Table II presents Jordà-style (2005) linear forecasting regressions of the form

$$Crisis_{i,t+1 \text{ to } t+h} = \alpha_i^{(h)} + \beta_i^{(h)} \cdot \Delta_3 X_{it} + \epsilon_{i,t+1 \text{ to } t+h} \tag{2.1}$$

h =1, 2, 3, and 4, where $\alpha_i^{(h)}$ is a country fixed effect, Δ_3 is the change in predictor X_{it} over the three years ending in t, and $Crisis_{i,t+1 \text{ to } t+h}$ is an indicator variable equal to one if a crisis begins in country i in any year between $t+1$ and year $t+h$ – i.e. defining $Crisis_{i,t}$ as an indicator that switches on if a crisis begins in country i in year t, we define $Crisis_{i,t+1 \text{ to } t+h} = \max\{Crisis_{i,t+1}, ..., Crisis_{i,t+h}\}$. In Table II and throughout the paper, we stop making forecasts in $t = 2012$, so we have the same number of observations for all prediction horizons. As we detail below, to draw appropriate statistical inferences, we compute t-statistics (shown in brackets) using Driscoll and Kraay (1998) standard errors.

As predictors, we examine three-year changes in the ratio of total private credit to GDP ($\Delta_3(Debt^{Priv}$ $/GDP)_{it}$), the ratio of business debt to GDP ($\Delta_3(Debt^{Bus}/GDP)_{it}$), and the ratio of household debt to GDP ($\Delta_3(Debt^{HH}/GDP)_{it}$). Our fourth predictor, which is closer to the original Schularick and Taylor (2012) variable, is the three-year log change in real total private debt outstanding ($\Delta_3 \log(Debt^{Priv}/CPI)_{it}$). Each of these variables is normalized by its sample standard deviation, so the coefficient $\beta^{(h)}$ gives the change in the probability of a crisis beginning within h years if past three-year debt growth rises by one standard deviation.

Table II shows that despite a shorter sample period and slightly different definitions of crises, we reproduce Schularick and Taylor's (2012) central result that credit growth forecasts the onset of a financial crisis. As shown in columns (1.1) and (3.1), a one-standard-deviation increase in $\Delta_3(Debt^{Priv}/GDP)_{it}$ is associated with a 2.6 and 5.3 percentage point increase in the probability of a crisis beginning within one and three years, respectively.

The remaining specifications in Table II separate private debt growth into its nonfinancial business and household components. Column (3.2) shows, for example, that a one-standard-deviation increase in $\Delta_3(Debt^{Bus}/GDP)_{it}$ is associated with a 3.4 percentage point increase in the probability of a crisis beginning within three years, and column (3.3) shows that a one-standard-deviation increase $\Delta_3(Debt^{HH}/GDP)_{it}$ it is associated with a 9.2 percentage point increase in the probability of a crisis within three years. Column (3.4) shows results when the predictor variable is the change in debt scaled by the Consumer Price Index (CPI) rather than by GDP.

While the results in Table II show that credit growth forecasts financial crises, the degree of predictability is low, lending credence to the view that crises are largely unpredictable. At a three-year horizon, for example, the within-R^2 in column (3.1) is only 2.5%, and the coefficient of 5.3 means that a two-standard-deviation increase in credit growth increases the probability of a crisis by only 10.6%.

1.3 Predicting Financial Crises with Past Credit Growth and Asset Price Growth

The univariate linear relationship between past credit growth and the probability of a future crisis in Table II masks stronger relationships in the data. In this section, motivated by prior work suggesting that credit booms are marked by increases in both asset prices and credit quantities (Borio and Lowe (2002) and Borio and Drehmann (2009)), we investigate whether refined measures of credit booms have greater success in predicting financial crises.

To start, we divide all country-years through 2012 in our sample into 15 bins based on past price growth tercile and past debt growth quintile for each sector (business or household). The assignment thresholds are based on the distribution of credit and price growth in our full panel data set and thus are the same for all 42 countries in the sample. For instance, country-years in the top quintile of business debt growth have $\Delta_3(Debt^{Bus}/GDP)_{it} > 8.99\%$.[8] We then compute the probability of a crisis beginning within the next h years conditional on being in price growth tercile T and debt growth quintile Q at time t: $p^{(h)}_{T,Q} = E[Crisis_{i,t+1 \text{ to } t+h} | \text{Tercile}(\Delta_3 \log(Price_{it})) = T, \text{Quintile}(\Delta_3(Debt/GDP)_{it}) = Q]$. This exercise, shown in Table III, is a simple nonparametric way of understanding the multivariate nonlinear relationship between past debt and asset price growth and the probability of a future crisis at various horizons h. Panel B of Table III reports the results of this exercise for the business sector, while Panel D reports the results for the household sector. Panels A and C report the distribution of country-year observations across these 15 bins.[9]

In Panel B of Table III, we capture debt growth using the three-year change in the ratio of nonfinancial business credit to GDP ($\Delta_3(Debt^{Bus}/GDP)_{it}$) and price growth using the three-year log change in the real equity price index ($\Delta_3 \log(Price^{Equity}_{it})$). In Panel B, the first matrix on the left reports the probability of a crisis arriving within one year based on past business debt growth and equity prices. The unconditional probability that a crisis begins within one year is 4.1%. When equity price growth is in the middle tercile and debt growth is in the middle quintile, the probability of a crisis in the next year is $p^{(1)}_{2,3}$= 4.5%. However, when price growth is in the top tercile and credit growth is in the top quintile, that probability rises to $p^{(1)}_{3,5}$ = 13.3%. The matrix on the right reports the difference between the conditional probability for each bin and the probability for the "median" bin where price growth is in the middle tercile and debt growth is the middle quintile, that is, $p^{(1)}_{T,Q} - p^{(1)}_{2,3}$. We also indicate whether this difference in probabilities is statistically distinguishable from zero at conventional significance levels. Specifically, $p^{(1)}_{3,5} - p^{(1)}_{2,3} = 8.8\%$, but at a one-year horizon this difference is not statistically significant.

Conditional on high credit growth and high price growth, the cumulative probability of crisis arrival rises sharply with the forecast horizon. This is because the incremental probability of crisis arrival remains persistently elevated for several years following rapid credit and price growth, implying that crises are slow to develop. Specifically, the probability of a crisis beginning within the next three years is $p^{(3)}_{3,5} = 45.3\%$ when equity price growth is in the top tercile and business credit growth is in the top quintile. The difference

[8]See Table I for the full set of thresholds. For example, country-years in the top quintile of household debt growth have $\Delta_3(Debt^{HH}/GDP)_{it} > 7.60\%$, those in the top tercile of equity price growth have $\Delta_3 \log(Price^{Equity}_{it}) > 26.56\%$, those in the top tercile of home price growth have $\Delta_3 \log(Price^{Home}_{it}) > 12.67\%$, and so on.

[9]In Table III and throughout the paper, we obtain qualitatively similar results if we use price growth quintiles as opposed to price growth terciles. We choose to use price growth terciles since doing so ensures that we have a similar number of observations in each of the 15 cells, enhancing statistical power.

between the probability of a crisis when credit and equity price are jointly elevated and the probability in a median year is highly significant: $p^{(3)}_{3,5} - p^{(3)}_{2,3} = 37.4\%$ (p-value = 0.006).

In Panel B, we repeat the analysis for the household sector, measuring debt growth by the three-year change in household credit to GDP ($\Delta_3(Debt^{HH}/GDP)_{it}$) and price growth by the three-year log change in the real home price index ($\Delta_3 \log(Price^{Home}_{it})$). We find a similar pattern: the crisis probability is highest following rapid growth in household credit that is accompanied by elevated home price growth. When home price growth is in the top tercile and household credit growth is in the top quintile, the probability of a crisis beginning in the next year is $p^{(1)}_{3,5} = 14.0\%$ and the probability of a crisis beginning within three years is $p^{(3)}_{3,5} = 36.8\%$.

To explore crisis prediction in greater detail, we define the three indicator variables

$$\begin{aligned} \textit{High-Debt-Growth}_{it} &= 1\{\Delta_3(Debt/GDP)_{it} > 80^{th} \text{ percentile}\}, && \text{(2.2a)} \\ \textit{High-Price-Growth}_{it} &= 1\{\Delta_3 \log(Price_{it}) > 80^{th} \text{ percentile}\}, && \text{(2.2b)} \\ \textit{R-zone}_{it} &= \textit{High-Debt-Growth}_{it} \cdot \textit{High-Price-Growth}_{it}, && \text{(2.2c)} \end{aligned}$$

where the cutoffs are based on the distribution of credit growth and price growth in our full country-year panel as in Table III. Thus, *High-Debt-Growth* is an indicator that switches on when credit growth is in the top quintile and *High-Price-Growth* is an indicator that price growth is in the top tercile. Finally, the Red zone, that is, *R-zone* is the interaction between these two indicators, so it only switches on when credit and asset price growth are jointly elevated. These three indicators can be defined based on either business sector variables—that is, business credit growth and equity price growth—or on household sector variables—that is, household credit growth and home price growth. Figure 1 shows the full chronology of BVX crises and *R-zone* events in our sample.

To assess how elevated credit and asset price growth jointly affect the probability of a future crisis, in Table IV we estimate the following Jordá-style (2005) forecasting regressions:

$$\begin{aligned} Crisis_{i,t+1 \text{ to } t+h} =& \alpha^{(h)}_i + \beta^{(h)}_i \cdot \textit{High-Debt-Growth}_{it} + \delta^{(h)}_i \cdot \textit{High-Price-Growth}_{it} \\ &+ \gamma^{(h)}_i \cdot \textit{R-zone}_{it} + \epsilon_{i,t+1 \text{ to } t+h} \end{aligned} \tag{2.3}$$

h = 1, 2, 3, and 4, where $Crisis_{i,t+1 \text{ to } t+h}$ is defined as above.[10] The sum of the coefficients $\beta^{(h)}_i + \delta^{(h)}_i + \gamma^{(h)}_i$ gives the increase in the probability that a crisis begins within h years when credit growth and price growth are jointly elevated. Compared to the findings reported in Table III, these predictive regressions allow us to separately estimate the direct relationship between high credit growth and high price growth and the future probability of a crisis, as well as their interaction, *R-zone*.[11] We include a full set of country fixed effects $\alpha^{(h)}_i$ to focus on within-country time-series variation, however, but we obtain very similar results in Table IV and throughout the paper if we omit the country fixed effects.[12]

[10] These forecasting regressions are in the spirit of Jordà (2005) local projection approach to estimating impulse response functions, which would entail controlling for lags of the independent variable as well as the contemporaneous and lagged values of the dependent variable. In Table IV and throughout the paper, we obtain qualitatively similar results if we explicitly use Jordà's (2005) local projection approach.

[11] These regressions also allow us to include other control variables, such as lags of GDP growth. However, adding controls has little impact on the estimated coefficients of interest.

[12] Equation (3) is a Linear Probability Model (LPM), but Table IAIV in the Internet Appendix shows that we obtain very similar marginal effects—corresponding to the coefficients in equation (3)—if we estimate logit or probit models. Indeed, if we omit the country effects, logit and probit models deliver the same marginal effects as LPMs in our setting.

To draw appropriate statistical inferences in this setting, we need to account for two features of the specification in equation (3). First, since we measure debt and price growth using cumulative growth rates over the prior three years, our *High-Debt-Growth*$_{it}$, *High-Price-Growth*$_{it}$, and *R-zone*$_{it}$ indicators tend to arrive in streaks in our country-year panel. For instance, Sweden was in the business *R-zone* in 1987 to 1989 and 1998. Similarly, even though each crisis has a unique onset date when *Crisis-Start*$_{i,t}$ switches on, our h-year cumulative crisis indicator $\textit{Crisis}_{i,t+1 \text{ to } t+h} = \max\{\textit{Crisis-Start}_{i,t+1}, ..., \textit{Crisis-Start}_{i,t+h}\}$ occurs in streaks. For instance, according to BVX, Sweden suffered financial crises that began in 1991 and 2008, so for Sweden $\textit{Crisis}_{i,t+1 \text{ to } t+3}$ is equal to one in the 1988 to 1990 and 2005 to 2007 periods. Taken together, these features mean that the residuals in equation (3) will be serially correlated within a given country when we forecast overlapping outcomes, that is, when h ¿ 1. Second, different countries in our panel are not statistically independent, so the residuals in equation (3) are likely to be contemporaneously correlated across countries at a given point in time. For example, in the mid-2000s, many countries experienced rapid credit and price growth that in many cases was followed by the arrival of a crisis in either 2007 or 2008.

To address both forms of residual correlation in our country-year panel, our t-statistics are computed using Driscoll and Kraay (1998) standard errors, the panel data analog of Newey and West (1987) time-series standard errors. When estimating equation (3) for $h > 1$, we allow for arbitrary residual correlation within our panel up to ceiling $(1.5 \times h)$ annual lags. More specifically, our t-statistics correct for residual serial correlation within a given country over time (e.g., we correct for the fact that the Sweden-1988 and Sweden-1989 observations are not statistically independent), contemporaneous residual correlation across countries at a point in time (e.g., the Sweden-2005 and Denmark-2005 observations are not independent), as well as residual cross-autocorrelation (e.g., Sweden-2005 and Denmark-2006 are not independent).[13] To address the tendency of statistical tests based on Driscoll and Kraay (1998) standard errors to overreject in finite samples, we compute p-values using the "fixed-b" asymptotic theory of Kiefer and Vogelsang (2005), which gives more conservative p-values and has better finite-sample properties than traditional Gaussian asymptotic theory. When $h = 1$, we do not allow for any residual autocorrelation, that is, we use Driscoll and Kraay (1998) errors with no lags, which is equivalent to clustering by time.

Table IV presents the results. Conditional on entering the *R-zone*, the cumulative probability that a financial crisis arrives increases sharply for the first three years and plateaus at 38.2% for the business *R-zone* (Panel A, column (4.3)) and at 30.1% for the household *R-zone* (Panel B, column (3.3)). This is because the incremental probability of crisis onset remains significantly elevated for three years following both business and household *R-zone* events.[14] Moreover, for both sectors there is a strong interaction between elevated debt growth and asset price growth above and beyond their direct effects on the probability of a crisis. Specifically, the coefficient on the *R-zone* interaction term is economically large and statistically significant in the presence of the High-Debt-Growth and High-Price-Growth main effects for both sectors at

[13] To see that Driscoll-Kraay standard errors are conservative, consider the specification in column (4.4) in Panel A. Using Driscoll-Kraay standard errors, we obtain a t-statistic of 3.1 on the business R-zone indicator. If we used heteroskedasticity robust standard errors, ignoring all residual correlation, the t-statistic would be 5.6. If we clustered by year, correcting only for contemporaneous correlation at a point in time, the t-statistic would be 4.2. If we clustered by country, correcting only for within-country serial correlation, the t-statistic would be 4.7. Finally, if we cluster by both country and year, thereby ignoring cross-autocorrelation, the t-statistic would be 3.8.

[14] As shown in Table IAV of the Internet Appendix, one can gauge the incremental probability of crisis onset at different horizons by tracking how the cumulative probability of onset grows with horizon. Specifically, since it is rare to observe multiple distinct crises in a country over a short period, we have $\textit{Crisis-Start}_{i,t+h} \approx \textit{Crisis}_{i,t+1 \text{ to } t+h} - \textit{Crisis}_{i,t+1 \text{ to } t+h-1}$ for small h. Thus, one can roughly deduce the coefficients from a regression in which $\textit{Crisis-Start}_{i,t+h}$ is the dependent variable, which describes the incremental probabilities, by comparing those from regressions involving $\textit{Crisis}_{i,t+1 \text{ to } t+h}$ and $\textit{Crisis}_{i,t+1 \text{ to } t+h-1}$ across columns in Table IV.

all prediction horizons except one- and two-year horizons in the business sector.

A practical question raised by these results is whether we need to include the *High-Debt-Growth* and *High-Price-Growth* variables to forecast crises, or whether simply using the *R-zone* indicator is enough. Comparing the full specifications, listed in the third columns at each horizon, and the specification only including the *R-zone* interaction effect listed in the fourth column at each horizon, we do not lose much forecasting ability in terms of R^2 if we leave out the main effects, *High-Debt-Growth* and *High-Price-Growth.* In Panel A, for example, compare the regressions in column (3.3), which includes the main effects of credit growth and price growth, and column (3.4), which does not. The differential probability of a crisis in the *R-zone* is similar (38.2% vs. 33.7%) across specifications and the R^2 drops from only 7.8% to 6.1% when we omit the main effects. The bottom line is that at horizons of three years and longer, crises seem highly predictable using a simple indicator variable that switches on when credit growth and asset price growth are jointly elevated.

While the probability of a crisis following the *R-zone* is high, the within-country forecasting R^2 is more modest. For example, at a three-year horizon, R^2 is 7.8% in the multivariate specification (3.3) for the business sector and 6.1% in the univariate specification (3.4). To see why, suppose we omit the country effects from equation (3). The R^2 from a univariate regression of $Crisis_{i,t+1 \text{ to } t+h}$ on $R\text{-}zone_{it}$ is $R^2 = (\gamma^{(h)})^2 \times [q^{R\text{-}zone}(1-q^{R\text{-}zone})] \div [\bar{p}^{(h)}(1-\bar{p}^{(h)})]$, where $\gamma^{(h)}$ is the regression coefficient on the *R-zone* indicator, that is, the change in the conditional probability of a crisis conditional on entering the *R-zone*, $q^{R\text{-}zone}$ is the probability of a *R-zone* event, and $\bar{p}^{(h)}$ is the unconditional probability of a crisis within h years. While the increase in the probability of a crisis conditional on entering the *R-zone* is large—for example, $\gamma^{(h)} = 33.7\%$ in column (3.4)—it is far from 100% since not every crisis is preceded by an *R-zone* event. As a result, *R-zone* events are a good deal rarer than crises; $q^{R\text{-}zone} = 6\%$ of country-years are in the Red zone, whereas $\bar{p}^{(3)} = 12.0\%$ of country-years are followed by a crisis within three years, explaining the modest forecasting R^2.

In summary, Tables III and IV point to a fundamental nonlinearity in the data in that financial crises are most likely to occur after periods of rapid growth of both credit and asset prices. These findings support the Kindleberger-Minsky view that debt-financed asset price booms predict future crises. Furthermore, because the incremental probability of crisis onset remains elevated for at least three years following *R-zone* events, the *R-zone* signal offers enough lead time to allow for countercyclical macrofinancial policies designed to "lean against the wind" of credit-market booms.

2 Understanding Crisis Predictability

Our findings in Section I raise several sets of questions. First, how robust are the results in Tables III and IV? For instance, are they driven by look-ahead bias, Stambaugh (1999) bias, or other finite-sample statistical problems? Are they driven by the 2008 GFC? What happens if we end our analysis earlier? Are the results sensitive to the specific thresholds used to classify past credit and asset price growth as "high"? Do the results hold for other crisis chronologies such as RR or JST, or are they specific to the BVX chronology? And do the results differ between developed and developing countries?

Second, do episodes of overheating in the markets for business and household credit reflect a single underlying factor, or are these separate phenomena? Do episodes of business credit overheating and household credit overheating have independent forecasting power for financial crises? What happens if both business and household credit markets are overheating at the same time?

Third, how much of the predictability is driven by global overheating in credit markets, as opposed to local, country-level credit-market overheating?

Fourth, what are the implications of credit-market overheating for future economic growth? Do episodes of high past credit and asset growth predict low future real GDP growth? How do these results vary with the forecast horizon?

Finally, while the results in Tables III and IV suggest that past credit and asset price growth have substantial predictive power for future financial crises, large prediction errors remain. Are there crises that are not preceded by rapid credit and asset price growth? What happens when credit and prices grow rapidly but there is no subsequent crisis? And how likely do crises need to become before warranting preemptive action by policymakers?

We address these questions in the remainder of the paper. In this section, we assess the robustness of our main findings, explore the relationship between business and household credit-market overheating, and examine the global component of credit-market overheating. Section III focuses on whether *R-zone* events negatively forecast economic growth, while Section IV addresses prediction errors and assesses implications for policymakers.

2.1 Robustness

Table V presents a series of robustness checks. Because we find that both business and household credit booms forecast crises, we perform separate robustness tests on each, reporting our results for the business sector in Panel A and for the household sector in Panel B. In each case, we present results from estimating equation (3) at the three-year horizon.

One concern is that the findings from our 1953 to 2012 country-year panel are due to finite-sample statistical problems that lead us to spuriously conclude that crises are predictable in-sample. Our first series of tests examines whether our assignment thresholds for high credit and high price growth are statistically problematic because they are based on in-sample quantiles. Since $\textit{High-Debt-Growth}_{it}$, $\textit{High-Price-Growth}_{it}$, and $\textit{R-zone}_{it}$ depend on information not available at time t, they might be mechanically correlated with future crises in a small sample. Specifically, suppose credit growth and crises are not truly predictable, but crises are contemporaneously associated with low credit growth. Conditioning on the fact that credit growth in year t is high relative to other years—including future years—in a small sample mechanically raises the likelihood that credit growth following year t is low. Using indicators based on full-sample quantiles could then lead us to spuriously find a positive relationship between high past credit growth and future crises in a small sample even if there is no genuine predictability. This concern has less bite because our assignment thresholds are not country-specific (the quantiles are based on the full panel), but it does remain.

We address this statistical concern in two ways. First, in row (i) of Table V, we use backward-looking definitions of $\textit{High-Debt-Growth}_{it}$, $\textit{High-Price-Growth}_{it}$, and $\textit{R-zone}_{it}$. Each year t beginning in 1973, we compute the sample quantiles of three-year credit and price growth using information only up to year t. Country-years in year t are then assigned to credit growth quintiles and price growth terciles based on these backward-looking cutoffs. The sum of the coefficients, which indicates the overall increase in the probability of a crisis in the R-zone, is 34.1% for the business sector compared to 38.2% in our baseline analysis. For the household sample, it is 23.8% compared to 30.1% in our baseline analysis. We therefore obtain largely similar, but marginally weaker, results if we instead base our indicator variables on backward-looking cutoffs.

Next, in row (ii), we use a leave-one-out, jackknife-type definition of the indicator variables. For year t, we compute the sample distribution of credit and price growth leaving out the three years prior to and the four years after t. Country-years in year t are then assigned to credit growth quintiles and price growth terciles based on these jackknife-type cutoffs. This approach ensures that our indicator variables are not mechanically endogenous in equation (3) as they may be when using full-sample quantiles in small samples. Using these leave-one-out definitions yields very similar results to our baseline, which suggests that any finite-sample look-ahead bias is minimal.

A related concern is that our results may be driven by Stambaugh (1999) bias. This small-sample estimation bias arises in predictive regressions in which the predictors are sequentially but not strictly exogenous.[15] In Table IAVI in Internet Appendix, we use a moving-blocks panel bootstrap to assess the magnitude of this estimation bias and find that it is negligible. We also use a bootstrap-t procedure to better judge statistical significance in our finite sample (Efron (1982), Hall (1988)). This bootstrap-t procedure allows us to simultaneously address multiple potential sources of small-sample statistical bias, including Stambaugh estimation bias, any estimation bias due to the fact that our *R-zone* indicators are based on full-sample cutoffs, and inferential biases due to our use of Driscoll and Kraay (1998) standard errors. The p-values that obtain from this bootstrap-t procedure are similar to the Kiefer and Vogelsang (2005) "fixed-b" p-values that are reported in our baseline tables.

A second set of issues concerns out-of-sample prediction. In particular, would we have reached similar conclusions in, say, 2000 before the 2008 GFC was added to the sample? The idea here is to guard against ex post hindsight bias, that is, situations in which researchers propose a theory only after looking at the data, to guard against functional-form overfitting, and to assess whether policymakers could have performed better in the past using information that was available in real time.[16]

In row (iii) of Table V, we explore the impact of ending the analysis in 2000 and thereby omitting the impact of the 2008 GFC, which affected many countries that experienced business or household *R-zones* over the 2004 to 2007 period. Since we are forecasting three years ahead, this means we now stop making forecasts in 1996. For the business sector, using only pre-2000 data in row (iii) has almost no effect on the results. For the household sector, predictability increases substantially in row (iii) when we restrict attention to the pre-2000 data.

More generally, Figure 2 shows how the coefficients on *R-zone* in equation (3) evolve over time as we expand the sample, varying the final prediction date from 1990 to 2012 as in our baseline analysis. For the business sector, Panel A shows that coefficients on *R-zone* are similar in magnitude and statistically significant—or at least marginally significant—in both univariate and multivariate forecasting regressions irrespective of when we end the analysis. Panel B shows that the predictability associated with household *R-zone* events has actually weakened somewhat in the past two decades, although it remains economically

[15]Stambaugh (1999) bias arises in finite samples when the regression residuals are uncorrelated with current and past values of the predictors but may be correlated with future values of the predictors. This estimation bias is familiar from pure time-series settings, but a similar bias can arise in panel forecasting regressions (Hjalmarsson (2008)). Our setting involves estimating multivariate forecasting regressions in a panel setting with overlapping observations. While there are analytical approaches to correcting for Stambaugh (1999) bias in panel settings (Hjalmarsson (2008)), when estimating multivariate regressions (Amihud, Hurvich, and Wang (2009)), and when using overlapping regressions (Boudoukh, Israel, and Richardson (2020)), we are not aware of an analytical approach that is appropriate in a setting like ours that combines these three elements. Accordingly, we use a nonparametric bootstrapping procedure to assess the finite-sample bias of our forecasting regressions.

[16]16 Since the Minsky-Kindleberger view—an outward shift in credit supply raises the risk of a financial crisis—is far older than the efficient-markets view that sees crises as unpredictable (Schularick and Taylor (2012)), we are less concerned about hindsight bias and theoretical overfitting here than we might be in other settings.

and statistically quite strong in our full sample.[17]

Row (iv) shows the impact of ending the analysis in 2000 and changing the definitions of High-Debt-Growth, High-Price-Growth, and *R-zone* by using pre-2000 sample quantiles as cutoffs. For the business sector, the 80th percentileof $\Delta_3(Debt/GDP)_{it}$ is 9.0% in the full sample but 6.7% in the pre-2000 sample. Similarly, the 66.67th percentile of $\Delta_3 \log(Price_{it})$ is 26.6% in the full sample and 22.7% in the pre-2000 sample. As a result, using pre-2000 cutoffs means that we are focusing on episodes in which the absolute degree of credit-market overheating was lower. The combination of these two changes weakens the results somewhat in row (iv). Since row (iii) shows that the former change—using pre- 2000 data while holding variable definitions fixed—had minimal impact, the differences between our baseline results and row (iv) largely reflect changing variable definitions. Thus, the modestly weaker results in row (iv) are not primarily due what have been known in 2000. Instead, the weaker results are driven by the nonlinear relationship between credit growth and asset price growth and the probability of a future crisis—the key theme that we emphasize throughout.[18]

To address concerns about functional form overfitting, in Table IAVII of Internet Appendix we examine whether our results are sensitive to the cutoffs that we use to construct our indicators for high debt growth and high asset price growth. We show that there is nothing special about the particular cutoffs used to construct our indicator variables: we obtain similar results in the full sample, the pre-2000 sample, and the post-2000 sample for a variety of cutoff values. Overall, our analysis suggests that economists and policymakers could have better understood that credit-market overheating poses significant macrofinancial risks prior the 2008 GFC if they had asked the right questions.

In rows (v) and (vi) of Table V, we use the JST and RR crisis indicators in place of the BVX indicator. These data sets are smaller, so our sample size declines somewhat, but the results are broadly similar to our baseline findings.

Next, we use the BVX data to separately examine the likelihood of: a crash in bank stock prices, defined as a more than 30% drop in bank stock prices, in row (vii); widespread bank failures in row (viii); a banking panic in row (ix); and a bank equity crisis, defined as an episode in which bank stocks crash and there are widespread failures, in row (x). The question is whether the *R-zone* indicator predicts each of these events. As shown in row (vii), R-zone is a strong predictor of a future crash in bank stock prices, consistent with Baron and Xiong (2017) finding that rapid credit growth predicts low bank stock returns. However, entering the *R-zone* is also a strong predictor of bank failures, banking panics, and bank equity crises.

Finally, in rows (xi) and (xii), we report the results separately for developed and developing countries. The business *R-zone* reliably predicts financial crises in both developed and developing countries. In the univariate specification, the estimated coefficient on $R\text{-}zone^{Bus}_{i,t}$ is $\gamma^{(3)} = 32.9\%$ (p-value = 0.011) for developed countries and $\gamma^{(3)} = 39.0\%$ (p-value = 0.003) for developing countries, with the estimates not statistically different from each other (p-value = 0.581). By contrast, the household *R-zone* is a reliable predictor for developed countries but is not informative in our small sample of developing countries. Specifically, the estimated coefficient on $R\text{-}zone^{HH}_{i,t}$ is $\gamma^{(3)} = 29.8\%$ (p-value = 0.002) for developed countries and $\gamma^{(3)} = 2.0\%$ (p-value = 0.910) for developing countries, with the estimates statistically different (p-value = 0.051). That said, we are reluctant to draw strong conclusions about the role of household credit in emerging countries because

[17] The predictability evidence weakens somewhat during the late 1990s for the business sector and just before the 2008 GFC for the household sector. Given the contrarian nature of our early warning signals, this makes sense since we know ex post that we were adding false positives, but no true positives, during these periods.

[18] Indeed, we obtain weaker results in the full sample and the post-2000 sample using the pre-2000 cutoffs.

we have only 106 country-year observations for these countries and because household credit markets have historically been less developed than business credit markets in emerging countries.

2.2 Business versus Household Credit-Market Overheating

Mian, Sufi, and Verner (2017) emphasize the importance of household credit growth in driving boom-bust economic cycles and highlight the differences between the dynamic implications of past growth in household and business credit.[19] So far, we have treated episodes of business and household credit overheating separately, presenting results for *R-zone* indicators constructed for each sector. This raises several questions. Do episodes of overheating in the markets for business and household credit reflect a single underlying creditmarket factor, or are these separate phenomena? If these are in fact separate phenomena, are business or household credit booms equally important for predicting future crises? And what happens if both business and household credit markets overheat at the same time?

The correlation between the housing sector *R-zone* and the business sector *R-zone* is surprisingly low at just 0.16. Of the 114 country-years in the household sector *R-zone*, only 19 are also in the business sector *R-zone*. This low correlation is driven by the modest underlying correlation between asset prices and credit growth in the two sectors. The correlation between real stock price growth and real home price growth is only 0.19 across country-years. Similarly, the correlation between nonfinancial business credit growth and household credit growth is only 0.26.

In Table VI, we combine our overheating indicators for the business and household sectors to predict financial crises over horizons from one to four years.We do so to test whether our indicators for the two sectors forecast crises independently of each other. We estimate regressions of the form

$$\begin{aligned} Crisis_{i,t+1\text{ to }t+h} =& \alpha_i^{(h)} + \gamma_i^{Bus(h)} \cdot R\text{-}zone_{it}^{Bus} + \gamma_i^{HH(h)} \cdot R\text{-}zone_{it}^{HH} \\ &+ \gamma_i^{Both(h)} \cdot R\text{-}zone_{it}^{Both} + \gamma_i^{Either(h)} \cdot R\text{-}zone_{it}^{Either} + \epsilon_{i,t+1\text{ to }t+h} \end{aligned} \tag{2.4}$$

$h = 1$, 2, 3, and 4. The first two predictors are the business and household *R-zones* . We also include $R\text{-}zone_{it}^{Both} = R\text{-}zone_{it}^{Bus} \times R\text{-}zone_{it}^{HH}$ — an indicator that switches on when *both* the business and household sectors are in their respective *R-zones*. Finally, we include $R\text{-}zone_{it}^{Either} = \max\{R\text{-}zone_{it}^{Bus}, R\text{-}zone_{it}^{HH}\}$, which switches on if *either* sector is in the *R-zone*.

Table VI reports the results. We focus our discussion here on forecasting crises at the three-year horizon. Column (3.1) shows that when $R\text{-}zone^{Bus}$ and $R\text{-}zone^{HH}$ are both included in the crisis forecasting regression, they each retain predictive power, with $R\text{-}zone^{Bus}$ attracting a coefficient of 28.7% and RzoneHH attracting a coefficient of 24.8%. Column (3.2) shows that in the small number of cases when the economy is in both the business and the household R-zones, the probability of a crisis occurring within the next three years rises by 68.6%, while column (3.3) shows that the degree of predictability remains if we exclude the main effects of business and household *R-zones* and only keep their interaction. Although this probability is extremely high, a simultaneous *R-zone* in the business and household sectors occurs only 19 times in our data. Most of these episodes are well known, including Japan in 1988 to 1989, Spain in 2005 to 2007, and Iceland 2005

[19]19 Mian, Sufi, and Verner (2017) find that an increase in household-credit-to-GDP is associated with a boom in real GDP over the following two years and a subsequent economic bust. By contrast, a similarly sized increase in business-credit-to-GDP is associated with a smaller but immediate decline in real GDP. However, changes in business-credit-to-GDP are roughly twice as volatile as changes in household-credit-to-GDP.

to 2007.

2.3 Local versus Global Credit-Market Overheating

As argued by Schularick and Taylor (2012), Agrippino and Rey (2020), and Mian, Sufi, and Verner (2017), credit cycles share an important global component. To assess the common global component of credit-market overheating and its role in forecasting crises, we construct global business R-zone and global household *R-zone* measures that give the fraction of sample countries that are in the *R-zone* in each year. In Figure 3, we plot these two series, $\textit{Global R-zone}_t^{Bus}$ and $\textit{Global R-zone}_t^{HH}$, over time. The figure shows that $\textit{Global R-zone}_t^{Bus}$ has surged three times in recent decades: from 1983 to 1989, from 1997 to 1999, and most recently from 2004 to 2007. By contrast, there are just two large surges in $\textit{Global R-zone}_t^{HH}$, from 1984 to 1989 and again from 1999 to 2007.

In Table VII, we ask whether these signals of global credit-market overheating improve our ability to predict crises. Using our country-year panel, we estimate regressions of the form

$$\begin{aligned} \textit{Crisis}_{i,t+1 \text{ to } t+h} =& \alpha_i^{(h)} + \gamma_i^{Bus(h)} \cdot \textit{Local R-zone}_{it}^{Bus} + \xi_i^{Bus(h)} \cdot \textit{Global R-zone}_t^{Bus} \\ & + \gamma_i^{HH(h)} \cdot \textit{Local R-zone}_{it}^{HH} + \xi_i^{HH(h)} \cdot \textit{Global R-zone}_t^{HH} + \epsilon_{i,t+1 \text{ to } t+h} \end{aligned} \tag{2.5}$$

h = 1, 2, 3, and 4. As shown in Table VII, both the local and the global *R-zone* variables independently signal an increased likelihood of a financial crisis. For instance, in column (3.1), the estimated coefficient on $\textit{Local R-zone}_{it}^{Bus}$ is 18.3% and that on $\textit{Global R-zone}_t^{Bus}$ is 116%. Since $\textit{Global R-zone}_t^{Bus}$ ranges from 0 to 0.325, this suggests that a country-year like Israel in 2001, which was the only one of the 33 sample countries in the business *R-zone* at the time, was facing an 21.8% = 18.3% + (1/33) × 116% greater crisis likelihood than in normal times. By contrast, a country-year like Denmark in 2007, which was in the business *R-zone* when 32.5% of the countries in our sample were also in the business *R-zone*, was facing a 56% = 18.3% + 32.5% ×116% greater crisis likelihood. Including these global variables in our forecasting regressions substantially increases the predictability of crises. For example, the R2 when forecasting crises at a three-year horizon is 19.2% is column (3.3), which far exceeds the goodness of fit measures reported in Tables IV, V, and VI.[20]

3 Credit-Market Overheating and Future Economic Growth

Economists have long understood that the ex post onset of a financial crisis is typically associated with a sizable contraction in real economic activity (Kaminsky and Reinhart (1999), Cecchetti, Kohler, and Upper (2009), and Reinhart and Rogoff (2009)). Strong evidence also suggests that crises typically lead to a permanent loss of future output—while output growth usually returns to its precrisis trend, the level of output often never returns to its precrisis trend line (Cerra and Saxena (2008)). A related literature argues that a current tightening of credit conditions—signaled by a rise in credit spreads or a tightening of lending

[20] As shown in Table IAVIII and IAIX of the Internet Appendix, the results in Table VII are almost unchanged if *Global R-zone* variable for each country-year is defined as the fraction of other countries that are in the *Local R-zone* in that year, that is, in a "leave one out" fashion. The results are also qualitatively similar if *Global R-zone* is defined as a GDP-weighted average across countries.

standards—negatively predicts real activity at short horizons (e.g., one to four quarters ahead).[21]

Recent research also shows that ex ante signals of credit-market overheating as measured by easy credit conditions, including rapid growth in outstanding credit, an erosion in borrower credit quality, or narrow credit spreads, negatively forecast real economic growth at intermediate horizons ranging from two to five years. For instance, López-Salido et al. (2017) show that overheating in the business credit market in year t—proxied using a low average quality of business borrowers and low credit spreads—predicts low GDP growth in year $t+3$ using U.S. data from 1929 to 2015. Mian, Sufi, and Verner (2017) find that rapid credit growth, and especially household credit growth, predicts low real GDP growth over the medium run in a panel of 30 countries from 1960 to 2012. Kirti (2020) argues that rapid credit growth that is accompanied by an erosion in lending standards predicts low GDP growth in an international panel. By contrast, when rapid credit growth is accompanied by stable lending standards, he finds no predictable decline in growth. Finally, Adrian et al. (2018) estimate quantile regressions which suggest that easy financial conditions and rapid credit growth raise the risk of a large decline in real growth over the next three years.

Combining these two strands of research, it appears that easy credit conditions are associated with higher economic growth in the near term but lower growth at intermediate horizons. In this section, we examine the implications of entering the *R-zone* for future economic growth. Two hypotheses drive this analysis. First, because the *R-zone* predicts financial crises, and financial crises are associated with output declines, at some horizon the *R-zone* likely predicts lower output growth. However, this inference is complicated by the fact that the *R-zone* is persistent and, so long as a credit boom continues, economic growth may remain elevated in the short run. Second, the *R-zone* is a strong but imperfect predictor of crises and may predict weak economic growth even when not followed by a crisis.

We begin by assessing the association between *R-zone* events and the distribution of future GDP growth. Figure 4 provides a first look at the data, plotting the distribution of cumulative annualized real GDP growth at horizons of $h = 1$ to 4 years following a *R-zone* event in either sector, that is, conditional on $R\text{-}zone_{it}^{Either} = \max\{R\text{-}zone_{it}^{Bus}, R\text{-}zone_{it}^{HH}\} = 1$. For comparison, we also plot the corresponding distribution of real GDP growth conditional on $R\text{-}zone_{it}^{Either} = 0$. At horizons of $h = 3$ and $h = 4$ years, Figure 4 shows that being in the *R-zone* is associated with a clear leftward shift in the distribution of future real GDP growth.

Table VIII reports the probability of a severe economic contraction within the next $h = 1$ to 4 years as a function of past three-year credit growth and price growth. We first construct a severe contraction indicator, $Contract_{it}$, that switches on if the log growth of real GDP is below -2% in country i in year t (real growth of -2% is just below the 5th percentile in our full sample). We say that country i experiences a severe contraction within $h = 3$ years following year t if real GDP contracts by 2% or more in year $t+1$, $t+2$, or $t+3$. As in Table III, we group country-years into bins based on terciles of past three-year price growth and quintiles of past three-year credit growth. The matrices on the left-hand side report the sample probability of experiencing a contraction within the next h years for each of the bins, that is, we report $p_{T,Q}^{(h)} = E[Contract_{i,t+1 \text{ to } t+h} | \text{Tercile}(\Delta_3 \log(Price_{it})) = T, \text{Quintile}(\Delta_3 (Debt/GDP)_{it}) = Q]$, where $Contract_{i,t+1 \text{ to } t+h} = \max\{Contract_{i,t+1}, ..., Contract_{i,t+h}\}$. The matrices on the right report $p_{T,Q}^{(h)} - p_{2,3}^{(h)}$ for each bin and thus show how these conditional probabilities differ from those in a median year when asset

[21]See, for example, Bernanke (1990), Friedman and Kuttner (1992), Gertler and Lown (1999), Gilchrist et al. (2009), and Gilchrist and Zakrajšek (2012). Adrian, Boyarchenko, and Giannone (2019) show that, in addition to this decline in the conditional mean of near-term growth, a current tightening of financial conditions is associated with increases in the volatility and skewness of near-term growth.

growth is in the second tercile and credit growth is in the third quintile. Panel A uses bins based on equity price growth and business credit growth, while Panel B uses bins based on house price growth and household credit growth.

Panel A of Table VIII reports the results for the business sector. At a horizon of one year, we see that $p_{1,5}^{(1)}$= 27.5% of the country-years with the lowest past growth in equity prices and the highest past growth in business credit experience a severe contraction in GDP in the following year. This is not surprising since this subset of country-years contains many countries that are already in the midst of a financial crisis. Furthermore, starting from this initial position of low equity price growth and high past business credit growth, the probability of experiencing a severe contraction does not rise meaningfully when we look at longer horizons, reaching $p_{1,5}^{(4)}$= 33.9% after four years.

A far more remarkable pattern arises following business *R-zone* events. While a severe economic contraction has never occurred in the first year following a business *R-zone* event, the probability of a severe contraction rises dramatically with each passing year, eventually reaching $p_{3,5}^{(4)} = 40.0\%$ after four years.

Table IX reports cumulative real GDP growth at horizons of one through four years as a function of past asset price growth and past credit-to-GDP growth. In other words, the table reports $g_{T,Q}^{(h)} = E[\log(GDP_{i,t+h}/GDP_{i,t})|\text{Tercile}(\Delta_3 \log(Price_{it})) = T, \text{Quintile}(\Delta_3(Debt/GDP)_{it}) = Q]$. Panel A presents the results for the business sector; Panel B presents the results for households. As in Table VIII, we present averages as well as differences from the median bin, $g_{T,Q}^{(h)} - g_{2,3}^{(h)}$. The results reveal a striking pattern: subsequent growth is low when credit growth is high and when asset price growth is either very high or very low. When credit growth and asset price growth are both high, the slow subsequent economic growth is naturally interpreted as the result of a future financial crisis and the ensuing decline in growth. When credit growth is high and asset price growth is low, the slow growth is naturally interpreted as a consequence of a crisis that is already underway.

4 Crisis Prediction and Financial Stability Policy

While the Red zone indicator has substantial predictive power for the arrival of a crisis within three years, there are still large prediction errors: *R-zone* fails to signal some crises and at the same time generates false alarms. This raises the question of how strong the predictability must be to warrant taking preemptive policy actions to either avert or mitigate the severity of financial crises.

In Section IV.A, we show that different ways of defining *R-zone* events are associated with a natural statistical trade-off between false negative errors (crises that are not preceded by an *R-zone* event) and false positive errors (*R-zone* events that do not precede crises).[22] We further show that many of the crises not preceded by an *R-zone* event are "near misses" in the sense that credit and asset price growth fall just short of our assignment thresholds. This observation motivates us to define a "Yellow zone" or *Y-zone*, in which credit and asset price growth are elevated but not as high as in the *R-zone*. The *Y-zone* provides an early warning signal for a larger fraction of crises than the *R-zone*, although it produces more false alarms.

In Section IV.B, we to construct a "policy possibility frontier," which provides a more formal summary of the statistical trade-off faced by policymakers. In Section IV.C, we examine the crises that *R-zone* and *Y-zone* fail to predict and the economic outcomes that follow the *R-zone*'s false alarms. Finally, in Section IV.D,

[22]False positives are analogous to Type I errors in hypothesis testing (falsely rejecting the null hypothesis when it is true). False negatives are analogous to Type II errors (falsely accepting the null hypothesis when it is false).

we develop a simple economic framework to quantify how a policymaker tasked with promoting financial stability should trade-off these false positive and false negative errors, for example, setting a threshold for when to lean against the wind of credit-market overheating. Taking the policy possibility frontier as given, the optimal choice depends on the relative costs of these two types of policy errors. While neither *R-zone* nor *Y-zone* are perfect predictors, we show there is a strong quantitative case for taking early action.

4.1 Assessing Predictive Efficacy

Table X summarizes the classification errors that arise when we use the *R-zone* indicator to predict crises. We start by analyzing the business *R-zone*. A simple representation of the predictive efficacy of the *R-zone* indicator is shown in the following contingency table:

	Crisis within three years:	**No crisis within three years:**
	$Crisis_{i,t+1 \text{ to } t+3}$=1	$Crisis_{i,t+1 \text{ to } t+3}$=0
R-zone: $R\text{-}zone_{it}$=1	*True Positives (#TP)*	*False Positives (#FP)*
R-zone: $R\text{-}zone_{it}$=0	*False Negatives (#FN)*	*True Negative (#TN)*

Thus far, we have emphasized the "precision" or positive predictive value (PPV) of *R-zone*—the percentage of *R-zone* events that are followed by a crisis within three years, computed as $PPV = \#TP/(\#TP + \#FP)$. As shown in column (1) of Table X, Panel A, 75 country-years in our sample qualify as business *R-zone* events. Of these, 34 are followed by a crisis within three years, so $PPV = 34/75 = 45.3\%$, which is the same conditional probability that we previously reported in Table III. Conditional on a true positive, Panel A of Table X shows that, on average, the business *R-zone* indicator first switches on 2.9 years prior to the onset of the crisis, providing ample early warning. Instead of looking across the rows of the contingency table, statisticians often use two measures of predictive efficacy that look at the columns of the contingency table. First, all else equal, we would like an indicator with a high "sensitivity" or TPR, that is, we want $TPR = \#TP/(\#TP + \#FN)$, the percentage of crises preceded by an *R-zone*, to be high. At the same time, we also want an indicator with a high "specificity" or *TNR*, that is; we want $TNR = \#TN/(\#TN + \#FP)$ to be high. Indeed, a perfect binary predictor would have $TPR = TNR$= 1.

A subtlety arises when calculating TPR and *TNR* in our setting because *R-zone* events often occur in streaks.We do not want a crisis that was preceded by an *R-zone* event in each of the previous three years to count as three separate true positives. For example, Denmark was in the business *R-zone* in 2005, 2006, and 2007 and experienced a crisis in 2008. We compute the true positive rate, TPR, as the percentage of crisis-onset country-years that were preceded by an *R-zone* event in any of the three prior years. Analogously, we compute the *TNR* as the percentage of noncrisis onset years that were preceded by zero *R-zone* events in the prior three years.[23]

As shown in column (1) of Panel A, the *TPR* for the business *R-zone* indicator is $TPR = 20/50 = 40\%$ because, of the 50 financial crises in our sample, 20 were preceded by a business *R-zone* event in the prior three years. The TNR for the business *R-zone* is $TNR = 1077/1208 = 89.2\%$ because, of the 1208 noncrisis years in our sample, 1077 were not preceded by a business *R-zone* event in the prior three years.

The remaining columns of Table X, Panel A repeat these calculations for different *R-zone* measures: a household *R-zone* event, an "either" *R-zone* event, and a "both" *R-zone* event. As shown in column (2), the

[23] More formally, when we compute *TPR* and *TNR*, the binary classifier in our contingency table is $\max\{R\text{-}zone_{i,t-1}, R\text{-}zone_{i,t-2}, R\text{-}zone_{i,t-3}\}$ and the binary outcome is $Crisis\text{-}Start_{i,t}$.

household *R-zone* is a more sensitive indicator of future crises (*TPR* = 47.7%) than the business analogue, but it is slightly less specific (*TNR* = 84.4%) and less precise (*PPV* = 36.8%). If we allow either household or business *R-zone* events to signal a crisis in column (3), sensitivity rises (*TPR* = 64.0%) but specificity (*TNR* = 78.7%) and precision (*PPV* = 35.9%) fall. When we require both the business and the household sector to be in the *R-zone* in column (4), sensitivity falls significantly (*TPR* = 15.9%) but there are large improvements in specificity (*TNR* = 97.1%) and precision (*PPV* = 78.9%).

This discussion illustrates the statistical trade-off between false negative errors (crises that are not preceded by an *R-zone* event) and false positive errors (*R-zone* events that do not precede a financial crisis). The general principle is that using a less stringent set of criteria for switching on the *R-zone* indicator of credit-market overheating reduces the number of false negatives but raises the number of false positives. As a result, a more liberal definition of the *R-zone* results in greater test sensitivity (higher *TPR*), but this comes at the expense of lower specificity (lower *TNR*) and, by extension, lower precision (lower *PPV*).

To explore this trade-off, in Panel B we loosen the criterion for switching on our credit-market overheating indicator. Specifically, we construct a new Yellow-zone variable, $Y\text{-}zone_{it} = 1\{\Delta_3(\text{Debt/GDP})_{it} > 60th \text{ percentile}\} \cdot 1\{\Delta_3 \log(\text{Price}_{it}) > 33.3th \text{ percentile}\}$. *R-zone* events are thus a subset of *Y-zone* events, with the latter corresponding to the four cells in the lower-right-hand corner of the matrices shown in Tables III, VIII, and IX. We construct the Yellow zone separately for the business sector ($Y\text{-}zone_{it}^{Bus}$) and the household sector ($Y\text{-}zone_{it}^{HH}$). Comparing results for the Yellow zone in Panel B with those for the Red zone in Panel A, across all four columns we see that adopting these looser criteria for credit-market overheating significantly raises the *TPR* and, conditional on a true positive, provides earlier warning of an incipient crisis. For example, $Y\text{-}zone^{HH}$ it signals crises about two years earlier than $R\text{-}zone^{HH}$ it on average. This increased sensitivity comes at the cost of a lower *TNR* and a lower positive predictive value (*PPV*).

4.2 Mapping the Trade-Off between False Positive and False Negative Errors

In Figure 5, we systematically map out the empirical trade-off between false positive and false negative errors that policymakers face. To do so, we vary the cutoffs for labeling past credit and asset price growth as "high." For each possible pair of cutoffs (c_D, c_P), we first recompute $Y\text{-}zone_{it} = 1\{\Delta_3(\text{Debt/GDP})_{it} > c_D\} \cdot 1\{\Delta_3 \log(\text{Price}_{it}) > c_P\}$. Using each candidate definition of *R-zone*, we next compute the *TPR*, the *TNR*, and the *PPV*. In Panel A, we first plot the outer boundary of the set of possible *R-zone*-style signals in (*PPV*, *TPR*) space. For each value of *TPR*, we compute the highest possible *PPV* among the set of *R-zone*-style signals that achieve at least this specified level of *TNR*. Similarly, Panel B plots the outer boundary in (*TNR*, *TPR*) space, tracing out a curve that we call the policy possibility frontier.[24]

Panel A plots the highest *PPV* on the vertical axis (the percentage of *R-zone* events succeeded by a crisis) that is attainable for each level of *TPR* on the horizontal axis (the percentage of crises preceded by an *R-zone*). Using our baseline definition of the business *R-zone* (setting c_D and c_P to the 80th and 66th percentiles of the sample distribution), Panel A shows that we detect *TPR* = 40% of crises and that *PPV*

[24]The plot of *TNR* against *TPR* is monotonically decreasing. To see why, note that the total number of observations in each column of the contingency table is fixed. As we reduce c_D or c_P, loosening the criterion for the *R-zone*, we move observations from the bottom to the top row. Thus, using a less stringent test must raise *TPR* and reduce *TNR*, tracing out a decreasing curve. However, the plot of *PPV* versus *TNR* can be locally increasing even though it is globally decreasing. Consider a small reduction in either c_D or c_P. If this change only moves false negatives to true positives, it will raise *PPV*. By contrast, if it only moves true negatives to false positives, it will lower *PPV*. The total impact on *PPV* depends on the net of these two forces, which can be either positive or negative.

= 45.3% of *R-zones* are followed by a crisis. If we require less extreme credit or asset price growth before switching on the *R-zone* indicator, this raises the *TPR* but reduces the *PPV*. For example, if we set the cutoffs so low that *TPR* = 80% of crises are preceded by business *R-zone* events, only *PPV* = 21.4% of *R-zones* events are followed by a crisis. At the other extreme, if we set the cutoffs so high that *TPR* = 20%, then *PPV* = 80% of *R-zone* events are followed by a crisis.

The middle figure in Panel A shows a similar trade-off for the household sector.[25] The right-most figure in Panel A shows the gains in the *PPV* for a given *TPR* that can be obtained by combining information from the business and household sectors. In addition to considering $R\text{-}zone_{it}^{Bus}$ and $R\text{-}zone_{it}^{HH}$ as we vary the cutoffs (c_D,c_P), we now also consider $R\text{-}zone_{it}^{Either} = \max\{R\text{-}zone_{it}^{Bus}, R\text{-}zone_{it}^{HH}\}$ and $R\text{-}zone_{it}^{Both} = R\text{-}zone_{it}^{Bus} \times R\text{-}zone_{it}^{HH}$. The figure shows that using $R\text{-}zone^{Both}$ it yields the highest level of *PPV* when *TPR* is low. At the same time, $R\text{-}zone^{Either}$ it performs best when *TPR* is high. In other words, the figure shows that one can improve predictive efficacy by combining information on the business and household sectors.

Panel B shows our empirical policy possibility frontier, plotting the highest *TNR* (the percentage of noncrises that are not preceded by an *R-zone* event) that is attainable for each *TPR*. This policy possibility frontier curve is a close cousin of the receiver operating characteristic (ROC) curve that is often used to assess the accuracy of a binary classification system.[26] As we loosen the criterion for entering the *R-zone*, reducing either c_D or c_P, this raises the *TPR*, but reduces the *TNR*. Using our baseline definition of the business *R-zone*, the left-most figure shows that *TPR* = 40% and *TNR* = 89.2%. However, if we relax the cutoffs so *TPR* = 80%, then *TNR* = 52.2%. The middle figure repeats this analysis for the household sector. The right-most figure shows that combining information from the business and household sectors shifts the policy possibility frontier outward.

4.3 Economic Outcomes Following False Negatives and False Alarms

Striking the appropriate trade-off between false negatives and false positives hinges on the real economic outcomes in each of these cases. To shed some preliminary light on these costs, we explore the crises that the *R-zone* fails to signal—the false negatives—and the economic outcomes that follow the false alarms that are generated by the *R-zone* indicator.

We begin by examining the crises the Red zone fails to signal. For each of the 50 country-years in our sample in which BVX code a crisis as beginning (Crisis-Starti,t = 1), Figure 6 plots the price growth and debt growth percentiles of the year closest to the *R-zone* out of the three years preceding the crisis. Business and household *R-zones* are shown using different markers. Subsequent three-year real GDP growth following the onset of the crisis is indicated using different colors. The top right area of the graph, shaded in red, shows the *R-zone* events for which price and credit growth are jointly elevated. As we see in Table X, *TPR* = 32/50 = 64% of crises were either preceded by a business *R-zone* or a household *R-zone*. Thus, the *R-zone* misses 36% of crises.

[25] Since the production possibility frontier is the outer boundary of all feasible *R-zone*-like signals, our baseline definition of *R-zone* need not lie on the frontier. It turns out that our baseline definition of the business *R-zone* lies on the frontier, but our baseline version of the household *R-zone* lies just inside the frontier.

[26] The ROC curve plots *TPR* on the vertical axis and $1 - TNR$ on the horizontal axis, whereas we are plotting TNR against *TPR* in Panel B. Thus, by construction, the area under the ROC (AROC) curve—a commonly used measure of the efficacy of a binary classification system—equals the area under the curve (AUC) for our policy possibility frontier. In Figure 5, we report the AUC for our empirical policy possibilities frontiers, which rise from 73.6% for $R\text{-}zone^{Bus}$ to 74.8% for $R\text{-}zone^{HH}$ and then 76.7% for $R\text{-}zone^{Either}$.

Figure 6 shows that many of the Red zone's "near misses" are associated with how we define the *R-zone*. For example, if we were to instead use the Yellow zone, which is shaded in yellow, adopting lower thresholds for past credit and asset price growth, we would have caught nine additional crises, bringing the true positive rate to $TPR = 41/50 = 82\%$. With the exceptions of Spain in 1975 and Turkey in 2001, subsequent GDP growth was very low or even negative following these nine crises, suggesting that these false negatives may have been costly and arguing in favor of adopting a less stringent test for responding to credit-market overheating, all else equal.

Even our expanded *Y-zone* indicator misses nine financial crises. Of the nine crises not preceded by a *Y-zone* event, seven followed shortly on the heels of an earlier crisis, including Turkey in 1994, Japan in 1997 and 2001, three European countries that were involved in the 2011 Eurozone crisis (Austria, Denmark, and Portugal), and Portugal in 2014. It is perhaps not surprising these "double-dip" crises were not preceded by elevated levels of credit and asset price growth. It may therefore be worthwhile to look for a different set of indicators that can be used to assess the risk of relapse following an initial crisis. We leave this topic to future research.

Finally, in Table XI, we examine the economic outcomes following false negatives, the *R-zone* events that were not followed by a crisis. We estimate regressions of the form

$$\begin{aligned}\log(GDP_{i,t+h}/GDP_{i,t}) =&\alpha_i^{(h)} + \gamma^{TP(h)} \cdot \textit{R-zone}_{it} \times \textit{Crisis}_{i,t+1 \text{ to } t+h} \\ &+ \gamma^{FP(h)} \cdot \textit{R-zone}_{it} \times (1 - \textit{Crisis}_{i,t+1 \text{ to } t+h}) + \epsilon_{i,t+1 \text{ to } t+h}\end{aligned} \tag{2.6}$$

for $h = 1$, 2, 3, and 4. The $\gamma^{TP(h)}$ coefficients trace out the change in the expected path of real GDP growth conditional on a true positive, whereas the $\gamma^{FP(h)}$ coefficients show the same change conditional on a false positive. We find that $\gamma^{TP(h)} < 0$, a result that is almost hardwired since we know that financial crises lead to large declines in real GDP. However, our main interest lies with $\gamma^{FP(h)}$. For the business *R-zone*, we find that $\gamma^{FP(h)}$ is positive but economically small: $\gamma^{FP(3)}$=1.3% (t = 1.0). For the household *R-zone*, $\gamma^{FP(h)}$ is negative but small: $\gamma^{FP(3)}$ =-0.9% (t=-1.0). Thus, economic output during false positive episodes is quite normal, hinting that the costs of false positives may be relatively small.

4.4 Are Crises Sufficiently Predictable to Warrant Early Action by Policymakers?

Given the statistical trade-off between false positives and false negatives, what should a policymaker tasked with promoting financial stability do? In other words, given a policy possibility frontier, what point on that frontier should a policymaker choose? Taking steps to avert crises runs the risk of slowing the economy based on false alarms. The optimal threshold for taking early action depends on the cost of acting based on a false alarm compared to the cost of failing to act when the risk of a crisis is truly elevated.

In this subsection, we develop a simple framework to formalize this tradeoff.[27] Using the policy possibility frontier that we estimate above, our analysis suggests that policymakers should adopt a do-nothing strategy—not taking preventative actions even if concerns about credit-market overheating become acute—if they think the costs of false positives are extremely high relative to the costs of false negatives.

[27] Our framework adapts the textbook approach for choosing the optimal threshold in a binary classification problem (see, for example, Pepe (2003) or Baker and Kramer (2007)) to a financial stability setting. Drehmann and Juselius (2014) also apply this textbook approach to the problem of deciding when to lean against the wind.

With probability p the risk of a crisis is high and with probability $1-p$ the risk of a crisis is low. The policymaker does not observe the true level of risk but has access to a continuum of informative but imperfect binary statistical tests that she can use to guide a binary policy action that may reduce the likelihood or severity of a future crisis. We assume that this policy action yields benefits if the risk of a crisis is truly high, but is costly otherwise.[28]

In a richer dynamic model, the set of optimal macroprudential policies would naturally depend on both the predictive accuracy and the timing of the early warning signals available to policymakers. For instance, reliable warning signals that offer sufficient lead time might allow policymakers to take preventative measures—for example, tightening monetary policy, increasing minimum bank capital requirements, and reducing maximum loan-to-value ratios—to lean against the wind of credit booms, and thereby reduce the buildup of systemic risk ex ante. By contrast, warning signals that offer minimal lead time might allow policymakers to take steps to reduce the expected severity of impending crises—for example, easing monetary policy and forcing banks to reduce equity payouts or issue new equity capital. As noted in Section I, we believe that our *R-zone* signal offers sufficient lead time to open the door to the types of countercyclical, preventative measures referenced above.

If the policymaker chooses a statistical test with a *TPR* of $\tau_{TPR} \in [0,1]$, the test has a *TNR* given by $\tau_{TNR} = T_{TNR}(\tau_{TPR})$. The plot of $\tau_{TNR} = T_{TNR}(\tau_{TPR})$ against τ_{TPR} is the policy possibility frontier. We assume that this frontier is downward-sloping: $T'_{TNR}(\tau_{TPR}) < 0$, that is, the policymaker faces the usual statistical trade-off between the *TNR* and *TPR*. We also assume that $T_{TNR}(0) = 1$, $T_{TNR}(1) = 0$, and $T''_{TNR}(\tau_{TPR}) < 0$. Finally, since these tests rely on informative signals, $T_{TNR}(\tau_{TPR}) > 1 - \tau_{TPR}$ for all $\tau_{TPR} \in (0,1)$.[29] There are four possible outcomes: ¨

- *True negative*: If the risk of a crisis is truly low and the test predicts low risk, the policymaker does not take the preventative action and total real economic output is $Y_G > 0$. If the policymaker chooses a test with a TPR given by τ_{TPR}, the unconditional probability of a true negative is $(1-p) \times T_{TNR}(\tau_{TPR})$.

- *False positive*: If the risk of a crisis is truly low but the test predicts high risk, the policymaker takes the action, leading output to fall to $Y_G - C_{FP}$. The cost of this false alarm, $C_{FP} > 0$, would be large if one thinks unnecessary actions to lean against the wind have a large social cost when the risk of a crisis is not truly high. The unconditional probability of a false positive is $(1-p) \times (1 - T_{TNR}(\tau_{TPR}))$.

- *True positive*: If the risk of a crisis is high and the test predicts high risk, the policymaker takes the action and real output is $Y_B > 0$. The probability of a true positive is $p \times \tau_{TPR}$.

- *False negative*: If the risk of a crisis is truly elevated but the test predicts low risk, the policymaker fails to take the preventative action and output falls to $Y_B - c_{FN}$. The cost of this false negative error, c_{FN} ¿ 0, would be large if one thinks that the preventative action yields large benefits when the risk of a crisis is truly elevated. The unconditional probability of a true positive is $p \times \tau_{TPR}$.

[28]Our assumption that the policymaker can take only a single binary action is made purely for simplicity. In a richer dynamic setting, a policymaker might take a series of incremental actions in response to the informative, but imperfect signals she receives about the evolving level of systemic financial risk. However, the basic trade-off would remain: the policymaker would need to balance the costs of underescalation if she were to underestimate the true level of systemic risk against the costs of overescalation if she were to overestimate risk.

[29]The positive predictive value is the probability that risk is truly high conditional on the test signalling high risk. We have $PPV(\tau_{TPR}) = [p\tau_{TPR}] \div [p\tau_{TPR} + (1-p)(1 - T_{TNR}(\tau_{TPR}))]$ and one can show that $PPV'(\tau_{TPR}) < 0$.

We assume that the social payoff from output level Y is $u(Y)$, where $u'(Y) > 0$ and $u''(Y) \leq 0$.[30] Putting everything together, the policymaker solves

$$\max_{\tau_{TPR} \in [0,1]} \{p \times [\tau_{TPR} \times u(Y_B) + (1 - \tau_{TPR}) \times u(Y_B - C_{FN})] + (1 - p) \times [T_{TNR}(\tau_{TPR}) \times u(Y_G) + (1 - T_{TNR}(\tau_{TPR})) \times u(Y_G - C_{FP})]\} \tag{2.7}$$

The first-order condition implies that, at an interior optimum where $\tau_{TPR} \in (0, 1)$, we have

$$\overbrace{T'_{TNR}(\tau^*_{TPR})}^{\substack{\text{Slope of policy} \\ \text{indifference curves}}} = \overbrace{-\frac{p}{1-p} \frac{u(Y_B) - u(Y_B - C_{FN})}{u(Y_G) - u(Y_G - C_{FP})}}^{\substack{\text{Slope of policy} \\ \text{indifference curves}}} = \overbrace{-\frac{p}{1-p} \frac{C_{FN}}{C_{FP}} \frac{u(\bar{Y}_B)}{u(\bar{Y}_G)}}^{\substack{\text{Slope of policy} \\ \text{indifference curves}}} \tag{2.8}$$

where $\bar{Y}_B \in (Y_B - C_{FN}, Y_B)$ and $\bar{Y}_G \in (Y_G - C_{FP}, Y_G)$. Assuming an interior solution, we have $\partial\tau^*_{TPR}/\partial C_{FN} > 0$, $\partial\tau^*_{TPR}/\partial C_{FP} < 0$, and $\partial\tau^*_{TPR}/\partial p > 0$. If $u''(Y) < 0$, we also have $\partial\tau^*_{TPR}/\partial Y_B < 0$ and $\partial\tau^*_{TPR}/\partial Y_G > 0$.

Figure 7 illustrates this trade-off graphically. The figure plots the policy possibility frontier, $\tau_{TNR} = T_{TNR}(\tau_{TPR})$, in (τ_{TNR}, τ_{TPR}) space together with policymakers' indifference curves. The optimal choice of τ_{TPR} occurs at the point τ^*_{TPR} where the policy possibility frontier is tangent to the indifference curves. Panel A illustrates this trade-off for an initial position of the policy possibility frontier. The flat, solid red line shows a case in which C_{FN}/C_{FP} is low—that is, false alarms are quite costly relative to misses, leading to a low level of τ^*_{TPR}. The steep, dashed red line shows a case in which C_{FN}/C_{FP} is high—that is, misses are quite costly relative to false alarms, leading to a high level of τ^*_{TPR}. Panel B illustrates how the trade-off changes when crises become more predictable, leading to an outward shift in the policy possibility frontier. When c_{FN}/c_{FP} is low, the policymaker's indifference curves are relatively flat. As a result, an outward shift in the policy possibility frontier raises the optimal level τ^*_{TPR}.[31]

If crises are completely unpredictable (i.e., if $T_{TNR}(\tau_{TPR}) = 1 - \tau_{TPR}$), the optimum must be at a corner, where policy is not state contingent. Specifically, if p or C_{FN}/C_{FP} is small enough, the policymaker never takes the action ($\tau^*_{TPR}= 0$); otherwise, she always take the action ($\tau^*_{TPR}= 1$). As crises become more predictable, the policy possibility frontier shifts out and these corner solutions remain optimal only if her indifference curves are extremely flat (implying $\tau^*_{TPR}= 0$) or extremely steep (implying $\tau^*_{TPR} = 1$). In other words, an increase is the predictability of financial crises should lead a policymaker to adopt state-contingent policies to lean against the wind.

The optimal level of τ^*_{TPR} depends on the specific action under consideration and on prevailing economic conditions that shape the costs of false negatives and false positives.[32] For example, a policymaker might decide to take mild preventative actions (c_{FN}/c_{FP} is larger) based on a looser criterion such as the *Y-zone*,

[30] Instead of inducing more or less favorable realizations of future output, different combinations of the true binary state—whether or not risk is truly high—and the binary policy action could lead to more or less favorable probability distributions for the present value of future output. Specifically, the expectation of u(Y) conditional on a true positive would exceed that conditional on a false negative; similarly, the expectation of u(Y) conditional on a true negative would exceed that conditional on a false positive. This is perhaps the most natural way to think about the choice confronting a policymaker who is using an early warning signal to lean against the wind.

[31] An outward shift in the policy possibility frontier has an ambiguous impact on τ^*_{TPR}. Such a shift must flatten the frontier for smaller τ_{TPR} and steepen the frontier for larger τ_{TPR}. Thus, there is some cutoff $\bar{\tau} \in (0, 1)$ such that an outward shift in the frontier raises τ^*_{TPR} when $\tau^*_{TPR} < \bar{\tau}$ and lowers τ^*_{TPR} when $\tau^*_{TPR} > \bar{\tau}$.

[32] Suppose the economy is near full employment and inflation is near target. Then moderately tightening monetary policy or moderately raising equity capital requirements for banks in response to concerns about credit-market overheating might be a case in which C_{FN}/C_{FP} is large, calling for a high value of τ^*_{TPR}. However, if unemployment is currently elevated, this would tend to raise c_{FP} and reduce τ^*_{TPR}.

and take stronger actions (C_{FN}/C_{FP} is smaller) based on a more stringent criterion like the *R-zone*.[33]

For our purposes, the main question is whether crises are sufficiently predictable—using past credit growth and past asset price growth alone—to justify preemptive action in response to rising financial stability concerns. Although the exact form of such an early policy intervention is beyond the scope of this paper, we can address the simpler question of whether, based on our evidence, a policymaker might reasonably argue that there are grounds for never taking any preventative actions, that is, for always setting $\tau^*_{TPR} = 0$. To address this question, we assume that the unconditional probability of an incipient crisis is $p = 4\%$, consistent with the annual probability of the onset of a crisis reported in Table I. We also assume that the policymaker is risk-neutral, implying $u'(\bar{Y}_B)/u'(\bar{Y}_G) = 1$. This assumption is conservative. It would be more reasonable to assume that the policymaker is risk averse and $\bar{Y}_B < \bar{Y}_G$, implying $u'(\bar{Y}_B)/u'(\bar{Y}_G) > 1$ and thus pushing toward a higher value for τ^*_{TPR} in equation (8).

Finally, we write $c_{FN}/c_{FP} = (C_{Crisis}\ /Y_G) \times (c_{FN}/c_{FP})$, where c_{FN} is the fraction of the costs of a financial crisis C_{Crisis} that can be mitigated by taking early preventative action and c_{FP} is the fraction of noncrisis output Y_G that is lost when the policymaker takes actions in response to a false alarm. Note that c_{FN}/c_{FP} is the ratio of two macroeconomic "treatment effects." Unfortunately, we lack rigorous, model-free estimates of c_{FN}/c_{FP} for different policy actions. However, the literature does provide guidance about the magnitude of C_{Crisis}/Y_G, that is, the cost of a crisis as a percentage of precrisis GDP. Beginning Cerra and Saxena (2008), most studies find that C_{Crisis}/Y_G is quite large because financial crises typically lead to a permanent loss of future output. Specifically, while output growth usually returns to its precrisis trend following a crisis, the level of output does not return to its precrisis trend line. The Basel Committee on Banking Supervision (2010, BCBS) undertakes a meta-analysis of studies that estimate the discounted present value of crisis-induced real output losses as a percentage of precrisis GDP. Averaging across studies that allow for crises to have a permanent effect on GDP, they estimate that the present value of output losses equal 145% of annual precrisis GDP. We set $C_{Crisis}/Y_G = 1.5$ for concreteness.[34]

Using these parameters and the estimated policy possibility frontier from the right-most column of Figure 5, Panel B, which combines information from the business and household sectors, Figure 8 plots τ^*_{TPR} as we vary c_{FP}/c_{FN}. We report the solution to[35]

$$T'_{TNR}(\tau^*_{TPR}) = -\frac{p}{1-p} \times \frac{u(\bar{Y}_B)}{u(\bar{Y}_G)} \times \frac{C_{Crisis}}{Y_G} \times \frac{c_{FN}}{c_{FP}} = -\frac{0.04}{0.96} \times 1 \times 1.5 \times \frac{c_{FN}}{c_{FP}} \tag{2.9}$$

For example, if a forceful early action to lean against the wind—such as, significantly raising bank capital requirements in response to credit-market overheating—lowers the expected severity of an incipient crisis

[33]From of a policymaking standpoint, a practical advantage of our approach is that our *R-zone* and *Y-zone* indictors are simple transformations of familiar data series that are available in real time and thus would be relatively straightforward to communicate to the public. Furthermore, having relatively stable input signals may be advantageous when adjusting macrofinancial policies over time (Drehmann and Juselius (2014)), so the fact that our *R-zone* and *Y-zone* indicators tend to arrive in streaks may be valuable.

[34]See table A1.1 in BCBS. BCBS suggests that these estimates are quite conservative since they are usually obtained by assuming that the appropriate real discount rate for computing the present value of crisis-induced real output losses exceeds the steady-state growth rate of real output by a hefty 5 percentage points. However, to the extent that output is abnormally elevated prior to financial crises, the approach in Cerra and Saxena (2008) would tend to overstate the cost of crises.

[35]To estimate $T_{TNR}(\tau_{TPR})$, we first estimate $T_{TNR}(\tau_{TPR})$ parametrically using nonlinear least squares. We assume that $T_{TNR}(\tau_{TPR}) = 1 - \Phi(\frac{\Phi^{-1}(\tau_{TPR})-a}{b})$, where $\Phi(\cdot)$ is the standard normal cumulative distribution function. We obtain a = 0.95 and b = 0.85 with R^2 = 99.96%. Using these estimates, we then obtain $T'_{TNR}(\tau_{TPR}) = -(1/b) \times [\phi(\frac{\Phi^{-1}(\tau_{TPR})-a)}{b})] \div [\phi(\Phi^{-1}(\tau_{TPR}))]$.

by 30% but reduces the level of GDP by 1 percentage point for two years if there is no crisis, we would have $c_{FN}/c_{FP} = 30\%/2\% = 15$, implying an optimal sensitivity of $\tau^*_{TPR} = 68\%$. Figure 8 also shows the positive predicted value—the fraction of *R-zone* signals that are followed by a crisis within three years—that corresponds to this optimal TPR. Specifically, if $c_{FN}/c_{FP} = 15$, Figure 8 indicates that policymakers should take early action once the probability of a crisis arriving within three years rises above 31%. Based on the results for our original *R-zone* definitions in Table X, Figure 8 suggests that a policymaker should be willing to take actions at $c_{FN}/c_{FP} = 15$ once the economy enters either the business or the household *R-zone*, which yields TPR = 64% and PPV = 36%. Figure 8 further suggests that a do-nothing strategy can be justified only for very small values of c_{FN}/c_{FP}. Based on our estimates, policymakers should set $\tau^*_{TPR} \leq 0.1$ only if they believe that c_{FN}/c_{FP} is less than 1.1, a number that seems almost implausibly small. For instance, a policymaker would need to believe that the action of leaning against the wind discussed above, which we assume would reduce GDP by 1 percentage point for two years if there is no crisis, would reduce the expected severity of an incipient crisis by only 2.2%. In other words, policymakers should only adopt a do-nothing strategy if they hold fairly extreme views about the costs of failing to respond to financial stability threats as compared to the costs of false alarms.

5 Conclusion

Using two simple variables, past credit growth and past asset price growth, we construct a danger zone, the *R-zone*, in which the probability of a financial crisis over the next three years is roughly 40%. In 2006, the United States and many other advanced economies were deep inside that danger zone, a clear harbinger of the GFC that would erupt in 2008. Does our finding that the conditional probability of a crisis occasionally rises above 40% warrant the conclusion that crises are predictable? A champion of unpredictability might say no. After all, even starting in the *R-zone*, which occurs in only 6% and 10% of all country-years for the business and household sectors, respectively, it is far from certain that a crisis will occur. In this regard, two points are in order. First, since financial crises typically lead to permanent reductions in real economic output (Cerra and Saxena (2008)), a 40% conditional probability might be more than enough to warrant some precautionary macrofinancial responses such as tightening monetary policy or raising bank capital requirements. Second, we reached these conclusions with just two country-level variables—past credit growth and asset price growth—because we are using a large historical data set. Even simply adding the global versions of our *R-zone* indicators sharply increases predictability. Moreover, several other variables appear to have incremental forecasting power for crises, including credit spreads and the leverage of financial institutions (Richter, Schularick, and Wachtel (2021)). A policymaker with access to such data would presumably have a better estimate of the likelihood of a crisis. Our conclusion is that financial crises are sufficiently predictable to justify taking early action in response to credit-market overheating. Our evidence supports the view that the economic system is vulnerable to predictable boom-bust cycles driven by credit expansion and asset price growth. This view, and the recent theoretical models that formalize it, make a case for prophylactic policy interventions that lean against the wind. Indeed, the post-GFC era has witnessed the advent of several macroprudential tools that are now being used in precisely this manner, including the introduction of time-varying bank capital requirements under Basel III and the increased use of time-varying maximum loan-to-value standards.[36] A little more policing, and a little less firefighting, would do the world some good.

[36]While there is a growing consensus that policymakers should use these new macroprudential tools to lean against the wind, disagreement remains about whether monetary policy should be tightened in response to credit market overheating. See Stein (2013, 2014), Adrian and Liang (2018), and Gourio, Kashyap, and Sim (2018) for arguments that monetary policy should be used in this way. See Svensson (2017) for the opposite view.

Table I. Summary Statistics

This table presents summary statistics for our main variables in percent. Our sample is an unbalanced panel from 42 countries over the period 1950 to 2016. Δ_3 denotes changes over three years. Outstanding debt covers loans and debt securities as retrieved from the IMF's *Global Debt Database* and supplemented with BIS's total credit statistics and loans data from MacroHistory.net. Equity price indices are retrieved primarily from GFD, supplemented with data from Bloomberg, the IMF, and MacroHistory.net. House price indices are retrieved from the BIS's *Selected Property Price Series* and supplemented with data from OECD and MacroHistory.net. An overview of data sources for outstanding debt and price indices is available in the Internet Appendix. Financial crisis indicators are from Baron, Verner, and Xiong (2021), Jordá, Schularick, and Taylor (2017), and Reinhart and Rogoff (2011), and data on real GDP and inflation are retrieved from the World Bank's *World Development Indicators* and the IMF's *International Financial Statistics*, respectively, both supplemented with data from MacroHistory.net. Inflation data for Argentina are retrieved from Banco Central de la República Argentina.

	N	Mean	SD	Quantiles			
Financial Crisis Indicators:							
Baron, Verner, and Xiong (2021) (%)	1281	3.98	19.56				
Jordá, Schularick, and Taylor (2017) (%)	909	2.64	16.04				
Reinhart and Rogoff (2011) (%)	1109	3.61	18.65				
Crashes, Failures, and Panics:							
Bank Equity Crash (%)	1280	8.52	27.92				
Bank Failures (%)	1281	3.51	18.42				
Panics (%)	1281	3.04	17.19				
GDP:							
Δ_1 log real GDP (%)	1281	3.28	3.21				
Debt Growth:				Q20	Q40	Q60	Q80
Δ_3 Business Debt / GDP (%)	1258	3.86	20.74	-2.76	1.03	3.99	9.03
Δ_3 Household Debt / GDP (%)	1107	3.58	5.74	-0.26	1.63	3.95	7.62
Δ_3 log real Debt (%)	1281	17.90	16.85	5.22	13.05	20.43	29.27
Price Growth:				Q33.3		Q66.7	
Δ_3 log real Equity Index (%)	1258	8.65	48.80	-8.53		26.57	
Δ_3 log real House Price Index (%)	1107	6.47	17.89	-0.35		12.68	

Table II. Linear Regression

This table presents results of the regression model

$$Crisis_{i,t+1 \ to \ t+h} = \alpha_i^h + b^h \Delta_3 x_{it} + \epsilon_{it}^h, \tag{2.10}$$

where h identifies the prediction horizon, $Crisis_{i,t+1 \ to \ t+h}$ is an indicator variable that takes the value of one if a crisis has occurred in country i between year $t+1$ and $t+h$, α_i^h captures country fixed effects, and $\Delta_3 x_t$ measures three-year normalized debt growth. We use four different measures of debt: i) Total private debt to GDP, ii) Business debt to GDP, iii) Household debt to GDP, and iv) Real log debt.
t-statistics are reported in brackets and based on Driscoll and Kraay (1998) standard errors with lags of zero, three, five, and six years for prediction horizons one, two, three, and four years, respectively. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively, using Kiefer and Vogelsang (2005) corrected p-values. Reported coefficients and R^2s are in percent.

	Dependent Variable											
	Crisis within 1 year				Crisis within 2 years				Crisis within 3 years			
	(1.1)	(1.2)	(1.3)	(1.4)	(2.1)	(2.2)	(2.3)	(2.4)	(3.1)	(3.2)	(3.3)	(3.4)
Δ_3 $Debt^{Priv}/GDP$	2.6*				4.0***				5.3**			
	[1.7]				[2.9]				[2.6]			
Δ_3 $Debt^{Bus}/GDP$		2.0				2.8**				3.4*		
		[1.5]				[2.6]				[2.1]		
Δ_3 $Debt^{HH}/GDP$			2.8**				6.1***				9.2***	
			[2.2]				[2.9]				[3.4]	
Δ_3 $\log(Debt^{Priv}/CPI)$				1.3				2.3				3.5
				[1.2]				[1.6]				[1.7]
R^2 *(within)*	1.5	0.9	1.7	0.4	1.9	0.9	4.4	0.6	2.5	1.0	7.3	1.0
N	1,281	1,258	1,107	1,281	1,281	1,258	1,107	1,281	1,281	1,258	1,107	1,281

Table III. Crisis Probabilities by Price and Debt Growth Quantiles

Panel A presents the empirical distribution of country-years across equity price growth terciles and business debt growth quintiles. Panel B presents the probability of a crisis within one to four years for the intersections of the equity price terciles and business debt quintiles. It also presents the difference in future crisis probability between each group and the median group, which is defined as the intersection of the second price tercile and the third debt growth quintile. Panel C presents the empirical distribution of country-years across house price growth terciles and household debt growth quintiles. Panel D presents the probability of a crisis within one to four years for the intersections of house price terciles and household debt quintiles, as well as differences with the median group. Debt is normalized by GDP for both sectors, and growth is measured over three years. p-values are based on Driscoll and Kraay (1998) standard errors with lags of zero, three, five, and six years for prediction horizons one, two, three, and four years, respectively, and corrected according to Kiefer and Vogelsang (2005). *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Distribution of Observations (%) by Growth in Business Debt and Equity Prices

	Debt Quintile				
Price Tercile	1	2	3	4	5
1	5.6	6.5	5.8	6.8	8.7
2	6.8	7.6	7.0	6.7	5.3
3	7.6	6.0	7.2	6.6	6.0

Panel B: Crisis Probabilities (%) by Growth in Business Debt and Equity Prices

	Crisis Frequency					*Diff. from Median*				
	Debt Quintile					Debt Quintile				
Price Tercile	1	2	3	4	5	1	2	3	4	5
1-year horizon										
1	1.4	2.4	0.0	3.5	6.4	-3.1	-2.1	-4.5**	-1.0	1.9
2	2.4	3.2	4.5	3.6	11.9	-2.2	-1.4	0.0	-1.0	7.4
3	2.1	1.3	2.2	3.6	13.3	-2.5	-3.2	-2.3	-0.9	8.8
2-year horizon										
1	1.4	4.9	2.7	4.7	14.7	-5.4	-1.9	-4.1	-2.1	7.9
2	2.4	4.2	6.8	7.1	16.4	-4.5	-2.6	0.0	0.3	9.6
3	8.3	5.3	8.9	8.4	26.7	1.5	-1.5	2.1	1.6	19.8*
3-year horizon										
1	4.2	4.9	4.1	7.1	19.3	-3.7	-3.1	-3.8	-0.9	11.3
2	3.5	5.3	8.0	9.5	19.4	-4.4	-2.7	0.0	1.6	11.4*
3	11.5	9.3	11.1	19.3	45.3	3.5	1.4	3.2	11.3	37.4***
4-year horizon										
1	5.6	13.4	4.1	8.2	20.2	-4.6	3.2	-6.1	-2.0	10.0
2	4.7	6.3	10.2	17.9	23.9	-5.5	-3.9	0.0	7.6	13.7*
3	12.5	12.0	13.3	26.5	48.0	2.3	1.8	3.1	16.3	37.8***

Panel C: Distribution of Observations (%) by Growth in Household Debt and House Prices

	Debt Quintile				
Price Tercile	1	2	3	4	5
1	10.5	7.5	5.7	5.5	4.2
2	6.2	6.8	8.1	6.7	5.5
3	3.3	5.7	6.2	7.8	10.3

Panel D: Crisis Probabilities (%) by Growth in Household Debt and House Prices

	1-year horizon									
	Crisis Frequency					*Diff. from Median*				
	Debt Quintile					Debt Quintile				
Price Tercile	1	2	3	4	5	1	2	3	4	5
1	2.6	2.4	3.2	3.3	10.9	-0.7	-0.9	-0.2	-0.1	7.5*
2	2.9	0.0	3.3	2.7	1.6	-0.4	-3.3*	0.0	-0.6	-1.7
3	2.7	3.2	0.0	4.7	14.0	-0.6	-0.2	-3.3*	1.3	10.7**

	2-year horizon									
	Crisis Frequency					*Diff. from Median*				
	Debt Quintile					Debt Quintile				
Price Tercile	1	2	3	4	5	1	2	3	4	5
1	6.0	3.6	7.9	4.9	21.7	2.7	0.3	4.6	1.6	18.4***
2	5.8	2.7	3.3	6.8	8.2	2.5	-0.7	0.0	3.4	4.9
3	2.7	3.2	1.4	10.5	26.3	-0.6	-0.2	-1.9	7.1	23.0**

	3-year horizon									
	Crisis Frequency					*Diff. from Median*				
	Debt Quintile					Debt Quintile				
Price Tercile	1	2	3	4	5	1	2	3	4	5
1	9.5	4.8	11.1	8.2	28.3	6.1**	1.5	7.8	4.9	24.9**
2	7.2	4.0	3.3	16.2	13.1	3.9	0.7	0.0	12.9**	9.8*
3	2.7	3.2	1.4	17.4	36.8	-0.6	-0.2	-1.9	14.1*	33.5***

	4-year horizon									
	Crisis Frequency					*Diff. from Median*				
	Debt Quintile					Debt Quintile				
Price Tercile	1	2	3	4	5	1	2	3	4	5
1	10.3	8.4	14.3	11.5	30.4	3.7	1.8	7.6	4.8	23.8**
2	8.7	4.0	6.7	20.3	23.0	2.0	-2.7	0.0	13.6**	16.3*
3	5.4	4.8	5.8	20.9	41.2	-1.3	-1.9	-0.9	14.3	34.6***

Table IV. Crisis Prediction with Debt Growth and Real Asset Appreciation by Sector

This table presents results of the regression model

$$Crisis_{i,t+1\ to\ t+h} = a_i^h + \beta^h \cdot \textit{High-Debt-Growth}_{it} + \delta^h \cdot \textit{High-Price-Growth}_{it} + \gamma^h \cdot \textit{R-zone}_{it} + \epsilon_{it}^h,$$

where $Crisis_{i,t+1\ to\ t+h}$ is an indicator variable that takes the value of one if a crisis has occurred in country i between year $t+1$ and $t+h$, $\textit{High-Debt-Growth} \equiv 1\{\Delta_3(Debt/GDP)_{it} > 80^{th}$ percentile$\}$ is an indicator variable that takes the value of one if three-year debt growth is in the highest quintile, and $\textit{High-Price-Growth} \equiv 1\{\Delta_3 \log(Price_{it}) > 66.7^{th}$ percentile$\}$ is an indicator variable which takes the value of one if three-year price growth is in its highest tercile, an *R-zone* is the intersection of high price growth and high debt growth: $\textit{R-zone} \equiv \textit{High-Debt-Growth} \cdot \textit{High-Price-Growth}$. We run the regression on both the business sector, using business debt and equity prices to define the indicators (Panel A), and the household sector, using household debt and house prices to define the indicators (Panel B). *Sum of coefficients* captures the aggregate effect of all indicators in the regression. t-statistics are reported in brackets and based on Driscoll and Kraay (1998) standard errors with lags of zero, three, five, and six years for prediction horizons one, two, three, and four years, respectively. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively, using Kiefer and Vogelsang (2005) corrected p-values. Reported coefficients and R^2s are in percent.

Panel A: Business Sector

	Crisis within 1 year				Crisis within 2 years				Crisis within 3 years				Crisis within 4 years			
	(1.1)	(1.2)	(1.3)	(1.4)	(2.1)	(2.2)	(2.3)	(2.4)	(3.1)	(3.2)	(3.3)	(3.4)	(4.1)	(4.2)	(4.3)	(4.4)
High-Debt-Growth$^{Bus.}$ (β^h)	6.9**		5.3**		11.6***		9.5**		16.8***		11.5**		15.6**		10.3*	
	[2.3]		[2.1]		[3.0]		[2.5]		[3.3]		[2.7]		[2.7]		[2.2]	
High-Price-Growth$^{Bus.}$ (δ^h)		0.4	-0.4			4.8	3.8			10.5	7.4			10.7	7.6	
		[0.1]	[-0.2]			[0.9]	[0.8]			[1.4]	[1.1]			[1.5]	[1.2]	
R-zone$^{Bus.}$ (γ^h)			5.3	9.0			7.8	17.9*			19.4**	33.7***			19.4**	33.0**
			[0.8]	[1.1]			[1.3]	[2.1]			[2.8]	[3.3]			[2.6]	[3.1]
Sum of coefficients ($\beta^h+\delta^h+\gamma^h$)	6.9	0.4	10.2	9.0	11.6	4.8	21.1	17.9	16.8	10.5	38.2	33.7	15.6	10.7	37.3	33.0
t-statistic ($\beta^h+\delta^h+\gamma^h$)			1.2				2.1				3.2				3.1	
R^2 *(within)*	1.6	0.0	1.9	1.1	2.5	0.7	3.6	2.3	3.8	2.4	7.8	6.1	2.8	2.1	6.2	4.8
N	1,258	1,258	1,258	1,258	1,258	1,258	1,258	1,258	1,258	1,258	1,258	1,258	1,258	1,258	1,258	1,258

Panel B: Household Sector

	Crisis within 1 year				Crisis within 2 years				Crisis within 3 years				Crisis within 4 years			
	(1.1)	(1.2)	(1.3)	(1.4)	(2.1)	(2.2)	(2.3)	(2.4)	(3.1)	(3.2)	(3.3)	(3.4)	(4.1)	(4.2)	(4.3)	(4.4)
High-Debt-Growth^{HH} (β^h)	7.3**		2.4		15.1**		7.3**		20.5***		9.1**		23.7***		14.2**	
	[2.2]		[1.6]		[2.8]		[2.2]		[3.3]		[2.3]		[3.9]		[2.5]	
High-Price-Growth^{HH} (δ^h)		3.6*	0.4			6.0	0.4			8.1	0.0			8.5	0.8	
		[1.7]	[0.3]			[1.4]	[0.2]			[1.5]	[0.001]			[1.5]	[0.2]	
R-zone^{HH} (γ^h)			8.9*	11.2**			14.1**	20.5**			20.9***	28.6***			17.1*	29.6***
			[1.8]	[2.2]			[2.4]	[2.7]			[3.2]	[3.4]			[2.0]	[4.1]
Sum of coefficients ($\beta^h+\delta^h+\gamma^h$)	7.3	3.6	11.7	11.2	15.1	6.0	21.8	20.5	20.5	8.1	30.1	28.6	23.7	8.5	32.1	29.6
t-statistic ($\beta^h+\delta^h+\gamma^h$)			2.2				2.7				3.3				4.0	
R^2 *(within)*	1.8	0.7	2.8	2.7	4.1	1.0	5.5	4.9	5.6	1.4	7.6	7.0	6.2	1.3	7.4	6.2
N	1,107	1,107	1,107	1,107	1,107	1,107	1,107	1,107	1,107	1,107	1,107	1,107	1,107	1,107	1,107	1,107

Table V. Robustness Table

This table presents different specifications of our main crisis prediction at the three-year horizon. Panels A and B present results of the regression specification detailed in Table IV, for the business sector and household sector, respectively:

$$Crisis_{i,t+1 \text{ to } t+3} = a_i + \beta \cdot \textit{High-Debt-Growth}_{it} + \delta \cdot \textit{High-Price-Growth}_{it} + \gamma \cdot \textit{R-zone}_{it} + \epsilon_{it},$$

The specifications are:

Baseline Sample: *R-zone* indicators are calculated using quantiles based on the entire sample, and the crisis definition is that of Baron, Verner, and Xiong (2021).

(i) *Rolling Sample:* *R-zone* indicators in each year t are based on a rolling sample using data before year $t+1$, that is, the *R-zone* indicator in 1980 is based on data from 1950 to 1980. We require at least 20 years of data, which means that the prediction model is based on data after 1970. The crisis definition is that of Baron, Verner, and Xiong (2021).

(ii) *Leaveout Sample:* *R-zone* indicators in each year t are based on a sample in which data from year $t-3$ to $t+4$ are excluded, that is, the *R-zone* indicator in 1980 is based on data from 1950 to 2016 excluding 1977 to 1984. The crisis definition is that of Baron, Verner, and Xiong (2021).

(iii) *Pre-2000 Sample*: We use the *R-zone* indicators from our full baseline sample and estimate the prediction model on data before 2000.

(iv) *Pre-2000 Sample, Pre-2000 Cutoff*: We estimate the *R-zone* indicators and the prediction model using data before 2000.

(v) *Jordá, Schularick, and Taylor:* We use our baseline sample but use the crisis definition of Jordá, Schularick, and Taylor's MacroHistory database.

(vi) *Reinhart and Rogoff:* We use our baseline sample but use the crisis definition of Reinhart and Rogoff (2011).

(vii) *Bank Equity Crash:* We use our baseline sample but use the bank equity crash indicator of Baron, Verner, and Xiong (2021) to define our dependent variable. This indicator takes the value of one if bank equity has fallen by 30% or more within a year.

(viii) *Bank Failures:* We use our baseline sample but use the bank failure indicator of Baron, Verner, and Xiong (2021) to define our dependent variable. The bank failure indicator takes the value of one when there is narrative evidence of widespread bank failures.

(ix) *Panics:* We use our baseline sample but use the panic indicator of Baron, Verner, and Xiong (2021) to define our dependent variable. The panic indicator takes the value of one when there is narrative evidence of a sudden and severe outflows of short-term funding.

(x) *Crisis (Bank Equity):* We use our baseline sample and an alternative crisis indicator to define our dependent variable. The indicator takes the value of one if both the *bank equity crash* indicator and the *bank failure* indicator take the value of one.

(xi) *Developed Countries:* We include only high-income countries as defined by the World Bank in 1995 (Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Iceland, Ireland, Israel, Italy, Japan, Korea, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, United Kingdom, United States).

(xii) *Developing Countries:* We include only low- or medium-income countries as defined by the World Bank in 1995 (Argentina, Brazil, Chile, Colombia, Czech Republic, Greece, Hungary, India, Indonesia, Malaysia, Mexico, Peru, Russia, South Africa, Thailand and Turkey).

t-statistics are based on Driscoll and Kraay (1998) with five lags. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively, using Kiefer and Vogelsang (2005) corrected p-values. Reported coefficients and R^2s are in percent.

Panel A: Business Sample Robustness Table

				Multiple Regression								Univariate		
				Debt Growth		Price Growth		R-zone				R-zone		
		N	#Countries	β	$[t]$	δ	$[t]$	γ	$[t]$	Sum of coef.	R^2_{within}	γ	$[t]$	R^2_{within}
	Baseline Sample	1258	42	11.5	[2.7**]	7.4	[1.1]	19.4	[2.8**]	38.2	7.8	33.7	[3.3***]	6.1
(i)	Rolling Sample	1003	42	9.3	[2.2*]	8.2	[1.1]	16.6	[2.6**]	34.1	7.2	29.2	[3.4***]	5.8
(ii)	Leaveout Sample	1258	42	11.8	[2.9**]	7.7	[1.1]	16.4	[2.3**]	35.8	7.5	30.6	[2.9**]	5.6
(iii)	Pre-2000 Sample	677	24	15.1	[3.8***]	-1.8	[-0.9]	23.2	[2.2*]	36.5	8.8	34.0	[2.8**]	6.4
(iv)	Pre-2000 Sample, Pre-2000 cutoffs	677	24	8.4	[2.7**]	-1.1	[-0.5]	11.1	[1.8]	18.4	3.9	17.0	[2.1*]	2.9
(v)	Jordà, Schularick and Taylor	893	17	4.5	[0.8]	7.2	[0.9]	13.0	[1.6]	24.7	4.4	22.2	[1.9*]	3.2
(vi)	Reinhart and Rogoff (2011)	1013	36	14.4	[1.6]	5.1	[0.9]	12.9	[1.4]	32.4	6.5	28.6	[3.1***]	4.7
(vii)	Bank Equity Crash	1255	42	16.9	[3.3***]	18.5	[2.1*]	14.8	[2.3**]	50.3	9.1	41.7	[7.1***]	5.2
(viii)	Bank Failures	1258	42	11.2	[2.5**]	4.3	[1.0]	16.0	[2.1*]	31.4	5.9	27.7	[3.1***]	4.5
(ix)	Panics	1258	42	5.1	[1.4]	8.0	[1.2]	21.6	[3.0**]	34.7	8.4	31.5	[3.2***]	6.9
(x)	Crisis (Bank Equity)	1258	42	7.8	[1.7]	3.9	[0.9]	15.4	[2.0*]	27.1	4.9	24.2	[2.8**]	4.0
(xi)	Developed Countries	1057	26	12.6	[2.6**]	8.2	[1.0]	17.0	[2.2*]	37.9	8.2	32.9	[3.0**]	6.0
(xii)	Developing Countries	201	16	3.1	[0.3]	3.2	[1.0]	34.5	[4.3***]	40.8	6.7	39.0	[4.6***]	6.5

Panel B: Household Sample Robustness Table

				Multiple Regression								Univariate		
				Debt Growth		Price Growth		R-zone				R-zone		
		N	#Countries	β	$[t]$	δ	$[t]$	γ	$[t]$	Sum of coef.	R^2_{within}	γ	$[t]$	R^2_{within}
	Baseline Sample	1107	40	9.1	[2.3**]	0.0	[0.0]	20.9	[3.2***]	30.1	7.6	28.6	[3.4***]	7.0
(i)	Rolling Sample	876	40	1.5	[0.5]	-1.2	[-0.4]	23.5	[3.6***]	23.8	6.0	23.6	[3.0**]	5.9
(ii)	Leaveout Sample	1107	40	11.1	[2.3**]	-1.7	[-0.7]	18.4	[2.7**]	27.7	8.1	26.3	[3.0**]	7.1
(iii)	Pre-2000 Sample	625	21	-0.1	[0.0]	-2.0	[-0.6]	47.4	[6.6***]	45.3	14.1	45.9	[5.6***]	14.0
(iv)	Pre-2000 Sample, Pre-2000 cutoffs	625	21	-2.8	[-1.0]	-2.9	[-1.0]	35.9	[3.3***]	30.2	10.5	31.4	[2.8**]	10.3
(v)	Jordà, Schularick and Taylor	867	17	7.1	[2.4**]	4.6	[1.6]	20.4	[3.3***]	32.1	10.7	30.1	[3.8***]	10.0
(vi)	Reinhart and Rogoff (2011)	896	31	7.6	[2.4**]	1.0	[0.4]	11.0	[1.8]	19.6	3.5	18.4	[2.9**]	3.1
(vii)	Bank Equity Crash	1107	40	14.7	[3.5***]	3.1	[0.8]	18.5	[2.8**]	36.3	6.3	33.2	[4.1***]	5.4
(viii)	Bank Failures	1107	40	8.0	[2.1*]	-2.5	[-1.1]	22.2	[3.3***]	27.7	7.5	27.0	[3.3***]	6.8
(ix)	Panics	1107	40	7.2	[2.6**]	2.5	[0.7]	16.8	[3.1***]	26.5	7.4	24.8	[3.4***]	6.9
(x)	Crisis (Bank Equity)	1107	40	9.5	[2.4**]	-1.3	[-0.6]	18.6	[3.7***]	26.8	7.9	25.5	[3.6***]	7.0
(xi)	Developed Countries	1001	26	5.3	[1.2]	-1.1	[-0.3]	26.1	[4.4***]	30.3	8.1	29.8	[3.7***]	7.9
(xii)	Developing Countries	106	14	39.2	[1.9]	10.0	[3.1**]	-21.9	[-1.3]	27.3	14.9	2.0	[0.1]	0.0

Table VI. Crisis Prediction with Data from both Households and Businesses

The table presents results of the regression model

$$\begin{aligned} Crisis_{i,t+1 \text{ to } t+h} = a_i^h &+ \gamma^{Bus,h} \cdot R\text{-}zone_{it}^{Bus.} + \gamma^{HH,h} \cdot R\text{-}zone_{it}^{HH} \\ &+ \lambda^h \cdot R\text{-}zone_{it}^{Bus.} \cdot R\text{-}zone_{it}^{HH} \\ &+ \kappa^h \cdot \max\{R\text{-}zone_{it}^{Bus.}, R\text{-}zone_{it}^{HH}\} + \epsilon_{i,t}^h, \end{aligned}$$

where $R\text{-}zone^{Bus.}$ is an indicator variable capturing episodes of high growth in business debt and equity prices, while $R\text{-}zone^{HH}$ is an indicator variable capturing episodes of high growth in household debt and house prices. t-statistics are reported in brackets and based on Driscoll and Kraay (1998) with lags of zero, three, five, and six years for prediction horizons one, two, three, and four years, respectively. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively, using Kiefer and Vogelsang (2005) corrected p-values. Reported coefficients and R^2s are in percent.

	Dependent Variable															
	Crisis within 1 year				Crisis within 2 years				Crisis within 3 years				Crisis within 4 years			
	(1.1)	(1.2)	(1.3)	(1.4)	(2.1)	(2.2)	(2.3)	(2.4)	(3.1)	(3.2)	(3.3)	(3.4)	(4.1)	(4.2)	(4.3)	(4.4)
R-zone$^{Bus.}$ ($\gamma^{Bus,h}$)	5.9	3.5			14.0*	6.6			28.7***	22.2*			28.1**	23.2		
	[0.9]	[0.6]			[1.9]	[1.0]			[3.2]	[2.0]			[2.7]	[1.7]		
R-zone^{HH} ($\gamma^{HH,h}$)	10.4**	9.2**			18.6**	14.8**			24.8***	21.6**			26.2***	23.6***		
	[2.3]	[2.3]			[2.7]	[2.3]			[3.5]	[2.7]			[4.5]	[3.3]		
R-zone$^{Bus.}$·R-zone^{HH} (λ^h)		9.2	20.8			28.6***	48.2***			24.8	65.4***			19.0	62.4***	
		[1.1]	[1.6]			[3.3]	[5.3]			[1.7]	[8.0]			[1.2]	[8.7]	
max{R-zone$^{Bus.}$,R-zone^{HH}} (κ^h)				9.7*				17.1**				28.1***				28.9***
				[1.7]				[2.5]				[3.4]				[3.5]
R^2 *(within)*	3.1	3.3	1.7	2.6	6.2	7.3	5.0	4.4	11.1	11.7	6.7	8.7	9.6	9.9	5.1	7.6
Observations	1,084	1,084	1,084	1,281	1,084	1,084	1,084	1,281	1,084	1,084	1,084	1,281	1,084	1,084	1,084	1,281

Table VII. Crisis Prediction with Global R-zones

The table presents the results of the regression model:

$$Crisis_{i,t+1 \text{ to } t+h} = a_i^h + \gamma^{Bus,h} \cdot Local\ R\text{-}zone_{it}^{Bus.} + \xi^{Bus,h} \cdot Global\ R\text{-}zone_t^{Bus.} + \gamma^{HH,h} \cdot Local\ R\text{-}zone_{it}^{HH} + \xi^{HH,h} \cdot Global\ R\text{-}zone_t^{HH} + \epsilon_{it}^h,$$

where *R-zone*$^{Bus.}$ is an indicator variable capturing episodes of high growth in business debt and equity prices, while *R-zone*^{HH} is an indicator variable capturing episodes of high growth in household debt and house prices. *Global R-zone*$_t^{Bus.}$ measures the fraction of countries in the business red zone at a given point in time, while *Global R-zone*$_t^{HH.}$ measures the fraction of countries in the household red zone at a given point in time. t-statistics are reported in brackets and based on Driscoll and Kraay (1998) with lags of zero, three, five, and six years for prediction horizons one, two, three, and four years, respectively. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively, using Kiefer and Vogelsang (2005) corrected p-values. Reported coefficients and R^2s are in percent.

	Dependent Variable											
	Crisis within 1 year			Crisis within 2 years			Crisis within 3 years			Crisis within 4 years		
	(1.1)	(1.2)	(1.3)	(2.1)	(2.2)	(2.3)	(3.1)	(3.2)	(3.3)	(4.1)	(4.2)	(4.3)
Local R-zone$^{Bus.}$ ($\gamma^{Bus,h}$)	1.6		-0.4	5.8		4.5	18.3**		16.0*	18.8*		17.2
	[0.5]		[-0.2]	[1.2]		[1.0]	[2.4]		[1.9]	[2.2]		[1.8]
Global R-zone$^{Bus.}$ ($\xi^{Bus,h}$)	55.8*		48.6	91.2***		56.5*	116.0***		77.0	107.3***		36.4
	[1.8]		[1.4]	[4.1]		[1.9]	[4.7]		[1.8]	[5.6]		[1.3]
Local R-zone^{HH} ($\gamma^{HH,h}$)		6.4**	6.4**		10.0**	9.6**		14.3***	13.1**		11.4***	10.6***
		[2.2]	[2.2]		[2.7]	[2.6]		[3.1]	[2.9]		[3.4]	[3.2]
Global R-zone$^{HH.}$ ($\xi^{HH,h}$)		26	6.1		56.2**	31.5*		76.6***	39.4**		97.3***	75.8***
		[1.4]	[0.9]		[2.7]	[1.9]		[4.9]	[2.4]		[7.3]	[4.9]
R^2 *(within)*	6.0	4.9	7.3	9.3	10.4	12.6	14.3	14.5	19.2	10.7	16.1	18.2
Observations	1,258	1,107	1,084	1,258	1,107	1,084	1,258	1,107	1,084	1,258	1,107	1,084

Table VIII. Probability of Experiencing Severe Economic Decline by Price and Debt Growth Quantiles

Panel A presents the probability of experiencing year-on-year real (log) GDP growth of -2% or less within one to four years, with country-year observations assigned to one of 15 groups based on three-year growth in business debt to GDP and real equity price growth. The panel also presents the difference in the probability of experiencing a severe economic decline between each group and the median group (the intersection of the second price tercile and the third debt growth quintile). Panel B presents the probabilities when debt and price growth are measured with household debt and house prices. p-values are based on Driscoll and Kraay (1998) standard errors with lags of zero, three, five, and six years for prediction horizons one, two, three, and four years, respectively, and are corrected according to Kiefer and Vogelsang (2005).

Panel A: Probability of Severe Economic Decline by Business Debt Growth and Equity Price Growth

1-year horizon

	Economic Decline Frequency					*Diff. from Median*				
	Debt Quintile					Debt Quintile				
Price Tercile	1	2	3	4	5	1	2	3	4	5
1	9.9	4.9	2.7	10.6	27.5	8.7**	3.7*	1.6	9.5*	26.4**
2	1.2	1.1	1.1	2.4	4.5	0.0	-0.1	0.0	1.2	3.3
3	0.0	0.0	0.0	0.0	0.0	-1.1	-1.1	-1.1	-1.1	-1.1

2-year horizon

	Economic Decline Frequency					*Diff. from Median*				
	Debt Quintile					Debt Quintile				
Price Tercile	1	2	3	4	5	1	2	3	4	5
1	11.3	4.9	5.5	14.1	31.2	6.7*	0.3	0.9	9.6	26.6***
2	2.4	3.2	4.5	8.3	9.0	-2.2	-1.4	0.0	3.8	4.4
3	3.1	5.3	3.3	7.2	14.7	-1.4	0.8	-1.2	2.7	10.1

3-year horizon

	Economic Decline Frequency					*Diff. from Median*				
	Debt Quintile					Debt Quintile				
Price Tercile	1	2	3	4	5	1	2	3	4	5
1	14.1	6.1	8.2	16.5	33.9	8.4*	0.4	2.5	10.8	28.3***
2	2.4	3.2	5.7	9.5	11.9	-3.3	-2.5	0.0	3.8	6.3
3	11.5	16.0	8.9	13.3	28.0	5.8	10.3	3.2	7.6	22.3*

4-year horizon

	Economic Decline Frequency					*Diff. from Median*				
	Debt Quintile					Debt Quintile				
Price Tercile	1	2	3	4	5	1	2	3	4	5
1	14.1	7.3	8.2	17.6	33.9	7.3*	0.5	1.4	10.8	27.1***
2	3.5	6.3	6.8	13.1	11.9	-3.3	-0.5	0.0	6.3	5.1
3	22.9	22.7	13.3	20.5	40.0	16.1	15.8*	6.5	13.7*	33.2*

Panel B: Probability of Severe Economic Decline by Household Debt Growth and House Price Growth

1-year horizon

	Economic Decline Frequency					*Diff. from Median*				
	Debt Quintile					Debt Quintile				
Price Tercile	1	2	3	4	5	1	2	3	4	5
1	2.6	4.8	4.8	6.6	19.6	-0.7	1.5	1.4	3.2	16.2***
2	4.3	1.3	3.3	5.4	6.6	1.0	-2.0	0.0	2.1	3.2
3	2.7	3.2	1.4	2.3	2.6	-0.6	-0.2	-1.9	-1.0	-0.7

2-year horizon

	Economic Decline Frequency					*Diff. from Median*				
	Debt Quintile					Debt Quintile				
Price Tercile	1	2	3	4	5	1	2	3	4	5
1	4.3	4.8	9.5	8.2	26.1	-1.2	-0.7	4.0	2.6	20.5***
2	10.1	2.7	5.6	8.1	8.2	4.6*	-2.9	0.0	2.6	2.6
3	5.4	4.8	2.9	5.8	13.2	-0.2	-0.8	-2.7	0.3	7.6

3-year horizon

	Economic Decline Frequency					*Diff. from Median*				
	Debt Quintile					Debt Quintile				
Price Tercile	1	2	3	4	5	1	2	3	4	5
1	6.9	4.8	14.3	13.1	30.4	0.2	-1.8	7.6	6.4	23.8***
2	14.5	4.0	6.7	9.5	11.5	7.8*	-2.7	0.0	2.8	4.8
3	8.1	6.3	2.9	10.5	24.6	1.4	-0.3	-3.8	3.8	17.9

4-year horizon

	Economic Decline Frequency					*Diff. from Median*				
	Debt Quintile					Debt Quintile				
Price Tercile	1	2	3	4	5	1	2	3	4	5
1	10.3	6.0	14.3	16.4	32.6	3.7	-0.6	7.6	9.7	25.9***
2	15.9	6.7	6.7	12.2	14.8	9.3*	0.0	0.0	5.5	8.1
3	13.5	6.3	2.9	20.9	30.7	6.8	-0.3	-3.8	14.3**	24.0*

Table IX. Cumulative GDP Growth by Price and Debt Growth Quantiles

Panel A presents the cumulative real (log) GDP growth from one to four years, with country-year observations assigned to one of 15 groups based on three-year growth in business debt to GDP and real equity price growth. The panel also presents the difference in GDP growth between each group and the median group (the intersection of the second price tercile and the third debt growth quintile). Panel B presents corresponding results when debt and price growth are measured with household debt and house prices. p-values are based on Driscoll and Kraay (1998) standard errors with lags of zero, three, five, and six years for prediction horizons one, two, three, and four years, respectively, and are corrected according to Kiefer and Vogelsang (2005).

Panel A: Future GDP growth by Business Debt Growth and Equity Price Growth

Horizon	Price Tercile	*Cumulative GDP growth* Debt Quintile 1	2	3	4	5	*Diff. from Median* Debt Quintile 1	2	3	4	5
1-year horizon	1	1.9	2.8	2.7	2.3	0.7	-2.3***	-1.4***	-1.4***	-1.9***	-3.4***
	2	3.3	3.2	4.2	4.1	2.8	-0.9**	-1.0**	0.0	-0.1	-1.4**
	3	4.2	4.0	4.4	4.4	4.2	0.0	-0.2	0.2	0.2	0.0
2-year horizon	1	5.3	6.1	6.1	5.4	3.1	-2.5**	-1.7*	-1.7*	-2.4**	-4.7***
	2	6.2	6.8	7.8	7.6	5.3	-1.6*	-1.0	0.0	-0.2	-2.5**
	3	7.8	7.0	7.8	7.9	6.6	0.0	-0.8	0.0	0.1	-1.2
3-year horizon	1	8.3	9.6	9.5	8.2	5.8	-3.2**	-1.9	-2.0	-3.3**	-5.7**
	2	9.5	10.7	11.5	10.4	8.7	-2.0	-0.8	0.0	-1.1	-2.8*
	3	10.9	9.4	11.1	10.9	8.7	-0.6	-2.1	-0.4	-0.7	-2.9
4-year horizon	1	11.6	12.5	12.8	11.2	8.5	-3.6*	-2.7*	-2.4	-4.0*	-6.7*
	2	12.5	13.9	15.2	13.6	12.5	-2.7	-1.3	0.0	-1.6	-2.8
	3	13.5	12.6	14.5	13.3	10.8	-1.7	-2.6	-0.7	-2.0	-4.5

Panel B: Future GDP growth by Household Debt Growth and House Price Growth

Horizon	Price Tercile	*Cumulative GDP growth* Debt Quintile 1	2	3	4	5	*Diff. from Median* Debt Quintile 1	2	3	4	5
1-year horizon	1	2.4	3.2	3.0	2.7	1.2	-0.9***	-0.1	-0.3	-0.6	-2.1***
	2	3.0	3.5	3.3	2.9	2.4	-0.3	0.2	0.0	-0.4	-0.9**
	3	3.0	4.3	4.2	3.6	2.8	-0.3	1.0*	0.9**	0.3	-0.5
2-year horizon	1	5.5	6.7	6.2	6.0	2.4	-1.3**	0.0	-0.5	-0.8	-4.4***
	2	5.8	6.9	6.8	5.7	4.9	-1.0*	0.1	0.0	-1.1	-1.9**
	3	6.0	9.0	8.1	6.1	4.5	-0.8	2.2*	1.4	-0.6	-2.3**
3-year horizon	1	8.6	10.4	9.3	9.2	4.0	-1.6	0.2	-0.9	-1.0	-6.1**
	2	8.7	10.3	10.2	8.4	7.2	-1.5**	0.1	0.0	-1.8	-3.0**
	3	9.4	13.7	11.9	8.4	5.8	-0.8	3.6*	1.7	-1.8	-4.4**
4-year horizon	1	11.6	13.9	12.2	12.2	6.2	-1.8	0.6	-1.2	-1.1	-7.1*
	2	11.8	13.7	13.4	11.1	9.0	-1.6*	0.3	0.0	-2.3	-4.3*
	3	12.5	18.5	15.5	10.6	7.1	-0.8	5.2*	2.2	-2.8*	-6.2**

Table X. Number of Crises Preceded by R-zone

Panel A presents the percentage of red zones followed by a financial crisis within three years (PPV), the percentage of financial crises preceded red zones within three years (TPR), and the percentage of non crisis years not preceeded by an red zone within three years (TNR) along with the numbers used for these metrics. We look at both of our red zone specifications: $R\text{-}zone^{Bus.}$, which captures episodes of high growth in business debt and equity prices, and $R\text{-}zone^{HH}$, which captures episodes of high growth in household debt and house prices. We also count the number of occurrences when we combine the indicators to either require both sectors to be in the red zone or either sector to be in the red zone:

$$\text{Both:} \quad R\text{-}zone^{Both} \equiv R\text{-}zone^{Bus.}_{it} \cdot R\text{-}zone^{HH}_{it}$$
$$\text{Either:} \quad R\text{-}zone^{Either} \equiv \max\{R\text{-}zone^{Bus.}_{it}, R\text{-}zone^{HH}_{it}\},$$

Panel B presents the results of an identical analysis with $Y\text{-}zone \equiv 1\{\Delta_3(Debt/GDP)_{it} > 60^{th} \text{ percentile}\} \cdot 1\{\Delta_3 \log(Price_{it}) > 33.3^{rd} \text{ percentile}\}$.

Panel A: R-zone

	Type			
	Business	Household	Either	Both
#R-zone Events followed by a Crisis	34	42	61	15
#R-zone Events	75	114	170	19
%R-zone Events followed by a Crisis (PPV)	45.3	36.8	35.9	78.9
#Crises Preceded By R-zone	20	21	32	7
#Crises	50	44	50	44
% of Crises preceded by R-zone (TPR)	40.0	47.7	64.0	15.9
#Non-crises not Preceded By R-zone	1077	897	969	1010
#Non-Crises	1208	1063	1231	1040
% of Non-Crises not preceded by R-zone (TNR)	89.2	84.4	78.7	97.1
Time to Crisis	2.9	3.7	3.6	3.0

Panel B: Y-zone

	Type			
	Business	Household	Either	Both
#Y-zone Events followed by a Crisis	71	77	103	45
#Y-zone Events	309	335	515	129
%Y-zone Events followed by a Crisis (PPV)	23.0	23.0	20.0	34.9
#Crises Preceded By Y-zone	33	32	41	22
#Crises	50	44	50	44
% of Crises preceded by Y-zone (TPR)	66.0	72.7	82.0	50.0
#Non-crises not Preceded By Y-zone	680	610	506	812
#Non-Crises	1208	1063	1231	1040
% of Non-Crises not preceded by Y-zone (TNR)	56.3	57.4	41.1	78.1
Time to Crisis	3.9	5.9	6.3	3.5

Table XI. GDP Growth Following True and False Positives

This table presents results of the regression model

$$\Delta_h \log GDP_{t+h} = a_i^h + \gamma^{h,tp} \cdot R\text{-}zone_{it} \cdot Crisis_{i,t+1 \text{ to } t+3} + \gamma^{h,fp} \cdot R\text{-}zone_{it} \cdot (1 - Crisis_{i,t+1 \text{ to } t+3}) + \epsilon_{it}^h,$$

where $\Delta_h \log GDP_{t+h}$ is the log GDP growth in country i from year t to $t+h$, $R\text{-}zone_{it}$ is an indicator variable capturing episodes of high growth in debt and prices, and $Crisis_{i,t+1 \text{ to } t+3}$ is an indicator variable that takes the value of one if there is a crisis within the next three years. We run the regression on both the business sector, using business debt and equity prices to define the *R-zone* indicator (Panel A), and the household sector, using household debt and house prices to define the *R-zone* indicator (Panel B). t-statistics are reported in brackets and based on Driscoll and Kraay (1998) with lags of zero, three, five, and six years for prediction horizons one, two, three, and four years, respectively. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively, using Kiefer and Vogelsang (2005) corrected p-values. Reported coefficients and R^2s are in percent.

Panel A: Cumulative GDP growth following false and true positives in the business R-zone

	Dependent Variable			
	1-year log GDP growth (1)	2-year log GDP growth (2)	3-year log GDP growth (3)	4-year log GDP growth (4)
True Positives ($\gamma^{h,tp}$)	0.7	-1.4	-4.7^{***}	-8.6^{***}
	[1.1]	[-1.1]	[-3.3]	[-5.3]
False Positives ($\gamma^{h,fp}$)	1.1^{*}	1.1	1.3	2.1
	[2.0]	[1.0]	[1.0]	[1.5]
R^2 (within)	0.5	0.4	1.4	3.1
N	1258	1258	1258	1258

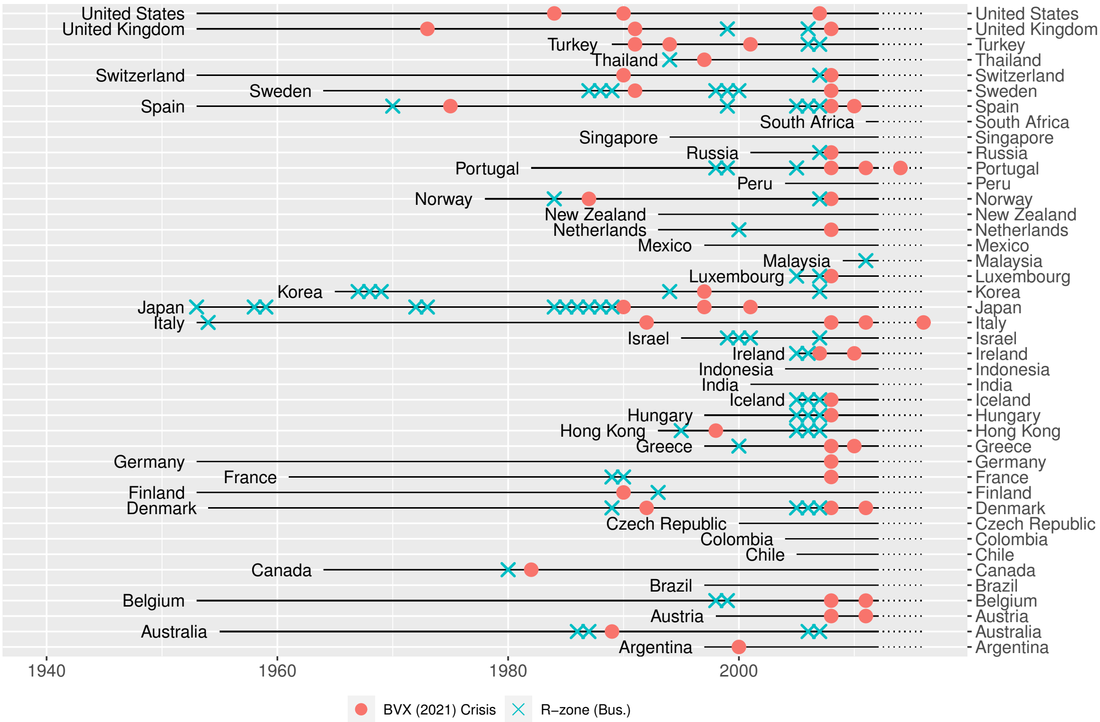
Panel B: Cumulative GDP growth following false and true positives in the household R-zone

	Dependent Variable			
	1-year log GDP growth (1)	2-year log GDP growth (2)	3-year log GDP growth (3)	4-year log GDP growth (4)
True Positives ($\gamma^{h,tp}$)	-0.3	-3.0^{***}	-6.7^{***}	-10.1^{***}
	[-0.5]	[-3.0]	[-6.0]	[-6.9]
False Positives ($\gamma^{h,fp}$)	0.1	-0.3	-0.9	-1.5
	[0.4]	[-0.4]	[-1.0]	[-1.3]
R^2 (within)	0.1	1.5	4.2	6.5
N	1107	1107	1107	1107

Figure 1. Event history.

Panel A plots red zone events as captured by business debt growth and equity price growth along with the advent of financial crises as defined by Baron, Verner, and Xiong (2021). Panel B presents a similar plot with red zone events defined using household debt growth and house price growth.

Panel A: Business R-zone



Panel B: Household R-zone

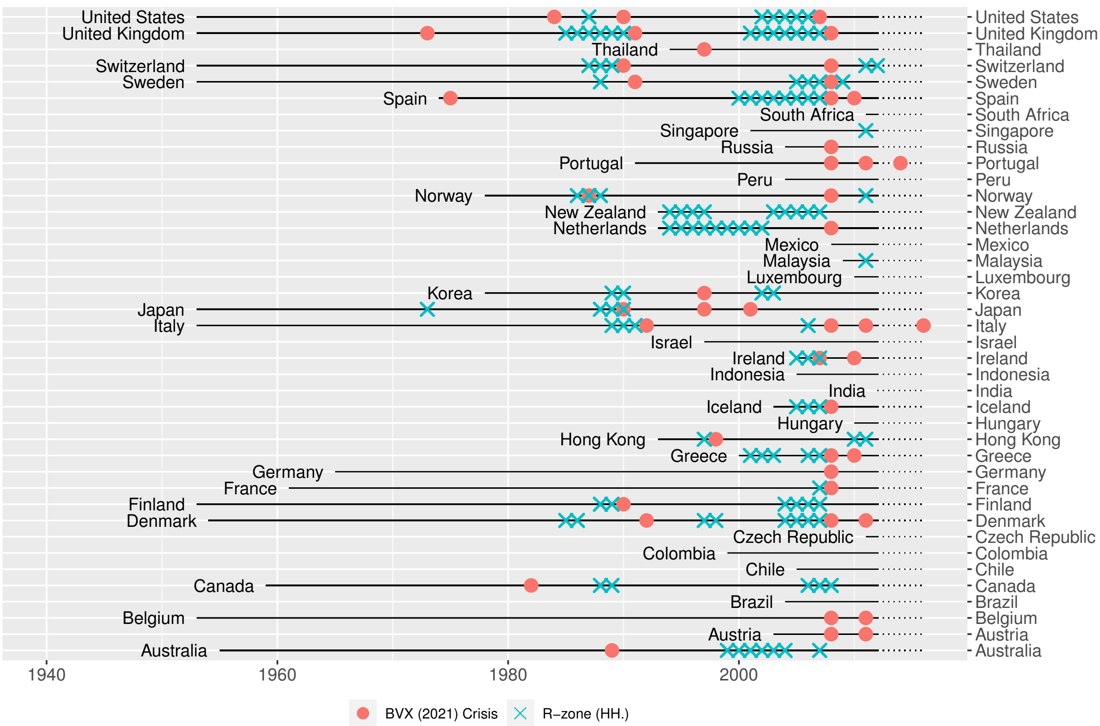


Figure 2. Crisis prediction on expanding sample.

This figure presents the γ-coefficient from our main three-year crisis prediction model when we iteratively test the model on an expanding sample starting in T =1990 and ending in 2012. The left figure of each panel presents the results from the univariate regression model

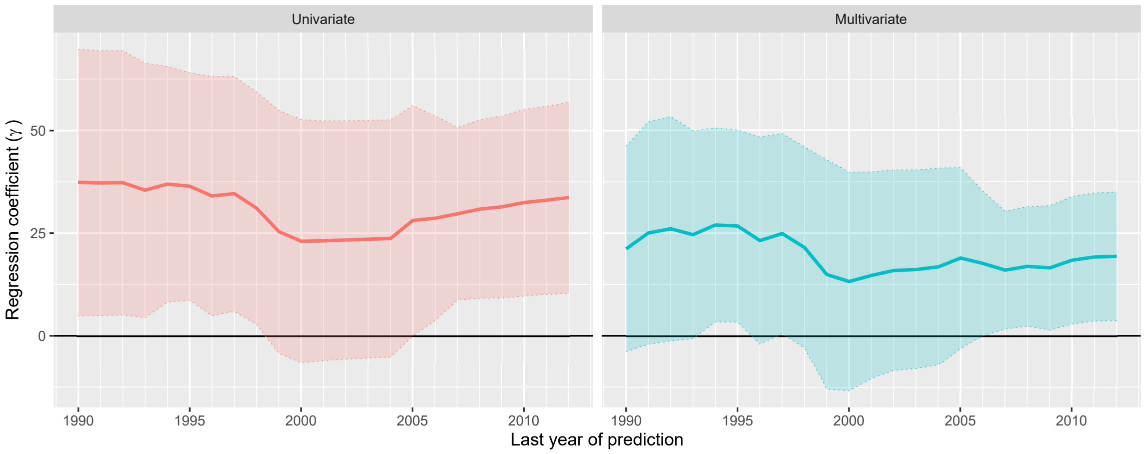
$$Crisis_{i,t+1 \text{ to } t+3} = a_i + \gamma \cdot R\text{-}zone_{it} + \epsilon_{it},$$

The right figure in each panel presents the γ-coefficient from the multivariate regression model

$$\begin{aligned} Crisis_{i,t+1 \text{ to } t+3} = a_i &+ \beta \cdot High\text{-}Debt\text{-}Growth_{it} \\ &+ \delta \cdot High\text{-}Price\text{-}Growth_{it} \\ &+ \gamma \cdot R\text{-}zone_{it} + \epsilon_{it}. \end{aligned}$$

$Crisis_{i,t+1 \text{ to } t+3}$ is an indicator variable equal to one if a crisis has occurred in country i within three years of time t. $High\text{-}Debt\text{-}Growth \equiv 1\{\Delta_3(Debt/GDP)_{it} > 80^{th}$ percentile$\}$ is an indicator variable equal to one if three-year debt growth is in the highest quintile of our full sample, while $High\text{-}Price\text{-}Growth \equiv 1\{\Delta_3 \log(Price_{it}) > 66.7^{th}$ percentile$\}$ is an indicator variable equal to one if three-year price growth is in its highest tercile of our full sample. The *R-zone* variable is the intersection of high price growth and high debt growth: $R\text{-}zone \equiv High\text{-}Debt\text{-}Growth \cdot High\text{-}Price\text{-}Growth$. We run the regressions on both the business sector, using business debt and equity prices to define the indicators (Panel A), and the household sector, using household debt and house prices to define the indicators (Panel B). 95% confidence intervals are calculated using Driscoll and Kraay (1998) standard errors with five lags and Kiefer and Vogelsang (2005) fixed-b asymptotics.

Panel A: Business Sector



Panel B: Household sector

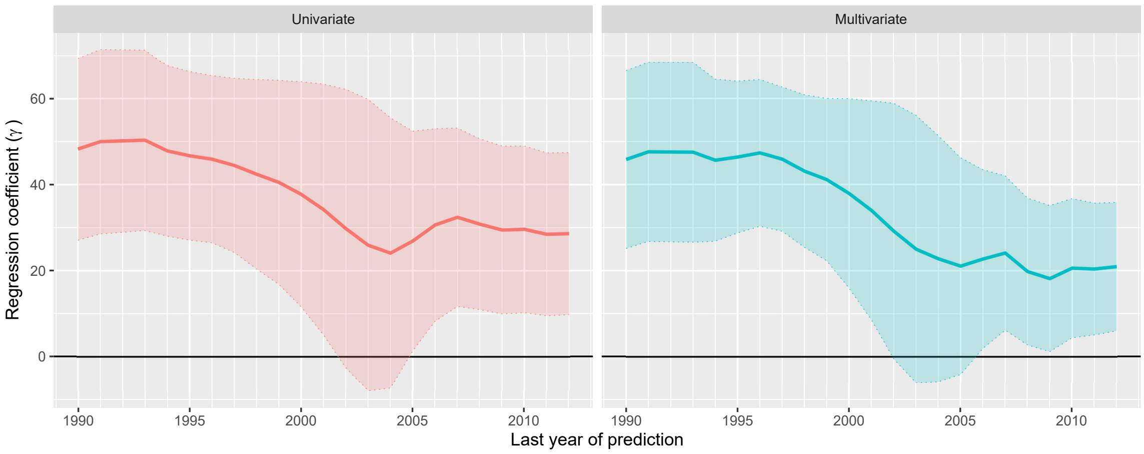


Figure 3. Fraction of Countries in R-zone.

The figure depicts the fraction of countries in the red zone at a given time,

$$Global\ R\text{-}zone_t \equiv \frac{1}{N_t} \sum_{i \in S_t} R\text{-}zone_{it},$$

where N_t is the number of countries in our sample at time t and S_t is the set of countries in the sample at time t. We calculate *Global R-zone*$_t$ for each sector, that is, using business debt growth paired with equity price growth and using household debt growth paired with house price growth, to define $R\text{-}zone_{it}$.

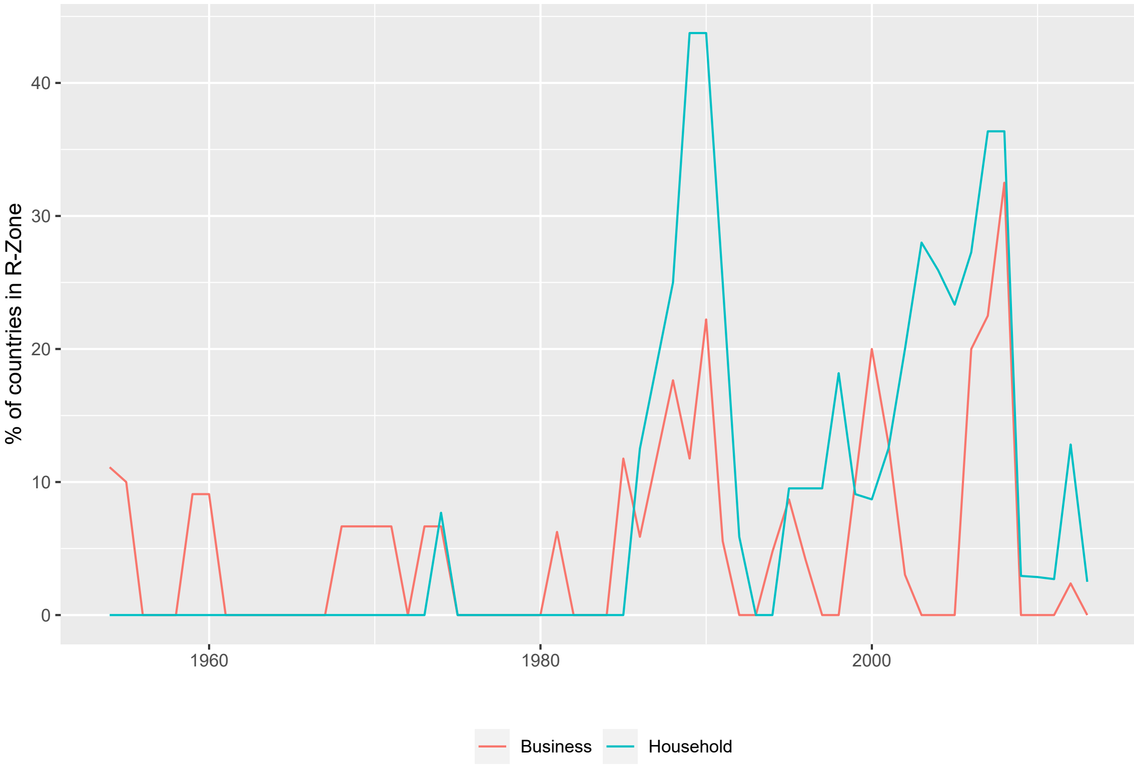


Figure 4. GDP growth following red zone events.

This figure presents the empirical distribution of (annualized) GDP growth over horizons of one to four years following a red zone event (either business or household) versus the empirical distribution of (annualized) GDP growth following country-years not in the red zone.

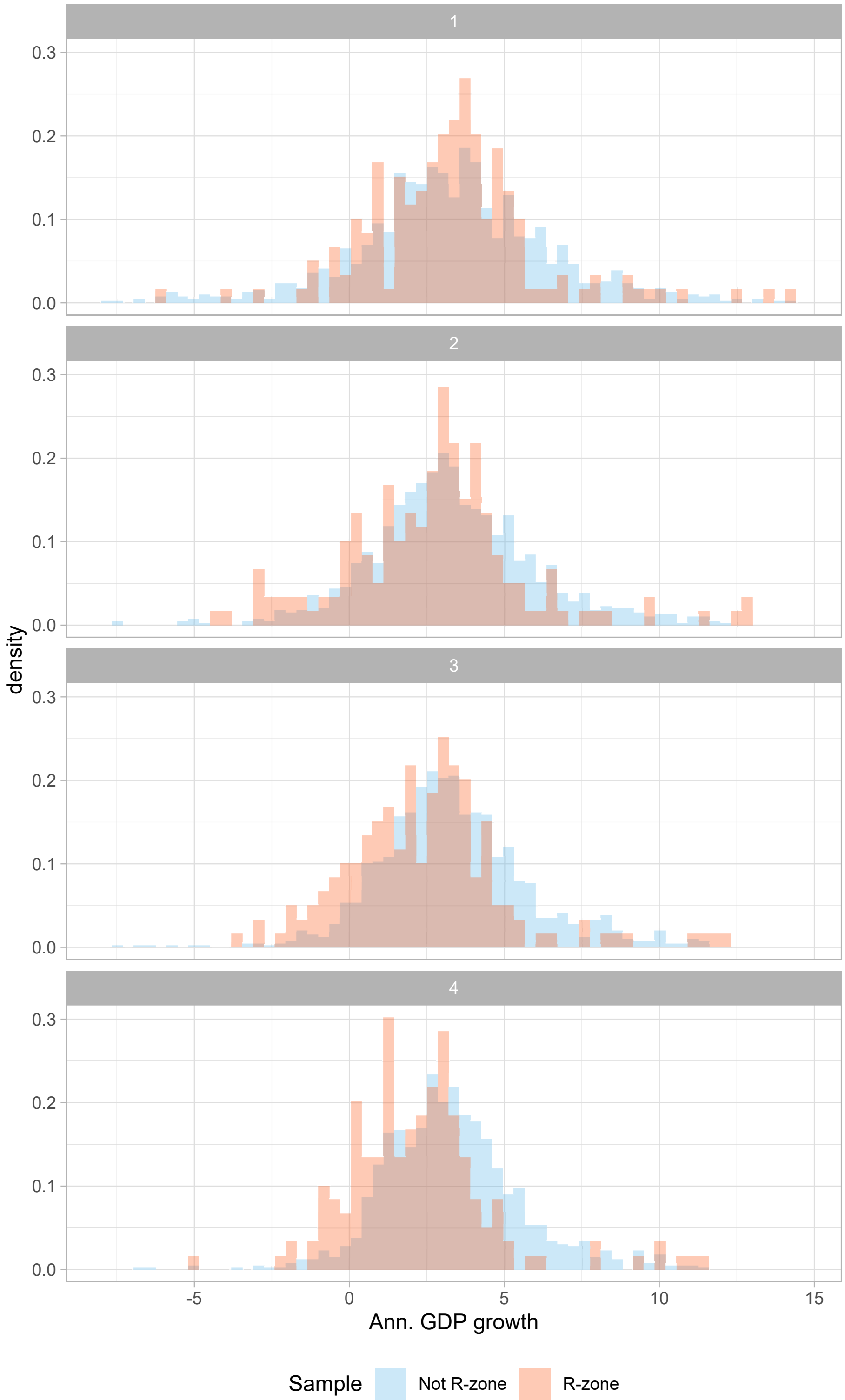
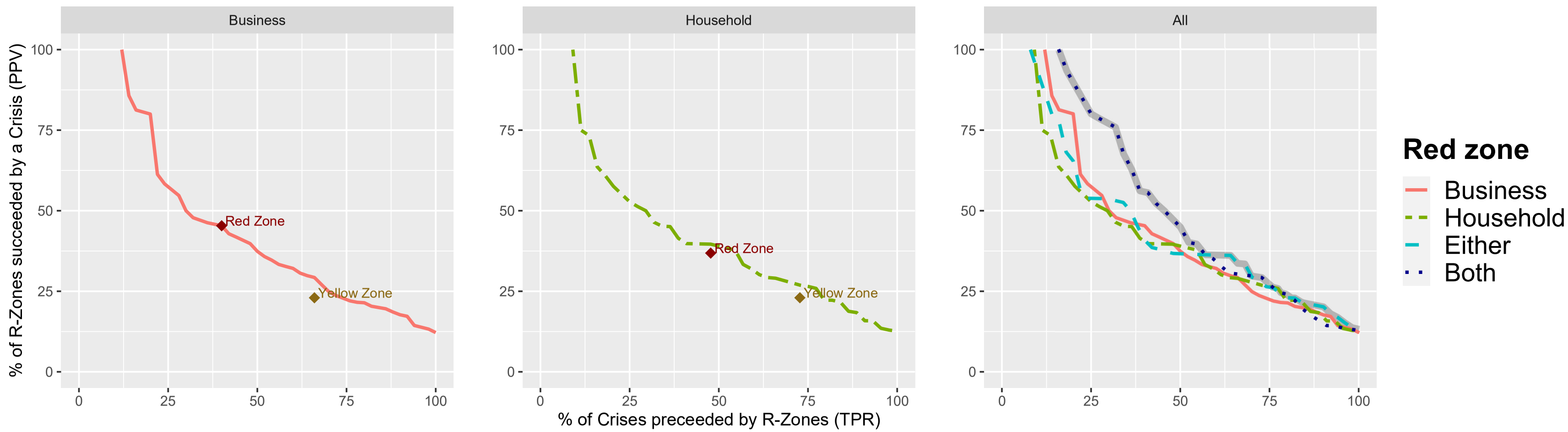


Figure 5. Empirical policy possibility frontier.

Panel A presents the optimal combinations of precision (the percentage of red zones followed by a crisis) and sensitivity (percentage of crises preceded by a red zone) attainable by varying the thresholds for entering the red zone. Panel B presents the optimal combinations of specificity (percentage of non crisis years not preceded by a red zone) and sensitivity (percentage of crises preceded by a red zone) attainable by varying the thresholds for entering the red zone.

Panel A: Precision (PPV) vs. Sensitivity (TPR)



Panel B: Specificity (TNR) vs. Sensitivity (TPR)

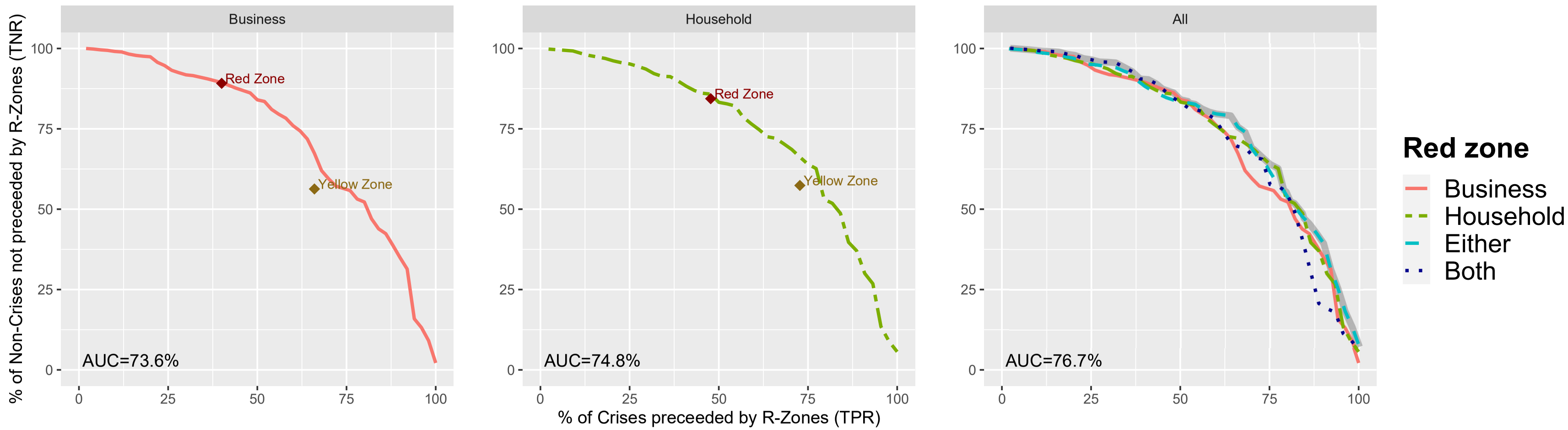


Figure 6. Financial crises in and out of the red zone.

The figure presents all crises and their severity plotted against the debt and price growth percentiles of the year closest to the red zone in the three years leading up to the crisis. The red zone is shaded area in the top right of the figure, and we measure how close each country-year-sector is to the red zone with the Euclidian distance of percentiles: $\sqrt{\max(0.8 - \text{debt growth percentile}, 0)^2 + \max(2/3 - \text{price growth percentile}, 0)^2}$. We measure the severity of a crisis as the three-year real (log) GDP growth following the crisis.

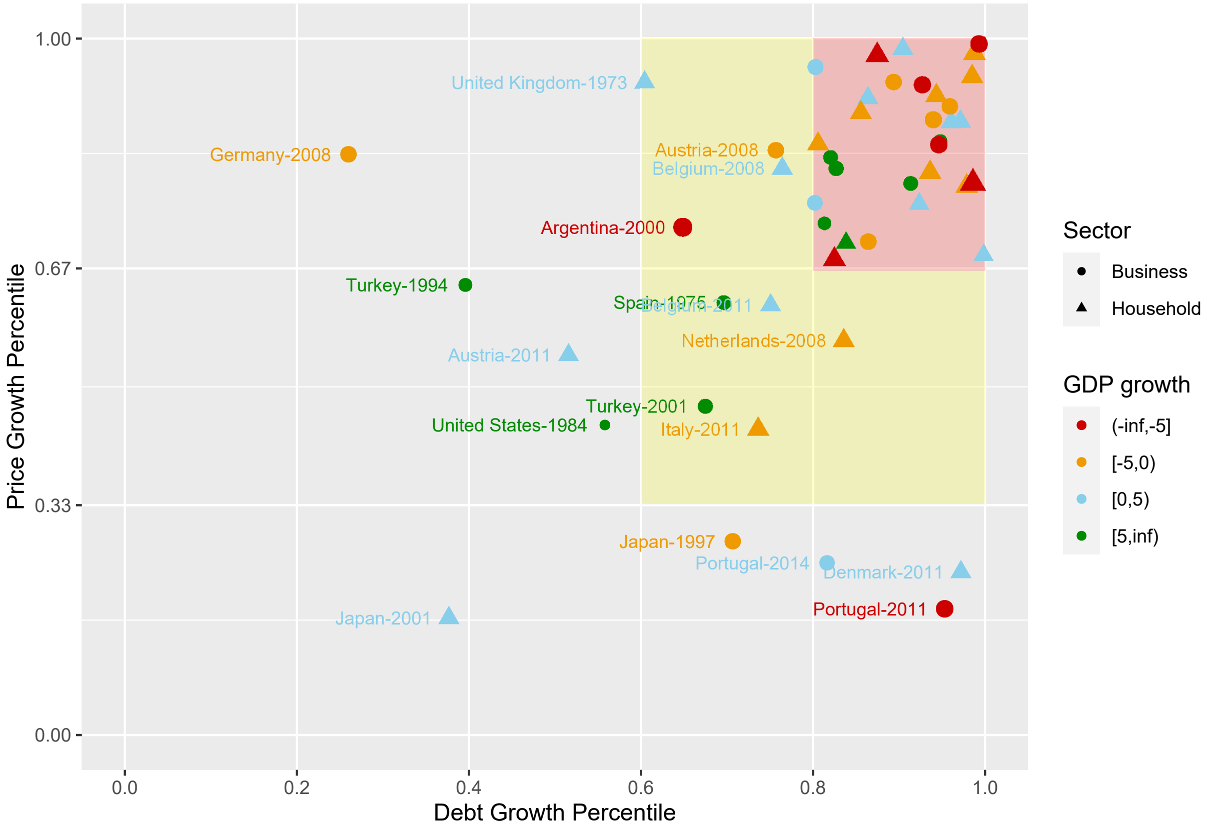


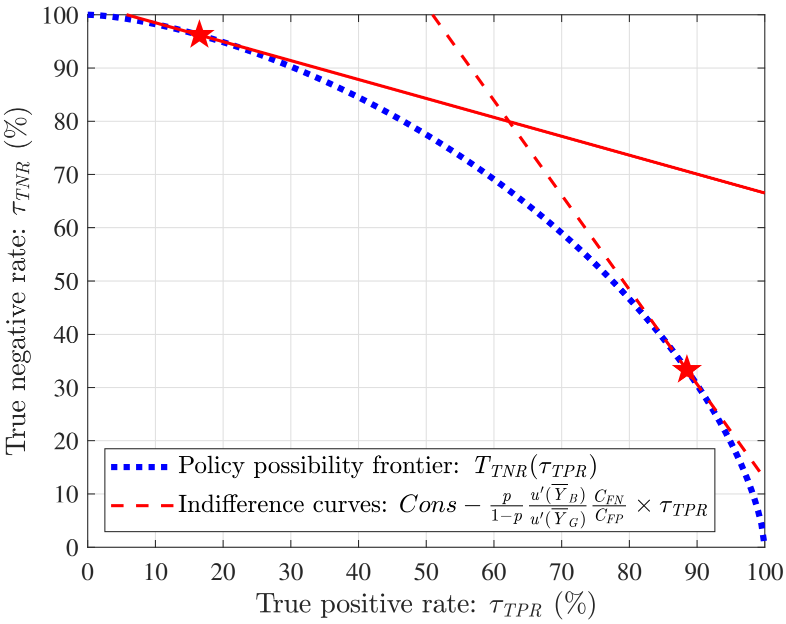
Figure 7. Policy production frontier.

This figure plots the policy production frontier, $\tau_{TNR} = T_{TNR}(\tau_{TPR})$, in (τ_{TPR}, τ_{TNR}) space together with policy-makers' linear indifference curves, which take the form

$$\textit{Indifference-Curve}_{TNR}(\tau_{TPR}) = Const - \frac{p}{1-p}\frac{u'(\bar{Y}_L)}{u'(\bar{Y}_H)}\frac{c_{FN}}{c_{FP}} \cdot \tau_{TPR}.$$

At the optimal value of τ_{TPR}, the slope of the policy production frontier is equal to the slope of the indifference curve. Panel A illustrates these trade-offs for an initial position of the policy production frontier. The solid red curve shows a case in which C_{FN}/C_{FP} is low, leading to a low level of τ^*_{TPR}. The dashed red curve shows a case in which C_{FN}/C_{FP} is high, leading to a high level of τ^*_{TPR}. Panel B illustrates how the trade-off changes when crises become more predictable, leading to an outward shift in the policy production frontier.

Panel A: Baseline position of the policy production frontier



Panel B: Outward shift in the policy production frontier

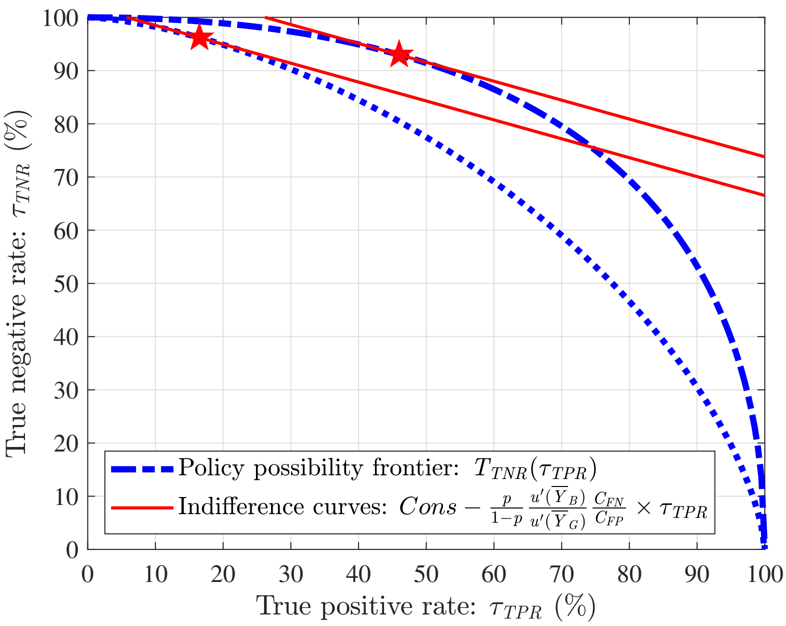
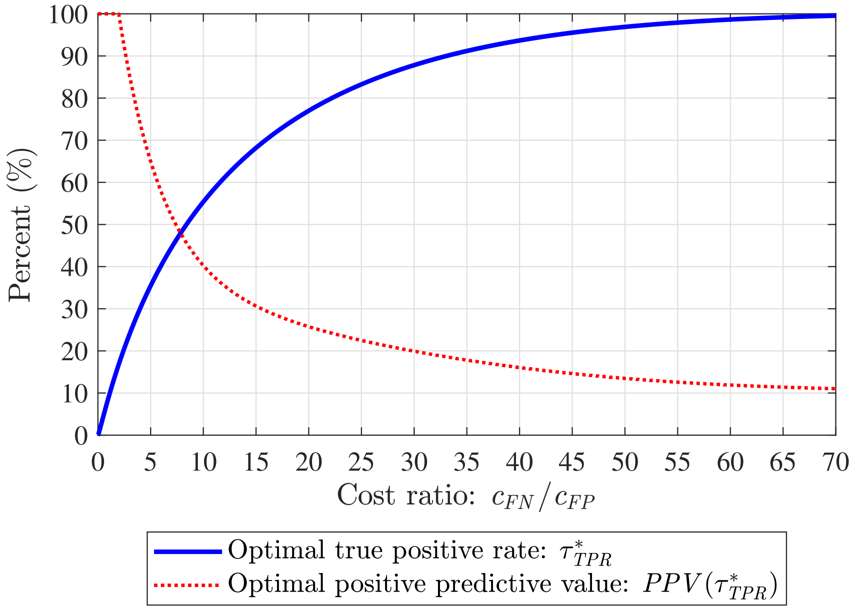


Figure 8. Model calibration.

This figure shows the model solution for optimal test sensitivity (τ^*_{TPR}) as we vary c_{FP}/c_{FN}. Recall that c_{FP}/c_{FN} is the ratio of two macroeconomic treatment effects. Specifically, conditional on the risk of a crisis truly being high, c_{FN} is the expected percentage increase in the present value of future real output given a policy action to lean against the wind relative to the baseline level of output absent that policy action. Similarly, c_{FP} gives the expected percentage decline in the present value of real output from taking the same policy action when risk is truly low. We assume p=4%, $u'(\bar{Y}_B)/u'(\bar{Y}_G) = 1$, $C_{Crisis}/Y_G = 1.5$. Thus, for each value of c_{FP}/c_{FN}, we report the solution to

$$\overbrace{T'_{TNR}(\tau_{TPR})}^{\substack{\text{Slope of policy}\\ \text{production frontier}}} = \overbrace{-\frac{p}{1-p}\cdot\frac{u'(\bar{Y}_B)}{u'(\bar{Y}_G)}\cdot\frac{C_{Crisis}}{Y_G}\cdot\frac{C_{FN}}{C_{FP}}}^{\text{Slope of policy indifference curves}} = -\frac{0.04}{0.96}\cdot 1\cdot 1.5\cdot\frac{C_{FN}}{C_{FP}}.$$

To estimate $T'_{TNR}(\tau_{TPR})$, we first estimate $T_{TPR}(\tau_{TPR})$ parametrically using nonlinear least squares, generating a smoothed version of our empirical policy production frontier. We use the empirical frontier from the right-most column of Figure 5, Panel B, which combines information from the business and household sectors. (Recall that our raw empirical policy production frontier plots the true negative rate — the fraction of non crisis years that are not preceded by a red zone event in the prior three years — as a function of the true positive rate — the fraction of crisis years preceded by a red zone event in the prior three years.) More specifically, we assume that $T_{TPR}(\tau_{TPR}) = 1 - \Phi\left(\left(\Phi^{-1}(\tau_{TPR}) - a\right)/b\right)$, where $\Phi(\cdot)$ is the standard normal cumulative distribution function. We obtain $a = 0.95$ and $b = 0.85$ with $R^2 = 99.96\%$. We then obtain $T'_{TNR}(\tau_{TPR}) = -(1/b)\cdot\left[\phi\left(\left(\Phi^{-1}(\tau_{TPR}) - a\right)/b\right)\right] \div \left[\phi\left(\Phi^{-1}(\tau_{TPR})\right)\right]$. Using this estimate of $T'_{TNR}(\tau_{TPR})$, we report the solution τ^*_{TPR} as we vary c_{FP}/c_{FN} from 0 to 70. We also report the positive predicted value $PPV(\tau^*_{TPR})$ — the fraction of red zone events that are followed by the onset of a crisis within three years — corresponding to the optimal test sensitivity. To do so, we use nonlinear least squares to fit a truncated fourth-order polynomial to the empirical plot of PPV versus TPR: $PPV(\tau_{TPR}) = \min\{1, a + b\cdot(\tau_{TPR}) + c\cdot(\tau_{TPR})^2 + d\cdot(\tau_{TPR})^3 + e\cdot(\tau_{TPR})^4\}$ which gives $R^2 = 99.92\%$.



Chapter 3

Asset-Driven Insurance Pricing

with Benjamin Knox.

Abstract

We develop a theory that connects insurance premiums, insurance companies' investment behavior, and equilibrium asset prices. Consistent with the model's key predictions, we show empirically that (1) insurers with more stable insurance funding take more investment risk and, therefore, earn higher average investment returns; (2) insurance premiums are lower when expected investment returns are higher, both in the cross section of insurance companies and in the time series. We show our results hold for both life insurance companies and, using a novel approach, for property and casualty insurance companies. Consistent findings across different regulatory frameworks helps identify asset-driven insurance pricing while controlling for alternative explanations.

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1 Introduction

This paper proposes and tests a new theory of insurance pricing, which shows that insurance premiums are lower when insurance companies have higher expected investment returns. We call this way of setting premiums "asset-driven insurance pricing". Our theory and evidence connects two important functions of the insurance industry, namely the pricing of insurance products and the allocation of its assets. Insurance products facilitate risk-sharing for 95% of all US households, and the premiums fund large asset portfolios, with US insurers holding marketable asset worth \$11.2 trillion as of Q4 2019.[1] Hence, insurance companies are both economically important asset allocators and facilitators of risk sharing, and we show that these two functions are more connected than previously thought.

The traditional view of insurers is that their main business – and therefore their main source of risk and return - is insurance underwriting. Such a view has little consideration for insurer's asset allocation decisions in the context of insurance premium pricing. However, recent evidence shows that there is significant risk in the asset portfolios of insurers (Ellul et al. (2011), Becker and Ivashina (2015), Becker et al. (2020), Ge and Weisbach (2020), Ellul et al. (2020)). Indeed, contrary to the traditional view, risk-free assets make up only 10% of investment portfolios, with insurers instead investing heavily in illiquid credit markets. This behaviour in their investment portfolios motivates our two main research questions: (1) Why do insurers have such high exposure to credit and liquidity risk in their asset portfolios? (2) Do the expected investment returns on these portfolios affect how they set premiums?

We address these questions by considering a model of insurance premiums and illiquid asset prices and by presenting consistent empirical evidence. We show asset-driven insurance pricing holds in both the time series and the cross section of insurance companies, in good and bad times, and for both life insurance companies and the property and casualty (P&C) industry. The P&C results use a novel approach, which, due to the industry's distinct regulatory framework relative to the life insurance industry, helps us to identify asset-driven insurance pricing from alternative mechanisms of insurance pricing. We also present evidence of asset-driven insurance pricing following changes to investment returns due to mergers.

Our model features two types of agents, investors and insurance companies. There are also two assets, one liquid and one illiquid. All agents face an exogenous cost from selling the illiquid asset before maturity, and, in the spirit of Diamond and Dybvig (1983), investors are *ex-ante* uncertain whether they are early or late consumers. These assumptions combine to generate an endogenous liquidity risk premium. The key insight of the model is that insurers enjoy relatively more certainty on the timing of cash flows due to the diversification benefit of underwriting many homogeneous insurance policies. This diversification creates stable insurance funding, which is an advantage when investing in illiquid assets.

Insurance companies with more stable insurance funding are able to extract more value from illiquid assets and therefore allocate a greater fraction of assets to illiquid investments (Proposition 1). In the time series, when the excess return on the illiquid asset is higher, the marginal cost of supplying insurance is lower, insurers compete for funding, and insurance premiums are set lower on average (Proposition 2). In the cross section, insurance companies that take more investment risk and have higher expected returns are able to set lower premiums relative to competitors (Proposition 3). The model's predictions rest on a violation of the Modigliani and Miller (1958) capital irrelevance theorem. We argue that an investor's funding structure

[1]For a sense of the order of magnitude, note that the total value of insurer marketable assets is in excess of 40% of the US Treasury and corporate bond markets combined. Data sources: Insurance Information Institute, Financial Accounts of the United States (Fed Reserve), SIFMA Fact Book.

matters when a liquidity premium is available in asset markets, and insurers' funding choices determine their ability to earn the liquidity premium.

We test if insurers with more stable funding take more liquidity risk (Proposition 1), by calculating 5-year rolling estimates of the standard deviation of insurer's underwriting profitability. Using data from 2001-2018, we find that insurers with more stable underwriting profitability have lower allocations to cash assets and higher allocations to credit assets (and take more credit risk within their credit portfolios). Our results extend on Ge and Weisbach (2020), who show that large insurers take more investment risk. Assuming large insurers have more diversification benefits in their underwriting businesses, this initial result is consistent with our model's prediction. However, our findings take this a step further, showing that, even when comparing firms of equal size, the insurers with less volatile underwriting performance takes more investment risk. The finding provides evidence that insurer's asset allocation decision depends on firm-level characteristics, and specifically on the stability of cash flows in their underwriting business. According to our model, the explanation is that insurers use the stability of the insurance funding to earn liquidity premium on their assets.

To test if insurers charge lower premiums when the liquidity premium is high (Proposition 2), we use credit spreads as a proxy for excess returns to illiquid assets. Figure 1 presents an illustrative example in the life insurance industry, plotting the industry average insurance premium against credit spreads (on an inverse axis scale). The figure shows that insurance premiums are lower when insurance companies have higher expected investment returns. Our main dependent variable in the life insurance industry are annuity markups as calculated in Koijen and Yogo (2015). Across products, we find a 100bp increase in credit spreads leads to a 50bp decrease in an annualised annuity markup on average, with a t-statistic of 4.03. The average markup is 1%, and hence the 50bps decrease mean insurers drop their markups by half when they can earn 100bp more buying corporate bonds. This sensitivity is an economically significant effect. In the P&C industry, we use insurers' reported underwriting profitability as the main dependent variable. This measure is the ratio of their insurance underwriting profit to their insurance underwriting liabilities. We interpret lower underwriting profit as evidence of lower premiums. We find that the industry average underwriting profitability ratio falls by 1.31 standard deviations (t-statistic of 4.68) when lagged credit spreads increase by one standard deviation.

To test if insurers with higher expected returns set lower insurance premiums (Proposition 3), we use insurer's reported accounting investment returns to measure cross sectional variation in investment opportunities. The analysis utilizes the rich heterogeneity in investment portfolios across insurers. At any point in time, we show that the level of credit risk in credit portfolios explains the majority of variation in accounting returns, and that this variation predicts future returns, consistent with our interpretation that accounting returns captures insurers' expected investment returns.[2] We consistently find that the insurers with higher expected investment returns set lower insurance prices. In the life insurance industry, an insurer with an expected investment return one standard deviation higher than competitors reduces their relative markup by 0.05 standard deviations (t-statistic 2.77). In the P&C industry, we find an insurer with a one standard deviation higher expected investment return has an underwriting profitability ratio 0.03 standard deviations lower than competitors (t-statistic 5.45). The magnitudes are not as large as in the time series, showing that investment returns have more effect on industry average premium, rather than relative pricing in the cross section of premiums.

[2] Anecdotal evidence from market participants corroborates the hypothesis that insurers consider accounting returns to reflect future expected investment returns.

We provide further evidence of asset-driven insurance pricing with three extensions to our analysis. First, in the cross section of P&C insurers, we implement an instrumental variable estimation, using underwriting funding volatility and firm size (from the test of Proposition 1) as instruments for insurer's investment returns. We show that when instrumented investment returns are 100bps higher, insurance premiums are 0.3 percentage points lower. Second, in the cross section of life insurers, we use a series of shocks to investment returns due to mergers. When insurance companies are purchased by other insurers, their investment returns change as their portfolios adapt to the investment strategy of their acquiring insurance company. Using a differences-in-differences analysis, we show how insurance premiums fall (rise) in response to increases (decreases) in investment returns that are driven specifically by merger events. Third, in the time series, we show that the sensitivity to credit spreads is driven by expected excess return on bonds, as proxied by the Gilchrist and Zakrajšek (2012) excess bond premium, rather than the component of credit spreads that reflects expected default risk.

To understand our contribution, it useful to think of insurance premiums as the product of:

$$\text{Premium} = \underbrace{\frac{E\left[Claim\right]}{1+R^F}}_{\substack{\text{Actuarial price:} \\ \text{(Hill, 1979)} \\ \text{(Kraus and Ross, 1982)}}} \times \underbrace{\text{Markup}}_{\substack{\text{Imperfect competition} \\ \text{(Mitchell et al., 1999)}}} \times \underbrace{\text{Shadow Cost}}_{\substack{\text{Regulatory capital constraints} \\ \text{(Froot and O'Connell, 1999)} \\ \text{(Koijen and Yogo, 2015)} \\ \text{(Ge, 2020)}}} \times \underbrace{\frac{1+R^F}{1+R^I}}_{\substack{\text{Asset-driven insurance pricing} \\ \text{(this paper)}}}$$

The first term is the expected claim discounted at the risk free rate. It is typically considered to be the insurers' marginal cost of underwriting a policy. The basic intuition is that an insurer can invest premiums received in a portfolio of Treasury bonds that replicate the expected liabilities. Due to the time value of money, the marginal cost is therefore lower than the expected claim. The second term stems from imperfect competition, which allows insurers to set above the marginal cost of providing insurance. The third term rests on theories of financial frictions. When insurers are capital constrained and their access to external finance is costly, they deviate from their optimal unconstrained premium price in order to improve their regulatory capital position. The contribution of this paper is to return to the fundamental question of what insurance companies consider to be their time value of money. We challenge whether it is the risk-free rate, as the actuarial price suggests, instead arguing that insurers' also use the liquidity premium in their expected investment return, R^I, such that the discount rate is higher than the risk-free rate. The rational is based on there being a liquidity friction in asset markets, with insurance companies able to take advantage of this due to their unique funding source.

We consider the other channels of insurance pricing in our analysis, with particular focus on capital constraints (Froot and O'Connell (1999), Koijen and Yogo (2015), Ge (2020)), which has previously been shown to drive insurance prices. To guide the empirical analysis, we first extend the model with a statutory capital constraint that, in the spirit of Koijen and Yogo (2015), shows how insurance premiums can change when the constraint is binding. To rule out capital constraints as the driver of our empirical results, we show that asset driven insurance pricing is present in the P&C markets industry, where binding capital constraints should result in higher premiums, thus alleviating the confounding variable problem. We further show that our results hold in periods where insurance companies are unlikely to have been capital constrained. We therefore argue that while capital constraints play an important role in insurance pricing, they are not the only factor. Instead, insurance companies also account for expected returns when setting prices, and this mechanism is especially important when insurance companies are unconstrained by regulatory capital requirements.

As a robustness test we consider two alternative explanations for our findings. First, a possible explanation of our cross sectional results is that the insurance companies which take more investment risk are more likely to default themselves. Lower insurance premiums could thus be driven by relatively lower demand for insurance relative to their competitors. To rule out this alternative mechanism, we use AM Best capital strength ratings, showing that our results hold for the subset of highly rated firms in the life industry. The results also hold after controlling for measures of balance sheet strength in the full sample of P&C insurers. Second, another potential explanation is that insurance companies that are better able to reinsure their liabilities are therefore able to set lower premiums.[3] We show our results are robust to controlling for the fraction of an insurer's underwriting premiums that are reinsured.

Our paper is also related to Stein (2012), Hanson, Shleifer, Stein, and Vishny (2015), and Chodorow-Reich, Ghent, and Haddad (2020) who also study the comparative advantage of intermediaries investing in illiquid assets. As in our paper, these theories rest on a violation of the Modigliani and Miller (1958) capital irrelevance theorem, with an asset's value dependent on the funding structure of the investor. In particular, intermediaries are able to earn excess returns relative to other investors because of their particular funding structure. However, in the referenced papers, the excess returns generated flows to the equity holder of the intermediary by assumption. The key contribution of our paper is to document that the value from stable funding can flow to the insurer's policy holders, rather than just the equity holders. Our finding has potential welfare implications, with insurers offering cheaper insurance to households when financial markets are distressed.

Novy-Marx and Rauh (2011) and Rauh (2016) document how US pension funds increase the discount rate on their existing liabilities to reduce the present value of their reported liabilities. We instead study how insurance companies set the price on new liabilities, highlighting the interconnectedness of an insurer's assets and liabilities. In this sense, our paper relates to Kashyap, Rajan, and Stein (2002), who show study the synergies of banks assets and liabilities. While their paper focuses on how banks provide immediate liquidity on both liabilities and assets (i.e. credit lines), we argue insurer's stable liabilities mean they can take liquidity risk on their assets.

More broadly, our results relates to the intermediary asset pricing literature. Constraints on the liability side of intermediary's balance sheets affect their asset preferences (Brunnermeier and Pedersen, 2009; He and Krishnamurthy, 2013; Brunnermeier and Sannikov, 2014) which ultimately ends up changing asset prices (Ellul et al., 2011; Adrian et al., 2014; He et al., 2017; Greenwood et al., 2019) due to intermediary's position as marginal investors in segmented markets. We not only study how intermediaries affect asset prices, but also consider how asset markets affect intermediary liability prices. The findings of our paper therefore sheds further light on the interdependencies of intermediaries and asset markets that has been widely discussed following the global financial crisis of 2008.

In summary, we contribute to the literature by uncovering a new stylised fact and presenting theory that explains this fact: insurance premiums are asset driven.

2 Model of Insurance Premiums and Illiquid Asset Prices

We consider an economy with three periods, $t = 0$, 1 and 2, two types of agents, investors and insurance companies, and two asset markets.

[3]We thank Stefano Rossi for this observation.

Assets. There is a liquid asset with exogenous return R^F, and an illiquid asset with fixed supply S. The illiquid asset pays one unit of wealth at maturity $t = 2$, and the price at $t = 0$ is determined endogenously. The defining characteristic of the illiquid asset is that it incurs a cost if sold before before maturity (i.e. sold at $t = 1$). The seller of the asset receives their initial investment less a cost of $\frac{1}{2}\lambda x^2$ dollar for every x dollar sold. The parameter λ therefore captures liquidity conditions in the secondary market of the illiquid asset.

Investors. A continuum of risk-neutral investors, each endowed with e, are identical at $t = 0$. In the spirit of Diamond and Dybvig (1983), they learn at $t = 1$ if they are early or late consumers. Early consumers only care about consumption at $t = 1$, while late consumers only care about consumption at $t = 2$. Each investor knows at $t = 0$ the probability ω of being an early consumer.

Given that the investor buys dollar amount θ of the illiquid asset their consumption is

$$c = \begin{cases} e\left(1 + R^F\right) - \frac{1}{2}\lambda\theta^2 & \text{with probability } \omega \qquad \text{(early consumer)} \\ e\left(1 + R^F\right) + \theta R & \text{with probability } 1 - \omega \qquad \text{(late consumer)} \end{cases} \tag{3.1}$$

where

$$R = \frac{1}{\text{Asset Price}} - \left(1 + R^F\right) \tag{3.2}$$

is the equilibrium excess return on the illiquid asset.

In the first case of equation (3.1), the investor learns they are an early consumer and sells all assets at time 1, paying the associated transaction costs on their illiquid asset holdings. In the second case, the investor learns they are a late consumer and holds all assets to maturity, earning the excess return on their illiquid asset holdings.

The problem facing the investor is to choose θ to maximise expected consumption

$$\max_{\theta} \ \mathbb{E}\left[c\right] = e\left(1 + R^F\right) + (1 - \omega)\,\theta R - \frac{1}{2}\omega\lambda\theta^2 \tag{3.3}$$

where we assume that investors can borrow at the risk-free rate to take short positions in the illiquid asset.

Insurance Companies. The economy's other agent is a representative insurance company. The risk-neutral insurer receives premiums on insurance policies at $t = 0$ and pays the policy claims at either $t = 1$ or 2. The premium P is set by the insurance company, and the number of policies sold is determined by the exogenously given downward sloping demand curve

$$Q\left(P\right) = kP^{-\epsilon} \tag{3.4}$$

where $\epsilon > 1$ is the elasticity of demand.

The insurer is endowed with equity capital E at $t = 0$ such that their total liabilities

$$L = E + QP \tag{3.5}$$

are the sum of equity and the funding generated from the insurance underwriting business. The total future claims underwritten are defined

$$C = Q\bar{C}. \tag{3.6}$$

where $\bar{C}$ is the policy claim on each individual contract.

We assume that the insurance business is sufficiently diversified that we can think of total claims, C, as being a known constant. Insurance companies are thus not worried about the size of the claims to be paid, but instead face liquidity risk as claims can arrive at either $t = 1$ or $t = 2$. We define the fraction of total claims arriving time 1 as $\tau \in \{\bar{\tau} - \sigma, \bar{\tau} + \sigma\}$ and assume that each state occurs with equal probability. The remaining fraction of claims, $(1 - \tau)$, arrive at time 2. We think of the insurance product as a car or property insurance insurance, which is held by households outside of the model, and which has claims that are uncorrelated with the investors' consumption risk.

The insurer buys dollar amount $\Theta \geq 0$ in the illiquid asset and puts remaining wealth $L - \Theta \geq 0$ in the liquid asset. We assume both allocations are greater than or equal to zero, so the insurer's only source of balance sheet leverage is the funds generated from insurance underwriting.

The insurer's final wealth depends on the dollar amount τC of claims to be paid at $t = 1$ relative to the dollar amount $L - \Theta$ invested in the liquid asset. If the insurer holds more liquid assets than early claims, there is no sale of illiquid assets at $t = 1$. However, if early claims exceed liquid asset holdings, the insurer is forced to sell a fraction of illiquid assets before maturity. The final wealth is thus expressed with two cases

$$W = \begin{cases} L\left(1 + R^F\right) - C + \Theta R & \text{if } \tau C \leq L - \Theta \\ L\left(1 + R^F\right) - C + \left(L - \tau C\right) R - \frac{1}{2}\lambda\left(\tau C - (L - \Theta)\right)^2 & \text{if } \tau C > L - \Theta. \end{cases} \tag{3.7}$$

The first case shows the simple outcome in which the insurer holds enough liquid assets to cover early claims and all illiquid asset holdings therefore earn the liquidity premium R. In the second case, the insurer sells all their liquid assets plus a portion of their illiquid asset portfolio to cover remaining $t = 1$ claims. Dollar amount $\tau C - (L - \Theta)$ of illiquid assets are sold before maturity and incur the associated sale cost, which we assume is paid at $t = 2$. The dollar amount of unsold illiquid assets is the initial holdings minus the sold holdings: $\Theta - (\tau C - (L - \Theta)) = L - \tau C$. These illiquid assets still earn the liquidity premium.

The insurer's objective function is to choose P and Θ to maximise their expected final wealth

$$\max_{P,\, \Theta} \;\; \mathbb{E}\left[W\right] \tag{3.8}$$

where wealth W is defined in equation (3.7).[4]

Equilibrium. We conclude this section by defining the equilibrium in the economy. The competitive equilibrium in the illiquid asset market is given by the market clearing condition

$$\theta^* + \Theta^* = S \tag{3.9}$$

where investor demand θ^* and insurer demand Θ^* are given by the optimisation problems (3.3) and (3.8)

[4]We could also have the insurer's equity be bought by investors, and insurance companies maximising the present value of final wealth. As long as the discount rate is a fixed required return (for example, the return on the liquid asset, R^F, or the return on the illiquid asset, $R^F + R$), it is independent of the insurance company's asset allocation, and the qualitative results of the model are unchanged. A fixed required return results from the fact that agents are risk-neutral.

respectively. Supply S of the illiquid asset is exogenously given. Equilibrium in the insurance market is also where demand equals supply, with supply given by the insurers profit maximisation (3.8) and demand exogenously given from demand curve (3.4).

3 Theoretical Results

We begin by considering the asset allocation decision of the two agents in the model. All proofs are in the Internet Appendix.

Proposition 1 (illiquid asset allocations).

1. *The investor's equilibrium dollar investment in the illiquid asset is*

$$\theta^* = \frac{(1-\omega)}{\omega}\frac{R}{\lambda}. \tag{3.10}$$

2. *The insurer's equilibrium dollar investment in the illiquid asset is*

$$\Theta^* = L - (\bar{\tau} + \sigma)\, C + \frac{R}{\lambda}. \tag{3.11}$$

The investor and insurer both increase their illiquid asset allocation in the illiquid asset excess return, R, and reduce their illiquid asset allocation in the cost λ of selling the illiquid asset in secondary markets. The investor and insurer also decrease their illiquid allocation in the probability of early consumption ω and the expected fraction of claims $\bar{\tau}$ to be paid early. These parameters increase the chance of costly $t = 1$ sales of the illiquid asset. For the insurer, the variance σ of claims arriving early also matters for the illiquid investment allocation. The more volatile an insurer's funding (i.e. higher σ), the less illiquid assets they hold.

We next consider the insurer's pricing decision on insurance policies. We assume that the insurer treats the excess return on the illiquid asset R as a fixed constant — that is, they do not internalize the incremental impact of their choices on the magnitude of the excess return. First-order conditions of equation (3.8) with respect to P therefore yields the following proposition.

Theorem 1 (asset-driven insurance pricing). *The equilibrium insurance premium P of a policy with claim $\bar{C}$ is*

$$P = \frac{\bar{C}}{1+R^F}\left(\frac{\varepsilon}{\varepsilon-1}\right)\left(\frac{1+R^F}{1+R^I}\right) \tag{3.12}$$

where R^I is the insurer's expected investment return on their asset holdings that are funded by premiums

$$R^I = \frac{1+R^F+R}{1+(\bar{\tau}+\sigma)\, R} - 1 > 0. \tag{3.13}$$

We can see that the insurance premium is the product of three components. The first term, the actuarial price, is the claim discounted by the risk-free rate. The second term, $\frac{\varepsilon}{\varepsilon-1} > 1$, is the markup the insurer can charge due to imperfect competition.[5] The final term, $\frac{1+R^F}{1+R^I} < 1$, is related to the insurer's expected

[5] As the elasticity of demand for insurance tends to infinity, the insurer has no market power and the markup tends to one.

excess return on their illiquid asset holdings. Given that the fraction of claims $\tau \in \{\bar{\tau} - \sigma, \bar{\tau} + \sigma\}$ arriving at $t = 1$ cannot exceed one, we know that $R^I > 0$. This means that insurers set lower premiums when illiquid investment returns are higher. We call this *asset-driven insurance pricing.*

Asset-driven insurance pricing means that the premium depends on the illiquid asset excess return R, and the funding characteristics ($\bar{\tau}$ and σ) of the insurer. The insurer's borrowing costs through insurance underwriting are now dependent on their asset allocation and funding decisions. This Modigliani and Miller (1958) violation occurs because insurance companies can earn a risk-free liquidity premium on illiquid investments due to their stable funding.

To understand the mechanism, note that the maximum amount of claims to be paid by the insurer at $t = 1$ is $(\bar{\tau} + \sigma)\,C$. This observation leads to the lower bound $\underline{\Theta}$ on the insurer's illiquid asset holdings

$$\underline{\Theta} = L - (\bar{\tau} + \sigma)\,C. \tag{3.14}$$

Investing less than this in illiquid assets would mean forgoing liquidity premium that is available to the insurer risk-free, so $\Theta^* \geq \underline{\Theta}$. Other investors in the economy, on the other hand, face the risk of selling all assets at $t = 1$. The $\underline{\Theta}$ component of the illiquid allocation is therefore the insurer's source of competitive advantage relative to other investors in the illiquid asset market. Indeed, as $\underline{\Theta}$ investments earn insurers R with zero risk, these investments lower the insurer's marginal cost of underwriting . Insurers therefore compete for funding and insurance premiums are set lower when R is higher.

The special case where $\bar{\tau} + \sigma = 1$ illuminates the point. In this case, the insurer faces the risk that all claims arrive at $t = 1$ and they thus have no competitive advantage. The expected investment return on the asset holdings funded by premiums is $R^I \approx R^F$, and our result nests Modigliani and Miller (1958). The insurance premium is priced by discounting the claim by the exogenously given liquid risk-free rate, and is no longer dependent on the insurer's illiquid asset allocation Θ or the equilibrium liquidity premium R.

The model's next prediction follows directly from the partial derivative of insurance premium with respect to illiquid asset returns. While insurance companies take the illiquid asset return as a fixed constant in their pricing decision, we also show how the illiquid asset return moves in equilibrium with respect to exogenous shocks to liquidity.

Proposition 2 (time series of insurance premiums and illiquid asset returns). *Insurance companies set lower premiums when the expected excess return on the illiquid asset is higher*

$$\frac{\partial P}{\partial R} < 0, \tag{3.15}$$

with increases in the equilibrium expected return to the illiquid asset resulting from either

1. *an exogenous increase in transaction costs for the illiquid asset* $\frac{\partial R}{\partial \lambda} > 0$*; or*

2. *an exogenous increase in demand for liquidity from other investors* $\frac{\partial R}{\partial \omega} > 0$.

Proposition 2 allows us to make predictions for the average insurance premium, which we expect to fluctuate over time in response to expected illiquid asset returns. When illiquid asset returns increase, either due to exogenous shocks to liquidity or exogenous shocks to liquidity demand from investors, insurers reduce premiums in order to increase investments. Note that this behaviour makes the insurer a counter-cyclical liquidity provider. When liquidity conditions deteriorate, insurers increase their balance sheet and illiquid asset holdings, dampening the impact of negative liquidity shocks on equilibrium returns.

We now consider the cross section of insurance premiums. We introduce a small insurer to the model, which we will denote with subscript i. We assume that the small insurer has mass zero, such that they do not affect equilibrium, and that they have less stable funding relative to competitors (i.e. $\sigma_i > \sigma$). We can see from equation (3.13) that the expected return on assets funded by insurance premiums are lower for the insurer with less stable funding (i.e., $R_i^I < R^I$). The next proposition follows from this observation.

Proposition 3 (**cross section of insurance premiums and illiquid asset returns**). *For insurer i, with an expected investment return on illiquid investments lower than that of the industry average ($R_i^I < R^I$), the insurance premium will be set higher relative to competitors ($P_i > P$).*

Proposition 3 allows us to make predictions for the cross section of insurance premiums, which we expect to vary in relation to individual insurer expected investment returns relative to their competitors.

Numerical Example. We conclude the model by illustrating how insurers' stable funding, σ, and exogenous shocks to asset market liquidity, λ, affect insurance premiums by way of a numerical example. We choose parameters as follows: asset supply is $S = 1$, investors have $\omega = 0.2$ probability of being early consumers, insurance claims arrive at $t = 1$ with fraction $\bar{\tau} = 0.5$, elasticity of insurance demand is $\epsilon = 15$, the fixed parameter in the demand function is $k = 1$, claims are $\bar{C} = 1$, and the insurer is endowed with equity capital $E = 0.25$.

In Figure 2, Panels A, we investigate how the expected return on the illiquid asset, R, depends on the transaction costs of selling the illiquid asset, λ. We show the solution for three choices of funding stability of the insurer: $\sigma = 0.1$, $\sigma = 0.3$ and $\sigma = 0.5$. A lower σ means the insurer has more stable insurance funding. We see that the illiquid asset return increases as transaction costs increase in the secondary market. However, the sensitivity is less steep when insurer's funding is more stable and σ is lower.

In Panel B, we see that insurer's illiquid asset allocation also increases in λ, as the higher expected return encourages them to increase their exposure to the asset. The effect is stronger the more stable the insurer's funding is. The insurer's stable funding therefore makes them a counter-cyclical investor, increasing allocations when expected returns are higher. This feedback affects the equilibrium return, explaining why the return on the illiquid asset is less sensitive to λ when the insurer has more stable funding. The insurer absorbs more of the illiquid asset when liquidity conditions deteriorate, dampening the effect of liquidity on the equilibrium illiquid asset return.

Panel C shows that the insurance premium markup falls as λ increases. The insurer is able to extract more illiquid investment returns on their assets, and thus the marginal cost of underwriting the claim $\hat{C}$ falls. In the case $\sigma = 0.5$, the insurer has no funding advantage, with $\bar{\tau} + \sigma = 1$ meaning they face the risk that all claims arrive at $t = 1$. The premium markup and insurer asset allocation are no longer dependent on λ, with our model nesting Modigliani and Miller (1958). The equilibrium return R is also now a linear function of λ, with no dampening impact of a counter-cyclical insurer allocation to the asset.

4 Data and Methodology

4.1 Measuring Insurance Prices

Life Insurance. To measure the price of life and term annuities we use the markups, which are defined as the percent deviation of the quoted price to the actuarial price. The actuarial price is defined as the expected claims discounted at the risk-free rate:

$$\text{Actuarial Price}_t = \sum_{k=1}^{T} \frac{E_t\left[C_{t+k}\right]}{\left(1+R^f_{t+k}\right)^k} \tag{3.16}$$

where C_{t+k} is the policy's claim k periods from its inception t, and R^f_{t+k} is the k-period risk-free rate at time t.

In addition to absolute markups, we also use annualised markups in our study. These are the markup divided by the duration of the expected cash flows of the product. Following Koijen and Yogo (2015), we calculate expected cash flows and present values based on appropriate mortality table from the American Society of Actuaries and the zero-coupon Treasury curve Gürkaynak, Sack, and Wright (2007).

P&C Insurance. For most types of P&C contracts neither actual nor actuarially fair prices are readily available, making it impossible to calculate a markup. However, P&C insurers do track their pricing and underwriting performance through a measure called *combined ratio*, which is reported quarterly to the market. It is defined as:

$$\text{Combined Ratio} = \frac{\text{Losses} + \text{Expenses}}{\text{Premium Earned}} \tag{3.17}$$

where *losses* are the claims paid out on policies in the quarter (plus any significant revisions to future expected claims), *expenses* are the operating expenses of running the underwriting business and *premium earned* are the premium received on policies spread evenly over the life of the contracts. For example, if an insurer receives premium $P_{t,n}$ at time t on a policy that has a life of n quarterly reporting periods, then the reported *premium earned* on this contract in future reporting periods t' will be

$$\text{Premium Earned}_{t'} = \begin{cases} \dfrac{P_{t,n}}{n}, & \text{if } t < t' \leq t+n. \\ 0, & \text{otherwise.} \end{cases} \tag{3.18}$$

Premium earned is used in the *combined ratio* to ensure that realised claims are offset against the premiums that were received to cover their payment, and prevents the measure from being biased by changes in an insurers' underwriting volume. If an insurer doubles the size of their underwriting business, premiums received, $P_{t,n}$, double immediately while realised claims, at that time, are unaffected. Calculating the combined ratio with premiums received would therefore suggest a sudden improvement in underwriting (high inflows to outflows) even though the profitability of the underwriting business is unchanged. Premium earned, on other hand, increase in future periods, at the same time that claims are increasing due to the increased volume of business.

In our empirical analysis, we define underwriting profitability as:

$$\text{Underwriting Profitability}_t = \frac{\text{Premium Earned}_t - \text{Losses}_t - \text{Expenses}_t}{\text{Insurance Liabilities}_{t-1}} \tag{3.19}$$

which is the profit from underwriting divided by the size of the underwriting business. Insurance liabilities are reported by insurance companies and are the sum of "management's best estimate" of future losses and reinsurance payables (Odomirok et al., 2014). An increase in an insurer's underwriting profit can either be created by higher premiums relative to expected claims, or realised claims that are lower than insurer expectations. The latter generates some noise in our measure of insurance premiums, but we assume the noise from claims is uncorrelated with investment returns for our empirical analysis.

Our theory states that the predictive variables for premiums should reflect expected investment returns at the time the policies are written, not when the earning from these policies are reported. In our regression analysis, we therefore use annual averages over the preceding 12 months, since the Property and Casualty insurance is usually short maturity contracts. For example, auto-mobile insurance policies (42% of the total P&C market) are typically standardised to have one year duration. We therefore only need expected returns over the previous four quarters for our regression analysis.

4.2 Data

Life Annuity Pricing. Koijen and Yogo (2015) collate prices on annuity products from WebAnnuities Insurance Agency over the period 1989 to 2011. Prices are available for three types of annuities: term annuities (products that provide guaranteed income for a fixed term), life annuities (products that provide guaranteed income for an unfixed term that is dependent on survival) and guarantee annuities (products that provide guaranteed income for fixed term and then for future dates dependent on survival). The maturity of term annuities range from 5 to 30 years, whilst guarantees are of term 10 or 20 years. Further, for life and guarantee annuities, pricing is distinguished for males and females, and for ages 50 to 85 (with every five years in between). The time series consists of roughly semi-annual observations, except for the life annuities (with and without guarantees) which is also semi-annual, but with monthly observations during the years around the financial crisis, 2007-2009, which is the focus of Koijen and Yogo (2015). To summarize we have 96 insurers quoting prices on 1, or more, of 54 different annuity products at 73 different dates, which gives us 1380 company-date observations.

P&C Insurer Financial Statements. Insurance entities are required to report financial statements to regulatory authorities on a quarterly basis. S&P Global: Market Intelligence collates and provides this data. Our sample period is 2001 to 2018 for both Life Insurance and P&C Insurance companies.

In total, there are 3,951 individual P&C insurance entities in our sample. Large insurance groups often have many separately regulated insurance entities. We aggregate P&C entities to their group level. For example, the two largest P&C insurance groups in our sample, State Farm and Berkshire Hathway, have been aggregated from 10 and 68 individual insurance entities respectively. To aggregate dollar financial variables we sum across entities. To aggregate percentages and ratios (such as investment yield) we use the asset-value weighted average.

Our final P&C sample consists of 1,070 insurance groups running P&C businesses over 68 quarters from

March 2001 through to December 2017. In total we have 44,780 firm-quarter observations, with a minimum of 184 insurance groups available in any given quarter and a maximum of 735. To get to this final sample we have excluded insurance companies with less than 4 years of data, companies who never exceed $10 million in net total assets, company-year observations where the company has less than $1 million in earned premium over the year, and observations with non-positive net total assets and net premium earned. We do this to ensure that the companies we are looking at are relatively large and active. All financial statement variables are winsorized at the 5th and 95th percentiles in each quarterly reporting period.

The financial statements provides balance sheet and net income variables. For cross sectional analysis, our main variable is the accounting investment returns as described in Section 5. We also use insurers' average credit portfolio ratings[6], asset allocations, and various measures of balance sheet strength: size (log of total assets), asset growth (annual change in total assets), leverage ratio, risk-based capital, amount of deferred annuities (life insurers only)[7], Unearned Premium to Earned Premium ratio[8] and reinsurance activity (net premiums reinsured / net premiums received). The last two are for P&C insurers only.

For cross sectional analysis on life insurance companies, we merge S&P Global financial statement data with the annuity markup data provided in Koijen and Yogo (2015). In the period 2000 to 2011, the intersection of our two datasets, we are able to merge both data with investment yields and annuity markups for 16 companies. Consistent with the P&C data construction, we have excluded insurance companies with less than 4 years of data.

Financial Market and Macroeconomic Variables. To measure the credit spread we use Moody's Seasoned Baa corporate bond yield relative to 10-Year Treasury, retrieved from St. Louis Fed's website (fred.stlouisfed.org). We also use the excess bond risk premium as provided in (Gilchrist and Zakrajšek (2012)). To proxy for general funding costs and liquidity premia we include the 6-month to 10-year Treasury Constant Maturity Rates and TED spread (downloaded from St. Louis Fed's website), respectively. The TED spread is the difference between the three-month Treasury bill and the three-month LIBOR based in US dollars. The CAPE ratio, which is real earnings per share over a 10-year period, is retrieved from the Robert Shiller website.

Mergers and Acquisitions. We have hand collected data on mergers and acquisitions across our sample of life insurers with annuity pricing. The insurer net yields on invested assets around these assets are taken from our S&P Global: Market Intelligence dataset (where available) or directly from insurer financial reports on line. The list of events that we use in our analysis is shown in table (AI).

4.3 Summary Statistics

Table I presents summary statistics for the key variables in our empirical analysis. The average annuity markup on an absolute basis is 6.75%, 5.31% and 4.24% for fixed term, life and guarantee annuities respectively. On an annualised basis, these markups are 1.03%, 1.12% and 0.50% respectively. Our main dependent variable in P&C markets is underwriting profitability, which across this sample has a mean of 0.31% and

[6]The insurance regulator assigns bonds into six broad categories (categories 1 through 6) based on their credit ratings, with higher categories reflecting higher credit risk. Level 1 is credit AAA-A, level 2 is BBB, level 3 BB, level 4 is B, level 5 CCC and level 6 is all other credit.

[7]these unprofitable products caused constraints in the financial crisis

[8]this gives an indication of the remaining unpaid liabilities relative to current volume of business

standard deviation of 3.24%. The average insurer-level 5-year rolling standard deviation of underwriting profitability is 2.35%. In our cross sectional analysis, the main independent variable is insurance companies' investment returns. This averages 2.75% in the P&C industry and 5.97% in our sub-sample of life insurers.

5 Preliminary Evidence

Before testing the model propositions in section 6, we provide preliminary evidence that shows the importance of investment returns to the insurance business model.

Table II presents the aggregated industry balance sheets for the Life Insurance industry and the P&C Insurance industry. There are two key takeaways that are relevant for our analysis. First, we see that the large asset portfolios are predominately funded by insurance underwriting. The Life Insurance industry has an average equity ratio of 9% and the P&C industry has an equity ratio of 38%, with the dominating source of leverage in both cases being insurance liabilities. Second, we see that insurance companies take lots of investment risk in their asset portfolios. Risk-free asset allocations (cash and Treasuries) are only 8% for the Life Insurance industry and 14% for the P&C industry. Instead, insurers invest in risky and often illiquid assets. Corporate bonds, mortgage loans and other credit (such as MBS, RMBS, and municipal bonds) make up 75% and 42% of the balance sheets for the Life and P&C industries respectively.

Figure 3 presents the P&C industry's aggregated net income. The total net income is split between the earnings reported from the asset portfolio investments, the earnings reported on the insurance underwriting business and (the residual) other income. The striking feature of Figure 3 is that the industry often loses money through insurance underwriting, and is only profitable once investment income is included. It should be noted that the industry standard for reporting underwriting losses, as shown in Panel A, do not take time value of money into account. This means insurers don't account for the fact that premiums are received before claims are paid and that the insurers can at least earn the risk-free rate. In Panel B, we adjust for the time-value of money, increasing (decreasing) underwriting (investment) income by the value of insurance liabilities multiplied by the risk-free rate. Even after this adjustment, we see that returns on investment portfolios are of first order importance to the insurance business model.[9]

Figure 4 presents boxplots of insurers' investment returns in each reporting quarter of our sample, highlighting both the time series trends in insurer investment returns, and the rich heterogeneity in investment returns in the cross section of insurers. In any given quarter of our sample, the range between the 25th and 75th percentiles of investment returns is in excess of 150 bps. These investment returns are insurer's accounting investment returns, which are reported on a quarterly basis. For fixed income assets, the accounting treatment of investment returns is to report the yield at purchase amortised smoothly over the life of the bond. If the bond defaults or the insurer sells with a gain/loss, this is also included in their investment return. However, so long as the insurer does not sell or the issuer does not default on the bond, the investment return methodology protects the insurer from mark-to-market volatility on their credit assets.[10] This treatment reflects insurers' long-term buy and hold approach to investing,[11] and is consistent with Chodorow-Reich, Ghent, and Haddad (2020) view of insurers as "asset insulators" that can ride out transitory dislocations in

[9]Life industry insurance companies don't report underwriting profits is the same way as P&C insurers, so the equivalent analysis is not possible in this industry. Refer to Appendix 10.1 for a discussion of profitability in the Life Insurance Industry.

[10]Refer to 10.2 for a more detailed description of how accounting investment returns are calculated by insurers.

[11]Schultz (2001) and Campbell and Taksler (2003) estimate that insurers hold between 30% and 40% of corporate bonds and yet account for only about 12% of trading volume

market prices. It is also consistent with our model of insurers being able to earn liquidity premium on illiquid investments.

Table III Panel A shows how variation in insurers' asset allocations explain cross sectional variation in insurer investment returns. We regress insurer investment returns (in bps) on asset allocations (in percent) with controls for time fixed effects. We see that insurers with large credit allocations have higher investment returns, while large allocations to Treasuries and cash mean lower investment returns. For example, column 1 shows that a 1 percentage point increase in credit and cash allocations result in a 1.25 bps increase and 1.50 bps decrease in investment returns respectively. In column 2 of Table III we interact credit allocations with the credit portfolios value-weighted average credit rating.[12] We can see that the effect of credit allocations on investment returns is largely driven by the level of credit risk in these portfolios. Finally, in column 3 of Table III, we interact credit rating with credit allocation and the previous quarter's credit spread. The effect on investment returns of investing in risk credit is larger when credit spreads are higher.

Table III Panel B explains the time series variation in individual insurance company's investment returns. Columns 1-2 show that there is a high degree of persistence in insurer investment returns, with an insurer's current quarter investment return explaining 57% of their next quarter investment return. Given insurer accounting returns predict next periods investment returns, we interpret cross sectional variation in this measure as cross sectional variation in insurer's *expected* investment return. The auto correlation of investment returns at an insurer level is not surprising given the accounting treatment of investment returns on fixed income assets.

Columns 3-4 of Table III Panel B show the macro-level time series drivers of investment returns. We see that the large fixed income allocations in insurer portfolios make the risk-free rate, the slope of the yield curve and the credit spread on corporate bonds all very significant drivers of investment returns. On the other hand, the CAPE ratio (capturing expected equity returns) and the TED spread (capturing financial market distress) are unimportant. Our finding that credit spreads predict insurer investment returns is consistent with previous work that show that corporate bonds deliver excess returns to Treasuries over the long-term (Krishnamurthy and Vissing-Jorgensen (2012), Gilchrist and Zakrajšek (2012)). In the long-term, the insurers accounting return on investments must equal their economic return. If the credit spread only reflected default losses, then credit spreads would have no predictability for insurer investment returns on average.

6 Empirical Results

6.1 Stable Insurance Funding and Illiquid Asset Allocations

We first test Proposition 1's prediction for insurance companies asset allocation decision: insurers with more stable insurance funding hold more illiquid assets. We take this prediction to the data using P&C insurers' historical volatility on insurance underwriting as a proxy for stable funding. For each insurer, we calculate rolling 5-year volatility estimates of insurance underwriting profitability (as defined in equation (3.19)). We then use volatility lagged one quarter as the independent variable. Our two variables for capturing insurer investment risk is their cash allocation and their credit allocation multiplied by the average credit rating

[12]The insurance regulator, NAIC, assigns credit into six broad categories (level 1 through 6) based on their credit ratings, with higher categories reflecting higher credit risk. Level 1 bonds are rated AAA-A, level 2 is BBB, level 3 BB, level 4 is B, level 5 CCC and level 6 is all other credit

of their portfolio.[13] We report the results in columns 1-6 of Table IV Panel C. We see that stable funding predicts low cash allocations and large allocations to risky credit. For example, a one standard deviation higher volatility of underwriting profitability increases an insurer's cash allocation by 0.22 standard deviations ($\approx$ 3 percentage points). Following Ge and Weisbach (2020), we include firm size and other variables that capture insurers balance sheet strength as controls. Consistent with their work, we find strong evidence that the size of an insurer is a determinant in the amount of risk in an insurer's investment portfolio. Assuming large insurers have more diversified and stable underwriting businesses, this result is consistent with our model's prediction. However, our results take this result a step further, showing that even when comparing firms of equal size, the insurer with less volatile underwriting performance takes more investment risk in their credit portfolio. This finding also holds after controlling for a vector of balance sheet strength variables.

Columns 7-9 of Table IV show that large insurers and those with stable underwriting cash flows also realise higher investment returns. In other words, the increased investment risk translates into higher investment returns. To give a sense of the order of magnitude, an insurer with funding volatility one standard deviation lower than competitors has an investment return that is 21 bps higher than it's competitors.

In summary, we have documented a relationship between the stability of the funding generated by insurance underwriting and the asset allocation decisions of insurance companies. Insurance companies that are large and have more stable funding take more investment risk and earn higher investment returns. According to our model, the explanation is that insurers use the stability of the insurance funding to earn liquidity premium on their assets.

6.2 Investment Returns Drive the Time Series of Premiums

We next test Proposition 2's prediction for insurance prices and illiquid investment returns in the time series: high expected asset returns mean lower insurance premiums. We take this prediction to the data using credit spreads as a proxy for the expected return on corporate bonds which make up the majority of insurers investment portfolios.

Figure 1 illustrates our central time series finding using our longest available sample. The figure presents the industry average markup on a 10 year fixed term annuity against the 10 year BAA credit spread from 1989 to 2011. Markups are defined as the quoted price relative to their actuarially fair price. The negative correlation between the markup (left hand axis) and credit spreads (right side axis, inverse) is obvious. In fact, the R-squared from the single variable regression of markups on credit spreads is as high as 77%.

We show that the relationship between annuity markups and credit spreads is present across different life products and sample periods and robust to controls for other market returns and macroeconomic variables. Motivated by our theory, we focus on the impact of expected investment returns on insurance premiums. To control for the competing hypothesis that price changes are driven by financial constraints (Koijen and Yogo (2015)) we include a dummy variable to capture the Global Financial Crisis - a period in which financial constraints are known to affect insurance premiums.[14] We also control for unemployment rate to proxy for shifts in the demand for insurance.

Table V reports the parameter estimates from the following regression:

$$m_{ikt} = \beta_c \cdot CS_t + \beta_{GFC} \cdot \mathbb{1}_{GFC} + \beta_{cGFC} \cdot CS_t \times \mathbb{1}_{GFC} + B' \cdot X_t + FE_i + FE_k + \epsilon_{ikt}$$

[13] We use a numeric measure of average credit rating, as assigned by the insurance regulator.

[14] Section 7 considers the impact of capital constraints within the context of asset-driven insurance pricing in detail.

where m_{ikt} is the annualised markup set by insurer i at time t for an annuity which is in subproduct category k. Subproducts vary depending on age, sex and maturity of the annuities. CS_t is Moody's credit spread of BAA corporate bonds, and $\mathbb{1}_{GFC}$ is an indicator variable set to one over the global financial crisis (November 2008 through February 2010). We include a vector of time series controls, X_t, which includes the risk-free rate, the slope of the yield curve, the TED spread, the CAPE ratio (to capture other drivers of expected investment returns), and US unemployment rate (to capture time variation in the demand for insurance). Columns 1-3 report the parameter estimates from time series regressions where for the dependent variable, $\overline{m}_t$, we have averaged across insurers and subproduct categories in each time period. Columns 4-5 report full panel specifications. Panel A, B and C show the results for markups on life, guarantee and fixed-term annuity products respectively.

Across specifications, we see that a 100bps increase in credit spreads lowers annualised markups by 52bps (t-statistic of 5.34). Given that annualised markups are 1% on average, this means that markups fall by 50% when insurers can earn more on their credit portfolios.[15] The explanatory power is also very large. Taking life annuities as an example, the credit spread alone explains 80% of the variation in levels (see the adjusted r-squared in column 1 of Panel A). The main result of this section is also robust to including the vector, X_t, of time series controls. We report estimates for all variables in vector X_t in Appendix Table AII. Note that the risk-free rate is not significant as the effect of risk-free rates on premiums is captured in the actuarial price (equation 3.16), which is used in our dependent variable.[16]

Koijen and Yogo (2015) highlight that the financial crisis saw a dramatic fall in markups from November 2008 through to February 2010. Figure 1 shows the annualised 10yr annuity markup fell from 1.25% to -0.75% across the dates. In Columns 3 and 5 of Table 5, Panel A we regress life annuity markups on credit spreads interacted with an indicator variable set to one over this same period, $\mathbb{1}_{GFC}$. Panel B and C repeats the analysis with guarantee annuity markups and fixed-term annuity markups as dependent variables, respectively. We see that for all products markups were on average lower during the global financial crisis. Further, the estimated coefficient on the interaction between credit spreads and the crisis indicator is positive for all products , and generally statistically significant. The positive interaction coefficient shows that the baseline coefficient is less negative in the financial crisis. Said differently, the negative relationship between premiums and credit spreads is stronger outside of the global financial crisis period. Nevertheless, our results suggests that credit spreads were still important in this period, with roughly 40% of this drop in markups due to sensitivity of markups to credit spreads. The remaining 60% was due other factors such as capital constraints.[17] We therefore argue that while capital constraints play an important role in insurance pricing, they are not the only factor. Instead, insurance companies also account for expected returns when setting prices, and this mechanism is especially important when insurance companies are unconstrained by regulatory capital requirements.

Table VI shows how insurance premiums in the P&C industry vary with credit spreads. The table has the same five column specifications as the previously discussed Table V. In the P&C industry we do not

[15]We use annualised markups (rather than absolute markups) so that it is easier to interpret coefficients across products with different durations. However, all results are qualitatively consistent to specifications with absolute markups.

[16]Table AIV in the appendix presents results from identical specifications as Table V, but with markups and investment returns in changes rather than levels. Our results are robust to this specification, with estimated sensitivities of similar magnitudes. We proceed with analysis in levels throughout the rest of the empirical results.

[17]Credit spreads and markups changed by 320bps and -200bps respectively. The credit spread coefficient, adjusting for the interaction coefficient, is $-0.59 + 0.36 = -0.23$ in the global financial crisis, and thus we see credit spreads account for $0.23 * 320 = 74$bps of the markup change.

observe prices directly but instead use underwriting profitability as defined in equation (3.19) as the main dependent variable. This measure is the ratio of their underwriting profit relative to their insurance liabilities. We interpret lower underwriting profitability as lower prices. Given that underwriting profitability reflects insurance premium pricing over the previous year, we use lagged credit spreads on the right hand side of the regression. We find a statistically significant impact of credit spreads, with a 100bps increase in credit spreads lowering underwriting profitability by one percentage point. For a one standard deviation increase in credit spreads, the industry's underwriting profitability decreases by 1.3 standard deviations. Table AIII in the appendix presents full specification results, including the control vector coefficients.

In summary, in this subsection we document an economically and statistically significant negative relationship between insurance premiums and the expected investment returns of insurance companies in the time series.

6.3 Investment Returns Drive the Cross Section of Premiums

We next test Proposition 3's prediction for insurance prices and investment returns in the cross section of insurers: insurers with higher expected investment returns set relatively lower prices. As with the time series results, we begin with an illustration of our key finding. We use the P&C industry because it is our richest cross section, grouping the 1,240 insurers into 20 portfolios ranked on their investment return. For each portfolio, we then calculate equal-weighted underwriting profitability and investment returns. Figure 5 presents a binned scatter plot of the portfolio averages with underwriting performance on the vertical axis and investment returns on the horizontal axis. There is a clear negative correlation with insurers with higher investment yields also reporting lower underwriting profitability.

We now formally test the relationship between insurance prices and the investment returns for both the Life Insurance industry and P&C industry, beginning with the Life Insurance. Table VII reports the parameter estimate from the following panel regression using the cross section of life insurers:

$$m_{ikt} = \beta_y \cdot y_{it} + \beta_{yFC} \cdot y_{it} \times \mathbb{1}_{GFC} + B' \cdot X_{it-1} + FE_i + FE_k + FE_t + \epsilon_{ikt}$$

where m_{ikt} is the annualised markup set by insurer i at time t for an annuity which is in sub-product category k, y_{it} is the insurer's expected investment return, and X_{it} is a vector of lagged variables measuring balance sheet strength (Koijen and Yogo (2015)). The control vector includes variables squared to capture any non-linear effects of capital constraints. We additionally control for date fixed effects, product fixed effects, and firm fixed effects. Panel A, B, and C show the results for markups on fixed-term, guarantee and life annuity products respectively. Across specifications and products, we see that an insurer with a investment return 100bps higher than competitors sets annualised markups 3bps lower. In the majority of specifications the relationship is statistically significant. Columns 4-5 interact investment return with an indicator variable $\mathbb{1}_{GFC}$ set equal to one during the financial crisis.

Table VIII tests the cross sectional relationship between insurance pricing and insurers' expected investment returns in the P&C industry. The table follows the same structure as Table VII, but with insurer underwriting profitability replacing markups as the dependent variable. We also include a variable that controls for the level of reinsurance activity by insurance companies. In the P&C industry, we find that an insurance company with a 100bps higher expected investment return compared to competitors reports underwriting profitability that is 10bps lower. To compare the cross sectional results in both the life industry and P&C industry, we have also calculated standardized coefficients. In the life insurance industry, a one standard deviation higher insurer investment return reduces an insurer's relative markup by 0.05 standard deviations. In the P&C industry, we find an insurer with a one standard deviation higher insurer investment return has an underwriting profitability ratio 0.03 standard deviations lower than competitors.

In summary, in this subsection we have shown that the negative time series relationship between insurance premiums and expected investment returns is also present in the cross section of insurance companies. Insurance companies that expect to earn higher returns on their investment portfolios set lower premiums relative to their competitors.

6.4 A Two-Stage Estimation of the Cross Sectional Analysis

To test the structure implied by the model, we next implement cross sectional analysis with a two-stage estimation. In the first stage of the estimation, investment returns are predicted by stability of funding. This is a replication of the analysis from Section 6.1, with the expected investment returns of insurance companies regressed on their underwriting volatility (Table IX Column 1) and both underwriting volatility and firm size (Table IX Column 2). The results show that stability of insurance underwriting is correlated with insurers investment returns, which is consistent with the economic mechanism at play in the model. Stable funding allows insurers to take more investment risk and thus earn higher investment returns.

In the second stage of the estimation, we take the predicted component of investment returns and regress insurance premiums on these investment returns. According to the model, it is these higher returns in particular (i.e. the returns that are due to insurer's competitive advantage of stable funding) that lead to lower premiums. Columns 3 and 4 of Table IX report the parameter estimate from this second stage regression. It shows that insurance premiums fall by 0.27 percentage points when investment returns are 100bps higher.

The two-stage estimation is an instrumental variable estimation with stable funding proxies being used as an instrument for insurer investment returns. To the degree that the relevance and exclusion restriction conditions hold, the results are therefore direct evidence of the causality implied by the model. To formally test the relevance condition, Table IX reports the Cragg-Donald Wald F-statistic. Running the specification with controls but only volatility as the instrument results in weak instrument concerns Stock and Yogo (2005). We therefore add firm size as an additional instrument. As discussed in Section 6.1, we view this variable as another proxy for the stability of insurance underwriting fund that insurers enjoy.

The exclusion restriction, which requires the instruments to be correlated with insurance premiums through their impact on investment returns only, cannot be formally tested. However, there is a concern that firm size is an endogenous choice of the insurance company. It is however worth noting that these are cross sectional regressions with date fixed effects. An insurance companies choice of size cannot be changed meaningfully from period to period, with any large change in size taking many periods to build. Indeed, looking at the large insurers in our sample, they have been very consistent through the sample. This makes it plausible that, in any given time period, size can be viewed as being exogenously given to the insurance firm.

When an instrumental variable estimation has multiple instruments, a formal Sargan's χ^2 test of overidentifying restrictions can be run. The large p-value in the Sargan test (Table IX Column 4) means that we can not statistically reject that the instruments are uncorrelated with the structural error term. While this is reassuring, it does not rule out the possibility that our instruments are endogenous.

In summary, in this subsection we have tested the structure of the model. Consistent with the model, we have shown that the predicted component of investment returns (due to stable funding) predicts insurance premiums. The coefficients in Table IX are more negative than those estimated in Table VIII, indicating a stronger effect than previously estimated by the raw cross sectional regressions. This is likely because the instrumented investment returns provide a cleaner estimate of the impact of investment strategy on insurance premiums.

6.5 Evidence from Mergers and Acquisitions

In this section, we present evidence on how changes in investment returns due to merger and acquisition affect insurance premiums. We argue that these exogenous shocks to the insurance companies allow us to extract a cleaner estimates of the cross sectional relationship between premiums and investment returns. Figure (6) presents a representative example from our sample. American Heritage was acquired by AllState Insurance in October 1999. In the 12 months proceeding the acquisition, American Heritage earned a return of 7.22% on their investment portfolio and AllState Insurance earned 5.80%. The figure shows that American Heritage's investment returns fell post acquisition, reflecting the more defensive strategy of their acquirer. Critically, the figure also shows an adjustment in pricing on 10yr fixed term annuities. American Heritage were consistently selling annuities at a discount to the industry pre-acquisition. However, following the acquisition, their markup pricing increased significantly.

We next show evidence consistent with the case study but with multiple merger events in Table X. We have five merger events in our sample, and study the premium impact on three products: 20yr fixed term annuity, life annuity for males aged 50, and 10 year guarantee life annuity for a male aged 50. In a difference-in-differences approach, we use life insurance companies involved in a merger and acquisition event as our treatment group, and other insurance companies as the control group. The treatment period is the two years after the merger event, and the control period is the two years before the merger event. Table X reports the parameter estimate from the following regression:

$$m_{ikt} = \beta_D \cdot D_{it} + FE_i + FE_k + FE_t + \epsilon_{ijt}$$

where m_{ikt} is the markup set by insurer i at time t on product k. Our explanatory variable, D_{it}, is the investment return differential between the treatment group insurance company and the other insurance company involved in the transaction. It is set equal to this value for the treatment insurer and treatment time period (i.e. in the two years following the merger for the treatment insurer), and set to zero in all other cases (i.e. two years pre merger event for the treatment group, and in all observations for control group insurers). The interpretation of a positive investment return differential is that insurer i is being acquired by an insurer with a more risky investment strategy, and thus going forward their own investment returns are expected to be higher. In each of our observations, we confirm that investment return differential do indeed lead to a change in the insurers investment returns post transaction in-line with this interpretation. This is illustrated in Figure 6 with the American Heritage example.

By controlling for time and firm fixed effects in the regression, the coefficient β_D captures the impact of the merger induced change in investment return on the treatment insurer's relative markup pricing as compared to the industry average. We see from Table X that a 1% increase in investment return following merger activity results in a 0.22% fall in an insurers markup relative to the industry. The t-statistic is 3.44. The coefficient is larger than in Table VIII, suggesting the merger sample is better able to identify the relationship between investment returns and insurance premiums. We also note that the sample includes examples of where the investment return differential is both negative and positive. This helps rule out competing interpretations of the results. For example, one could imagine insurers discount products ahead of a merger to increase the value of the merger, which would lead to an increase in markups post merger. However, this can't explain the observations in the sample with an increase in investment returns and fall in markups.

In summary, in this subsection we extend our analysis to show the negative relationship between insurance premiums and expected investment returns in the cross section of insurance companies holds following exogenous shocks to returns and premiums that are due to merger activity.

6.6 Evidence from Excess Bond Returns

Credit spreads can be split into spread that compensates investors for expected default losses and a premium in excess of this. It is the latter component, the excess return, that our model predicts is driving the correlation between credit spreads insurance premiums. Insurance companies use their stable insurance funding to extract liquidity premium on their asset portfolios, with some of the excess return passed on to policyholders through lower premiums.

We test this interpretation in Table XI by re-estimating the regression specifications in Table V, but splitting credit spreads between excess bond premium and the fair credit spread given the underlying default risk (Gilchrist and Zakrajšek (2012)). As per our previous analysis, we run specifications with time series averages and the full panel of insurers, as well as specifications with / without an interaction with the financial crisis period. We see that negative correlation between premiums and credit spreads is driven entirely by the excess bond return component of credit spreads, with 100bps increase in excess bond returns reducing the markup by 50bps depending on specification and product. The default risk component of credit is statistically significant only in the panel C (fixed-term annuities). The coefficient on the excess bond return suggests that insurance companies pass back 50bps of excess returns on their credit portfolios to policyholders, and maintain 50bps for equity holders.

In summary, in this subsection we extend our analysis to show the time series correlation between credit spreads and insurance premiums are driven by the excess bond return component of credit spreads. This finding is strong evidence in support of asset-driven insurance pricing.

7 Introducing Insurer Capital Constraints

7.1 Theoretical Background

Capital constraints also affect insurance premiums (Gron (1994), Froot and O'Connell (1999), Koijen and Yogo (2015) andGe (2020). We embed this additional premium pricing mechanism into our existing framework by subjecting the insurer to a statutory capital constraint. The statutory value of each insurance policy is

$$\bar{V} = \frac{\bar{C}}{1 + R^S} \tag{3.20}$$

where R^S is the statutory discount rate for claims. The total statutory value of all Q claims is therefore $V = Q\bar{V}$. In the spirit of Koijen and Yogo (2015), the insurance company faces a capital constraint

$$\frac{V}{L} \leq \phi \tag{3.21}$$

where $\phi \leq 1$ is the maximum statutory leverage ratio and L is their total liabilities (equation 3.5). The likelihood of this constraint binding is decreasing in the statutory discount rate R^S. A higher discount rate reduces the statutory value of each policy and therefore reduces statutory leverage.

The first-order condition of equation (3.8) with respect to P when the insurer is subject to (3.21) yields the following proposition.

Proposition 4 (**insurance premium with capital constraints**). *In equilibrium, a policy with claim $\bar{C}$ will be underwritten with premium*

$$\hat{P} = \frac{\bar{C}}{1+R^I}\left(\frac{\varepsilon}{\varepsilon-1}\right)\left(\frac{1+(\bar{\tau}+\sigma)R+\frac{\eta}{\phi(1+R^S)}}{1+(\bar{\tau}+\sigma)R+\frac{\eta}{(1+R^I)}}\right). \tag{3.22}$$

where $\eta \geq 0$ be the Lagrange multiplier on the capital constraint (3.21).

Note that when the capital constraint is not binding, then $\eta = 0$ and therefore $\hat{P} = P$ as defined in (3.12). However, our interest in this section is for the case $\eta > 0$, which we explore in detail below.

Proposition 5 (**capital constraints vs. no capital constraints**). *When an insurer is capital constrained so eq. (3.21) holds with equality, the optimal price $\hat{P}$ relative to optimal price in the unconstrained case P depends on the relationship between the insurers time value of money R^I, the statutory discounting of claims R^S, and the maximum statutory leverage ratio ϕ. In particular:*

(i) When $\left(1+R^I\right) < \phi\left(1+R^S\right)$ then $\hat{P} < P$

(ii) When $\left(1+R^I\right) > \phi\left(1+R^S\right)$ then $\hat{P} > P$

(iii) When $\left(1+R^I\right) = \phi\left(1+R^S\right)$ then $\hat{P} = P$

This three case proposition extends the main theoretical result of Koijen and Yogo (2015), showing that the impact of insurer investment returns R^I is also important when the regulatory constraint binds. We describe the economic mechanisms below.

Case 1: $\left(1+R^I\right) < \phi\left(1+R^S\right)$. In this case the discount rate applied to statutory liabilities is higher than the expected return on assets multiplied by a factor of $\phi^{-1} > 1$. A new policy increases liabilities by $\bar{V}\phi^{-1}$ and increases assets by the premium received P. A higher R^S reduces $\bar{V}$ through the statutory discounting, and if R^S is sufficiently high it can mean new policies create an instantaneous improvement in an insurers statutory capital position. The result is that constrained insurers write policies at cheaper prices than an unconstrained competitor. Although writing policies cheaper reduces final wealth, insurer do it due to the temporary statutory capital relief it creates. Koijen and Yogo (2015) provide a detailed description of the calculation of R^S for different products in the life industry, showing that it was particularly high in the financial crisis. Consistent with their model prediction, they find constrained life insurers reduced annuity and guarantee markups significantly during the financial crisis.

Case 2: $\left(1 + R^I\right) > \phi\left(1 + R^S\right)$**.** In this case capital constraints lead to an increase in insurance prices. If the insurer sets the unconstrained premium price P, a new policy creates more statutory liabilities than assets, as $\tilde{V}\phi^{-1} > P$. Constrained insurers are therefore forced to increase prices to a level such that the premium received offsets the increase in liabilities. Froot and O'Connell (1999) provide an example of such a case by documenting how supply of catastrophe insurance fell following a negative shock to insurers' capital.

Case 3: $\left(1 + R^I\right) = \phi\left(1 + R^S\right)$**.** This is a special case where the mechanisms underlying case 1 and 2 offset each other. It means that a binding capital constraint has no impact on an insurer's optimal premium.

Our main time series empirical implementation uses credit spreads, which are likely to be positively correlated with capital constraints, to proxy R^I. Proposition 2 predicts lower premiums when credit spreads (expected returns) increase. At the same time, proposition 5 case 1 predicts lower premiums with higher credit spreads (assuming higher credit spreads mean more financial constraints and lower insurance capital). The predicted impact of capital constraints on premiums is therefore the same as asset-driven insurance pricing, which makes it hard to empirically separate the two channels. However, in case 2 of proposition 5, the sign of the effect of capital constraints is reversed. This means that the asset-driven insurance pricing and capital constraint effects move in opposite directions.

7.2 Controlling for Capital Constraints Empirically

The financial crisis was a period of particularly high capital constraints in the Life Insurance industry (Koijen and Yogo (2015)). We have therefore been careful to separate out the financial crisis in all of our previously discussed results. We show that our findings are robust across periods and apply in *normal* times only. In fact, in most specifications, we find the negative relation between insurance prices and investment returns is less strong in the financial crisis. Said differently, the asset-driven insurance pricing effect holds stronger in normal times where capital constraints are less prevalent. To see this, note the coefficient on credit spreads interacted with the financial crisis indicator is positive and statistically significant. For example, in Table V Panel A, we find a coefficient of 0.31 (t-statistic 2.85).

Proposition 5 highlights that the impact of capital constraints on the insurance premiums depends on the level of statutory discount rates relative to expected investment returns. In the second case of the proposition 5, capital constraints predict higher premiums in times of stress, while asset-driven pricing predicts premiums are lower when credit spreads are higher. Empirical settings where insurers are in case two therefore makes it easier to disentangling capital constraints and asset-driven pricing empirically. For P&C markets, liabilities are not discounted ($R^S = 0$) for typical products such as car insurance, with the regulator making no adjustment for the premium's time-value of money (NAIC (2018)). This regulatory feature of the industry means case two always applies in this market. Our time series empirical results in the P&C industry, as documented in Table VI, therefore help to identify asset-driven insurance pricing while controlling for the potential impact of capital constraints.

In the cross sectional analysis, the result that insurer-specific asset portfolios affects relative insurance pricing across insurers is evidence that insurer investment portfolios matter for insurance pricing. However, it is possible that insurers with higher investment returns are also financially constrained and *gambling on resurrection*. To control for this potentially confounding factor, we include standard controls for insurer capital constraints (i.e. leverage, risk-cased statutory capital, asset growth). The results are once again robust.

8 Alternative Mechanisms

8.1 Insurer Default Risk

An alternative interpretation of our cross sectional results is that the insurers taking increased investment risk have higher probability of default, and thus face less demand for the insurance contracts they offer. In respect to this possible channel of insurance pricing, it is important to first note that the insurance industry is tightly regulated from a capital standpoint, with the key purpose of minimising the risk of insurer defaults on policyholders. Insurers are regulated on a risk based capital measure, and have to hold more capital when taking increased risk (including in their investment portfolios). In fact, the measure of investment portfolio credit risk that we use on the right hand side in Table III Panel A is the variable used by regulators when assessing how much capital insurers must hold for their credit portfolio investment risk. This means an increase in investment returns is also associated with an increase in the regulatory capital buffer an insurer must hold. All else equal, this should reduce the probability of default.

Finally, A.M. Best provide all insurers with a financial strength rating that ranges from A++ to C-. A lower rating would signify a higher probability of default. The life insurance data we have, taken from from Koijen and Yogo (2015), is for the subset of insurers with an A rating. The fact that we see a sensitivity between investment returns and insurance premiums *within* this group is further evidence of asset-driven insurance pricing at play, controlling for default risk. Further, our cross sectional specifications control for financial variables that demonstrate balance sheet strength. These should also absorb the impact of insurer default risk.

8.2 Reinsurance

Insurance companies use reinsurance markets to hedge or remove some of the underlying risk on the contracts they write. The level of reinsurance activity could therefore be expected to affect profitability of insurance underwriting. To rule out this alternative hypothesis as a driver of our results in Table VIII, we include the fraction of underwriting premiums which are reinsured as a control variable. We find that while premiums are significantly lower when an insurer's reinsurance activity is higher (Table AV), our main result that insurance premiums are lower when investment return are higher is still robust to the inclusion of this variable. The negative effect of reinsurance on premiums suggest that insurance companies that hedge more of the risks on their liabilities through reinsurance are able to charge lower premiums.[18]

[18] We thank Stefano Rossi for this observation.

9 Conclusion

Asset-driven insurance pricing is a new channel of insurance pricing, which shows that insurance premiums are lower when insurance companies have higher expected investment returns. In a violation of the Modigliani and Miller (1958) capital irrelevance theorem, the pricing of insurer liabilities depends on the expected returns on their asset portfolios. Specifically, insurance companies use the stable nature of insurance funding to take advantage of liquidity premium in illiquid asset markets. When expected returns are higher, insurers compete for funding, and insurance premiums fall.

A recent directive in Solvency II insurance regulation[19] means life insurers can now apply for a *matching adjustment* on some products, which allows them to apply to discount liabilities with the expected return on assets:

"The matching adjustment is an adjustment made to the risk-free interest rate when the insurer sets aside a portfolio of assets to back a predictable portion of their liabilities. It is based on the yield spread over the risk-free rate credit spread of the assigned portfolio of matching assets, minus a fundamental spread that accounts for expected default and downgrade risk. It is designed to reflect the fact that long-term, buy-and-hold investors only bear downgrade and default risks as they seek to hold assets to maturity, and allows them to capture other aspects of the spread such as the liquidity premium" – The Actuary [20]

The matching adjustment directive shows that insurers also think about their funding and investing in a similar manner to the arguments put forth in this paper.

We conclude by noting that asset-driven insurance pricing has two potential welfare implications. Firstly, insurers act as pro-cyclical investors, increasing asset allocations to illiquid investments when liquidity premium are higher, dampening asset market volatility. Second, insurers provide households with cheaper access to insurance when financial markets are distressed. These interesting macroeconomic implications of our findings offer interesting avenues for future research.

[19] see Solvency II, art. 77b and 77c

[20] https://www.theactuary.com/features/2016/06/2016/05/23/matching-adjustment-fit

Table I. Summary statistics

This table presents summary statistics of the variables used in the empirical analysis. The markups on life insurance are available biannually from 1989 through 2011 (Koijen and Yogo (2015)) and are shown both as total and annualized numbers. Financial variables (for both P&C and Life insurance) are available quarterly from March 2001 through December 2017. The financial market and macroeconomic variables are available at monthly frequencies.

	Count	Mean	SD	p05	p25	p50	p75	p95
Annuity Markups								
Life	19,923	6.75	7.07	-24.49	2.45	7.12	11.37	32.34
Life (ann.)	19,923	1.03	0.98	-1.92	0.38	0.96	1.62	4.36
Term	2,927	5.31	5.00	-17.32	2.65	5.79	8.41	32.64
Term (ann.)	2,927	1.12	1.06	-1.73	0.37	0.99	1.81	5.55
Guarantee	10,221	4.24	6.43	-24.70	0.41	4.94	8.34	32.35
Guarantee (ann.)	10,221	0.50	0.68	-2.00	0.05	0.52	0.94	2.93
Property & Casualty Financial Variables								
Underwriting Profitability	44,780	0.31	3.24	-5.09	-1.27	0.14	1.70	6.23
Underwriting Profits Volatility	27,787	2.35	1.34	0.58	1.25	2.17	3.23	4.85
Investment Return	44,780	3.08	1.29	0.95	2.13	3.08	3.97	5.22
Credit Allocation	44,780	54.09	22.40	13.17	37.68	57.98	72.58	84.68
Credit Risk	44,780	1.72	0.97	1.04	1.19	1.38	1.81	3.77
Cash Allocation	44,780	13.59	13.38	1.26	4.29	8.65	17.78	46.58
Treasuries Allocation	44,780	15.98	15.02	0.22	4.33	11.25	23.70	48.59
Stocks Allocation	44,780	11.57	11.38	0.00	1.34	8.72	17.98	36.31
Other Allocation	44,780	3.77	4.90	0.00	0.00	1.76	5.79	14.78
Size (t-1)	41,589	4.92	1.87	2.40	3.33	4.63	6.19	8.53
Asset Growth (t-1)	37,044	6.32	20.61	-11.78	0.00	5.63	11.78	27.29
Leverage (t-1)	41,589	42.54	14.44	21.17	31.62	40.51	52.24	70.58
Risk Based Capital (t-1)	41,589	4.74	2.95	1.32	2.56	3.96	6.03	11.75
Unearned Premia (t-1)	41,589	1.94	0.84	0.36	1.50	1.97	2.31	3.56
Reinsurance Activity (t-1)	41,589	0.13	0.40	-0.73	0.00	0.13	0.33	0.76
Life Financial Variables								
Investment Return	258	5.97	1.68	4.15	5.19	5.62	6.42	8.49
Size	258	16.36	1.12	14.69	15.36	16.38	17.36	18.10
Asset Growth	258	8.30	12.86	-7.99	0.11	7.34	12.91	30.98
Leverage	258	90.86	4.22	83.00	88.19	91.35	93.99	96.97
Risk Based Capital	258	14.60	45.86	-39.00	-24.00	2.00	50.00	102.00
Deferred Annuities	258	11.03	14.24	0.49	1.77	5.87	14.34	45.41
Financial Market and Macroeconomic Variables								
Credit Spread (BAA)	403	2.33	0.72	1.29	1.77	2.20	2.76	6.01
Risk Free (1yr)	469	4.65	3.73	0.10	1.30	4.63	6.64	16.72
Risk Free (5yr)	469	5.54	3.52	0.62	2.54	5.09	7.71	15.93
Slope (5yr - 1yr)	469	0.89	0.74	-1.63	0.38	0.87	1.46	2.50
TED Spread	403	0.57	0.42	0.12	0.26	0.46	0.73	3.35
Excess Bond Risk Premia	434	0.06	0.55	-1.14	-0.31	-0.04	0.28	3.00
US Unemployment Rate	469	6.22	1.68	3.60	5.00	5.70	7.30	10.80
CAPE ratio	469	22.35	8.43	6.64	16.43	22.42	26.79	44.20

Table II. Insurance funding is invested in illiquid credit assets

This table shows the aggregated balance sheets of the Life Insurance industry and the P&C Insurance Industry as of December 2017. The assets are split by the largest investment allocations, and the liabilities are split into insurance liabilities and other liabilities. The shaded regions highlight two important observations: a) there is a significant amount of credit and liquidity risk taken in insurer asset portfolios, and b) the asset portfolios are predominantly funded by insurance liabilities. The data comes from US insurance company statutory filings and is provided by SNL Global. Individual company data has been aggregated to show the industry-wide balance sheet.

	Life Insurance ($bn)	Property and Casualty ($bn)	Life Insurance (%)	Property and Casualty (%)
Total Assets	**4301**	**1998**	**100%**	**100%**
Cash & Short Term Investments	105	116	2%	6%
Bonds - US Government	235	162	5%	8%
Bonds – Corporate	2199	414	51%	21%
Bonds – Other Credit	539	404	13%	20%
Mortgage Loans	477	17	11%	1%
Stocks	105	415	2%	21%
Other Investments	414	163	9%	9%
Total Cash & Investments	4075	1691	95%	85%
None-Financial Assets	227	306	5%	15%
Total Liabilities	**4301**	**1998**	**100%**	**100%**
Insurance Liabilities	3294	1021	77%	51%
Other Liabilities	615	211	14%	11%
Capital And Surplus (Equity)	393	765	9%	38%

Table III. Understanding the investment returns of insurance companies

This table explains variation in the investment returns of insurance companies. Panel A reports the parameter estimate from the following panel regression:

$$y_{it} = \mathrm{B}'W_{it} + \beta_r \cdot risk_{it} + \beta_{w^c r} \cdot w_{it}^{credit} \times risk_{it} + \beta_{w^c rCS} \cdot w_{it}^{credit} \times risk_{it} \times CS_{t-1} + FE_t + \epsilon_{it}$$

where y_{it} is insurer i's investment return at time t and W_{it} is a vector of asset allocations including the allocation to credit, w_{it}^{credit}. We also include a numeric measure of the credit risk in the insurer's credit portfolio, $risk_{it}$, and the previous period's credit spread, CS_{t-1} (Moody's Seasoned Baa corporate bond yield over the 10-year Treasury bonds). All specifications in Panel A include time fixed effects FE_t. Investment returns are measured in bps, asset allocations are in percent, and the measure of credit risk range from 1-6 (and are as assigned by the insurance regulator).
Panel B reports the parameter estimate from the following panel regression:

$$y_{it} = \beta_y \cdot y_{i,t-k} + \mathrm{B}' \cdot X_t + FE_i + \epsilon_{it}$$

where $y_{i,t-k}$ is lagged insurer returns, X_t is a vector of time series variables that capture insurer investment opportunities or macroeconomic conditions, and FE_i captures firm fixed effects. All variables in panel B are measured in percent. The sample consists of quarterly observations from March 2001 through March 2018. t-statistics are reported in the brackets and are calculated using standard errors clustered by date and firm. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Panel A: Investment Returns: Asset Allocation and Credit Portfolio Risk

	Investment Return (bps)		
	(1)	(2)	(3)
Credit Allocation	1.25***	0.54*	0.50*
	(11.24)	(1.90)	(1.81)
Cash Allocation	-1.50***	-1.42***	-1.41***
	(-7.89)	(-6.02)	(-5.96)
Credit Risk		14.62***	14.12***
		(4.99)	(4.90)
Credit Allocation × Credit Risk		0.93***	-0.11
		(5.61)	(-0.42)
Treasuries Allocation		-0.99***	-1.00***
		(-3.06)	(-3.16)
Stocks Allocation		-0.19	-0.20
		(-0.61)	(-0.66)
Other Allocation		-0.81*	-0.74*
		(-1.94)	(-1.81)
Credit Allocation × Credit Risk × Credit Spread (t-1)			0.40***
			(4.50)
Date FE	yes	yes	yes
Adj R-sq (Within)	0.168	0.202	0.207
Observations	44,780	44,780	44,780

Panel B: Investment Returns: Persistence and Time Series Variation

	Investment Return (it)			
	(1)	(2)	(3)	(4)
Investment Return (i,t-1)	0.76***	0.57***		
	(32.19)	(24.84)		
Investment Return (i,t-5)		0.23***		
		(14.42)		
Credit Spread (t-1)			0.39***	0.25*
			(7.14)	(1.85)
Risk-free Rate (t-1)			0.52***	0.51***
			(17.36)	(13.68)
Slope (t-1)			0.45***	0.48***
			(6.19)	(6.53)
TED (t-1)				0.10
				(0.61)
CAPE (t-1)				-0.03
				(-1.31)
Firm FE	no	no	yes	yes
Adj R-sq (Within)	0.577	0.600	0.341	0.346
Observations	37,044	37,044	37,044	37,044

Table IV. Insurers with stable funding take more investment risk

This table shows the relation between insurer's investment allocation and their insurance funding. The table reports the standardized parameter estimates from the following panel regression:

$$y_{it} = \beta_{vol} \cdot Volatility_{i,t-1} + \beta_{Size} \cdot Size_{i,t-1} + B' \cdot X_{i,t-1} + FE_t + \epsilon_{it}$$

where y_{it} is either insurer i's cash allocation at time t (columns 1-3), insurer i's credit asset allocation at time t multiplied by a numeric measure of the credit risk in these portfolios at time t (columns 4-6), or insurer i's investment return at time t (columns 7-9). Independent variables include, the historical 5-year volatility of insurer i's underwriting profitability up to time and including time $t-1$, $Volatility_{i,t-1}$, the insurers size (log assets), and a vector of other balance sheet measures, X_{it}, that capture balance sheet strength. All specifications include time fixed effects FE_t. Asset allocations and funding volatility are measured in percentage and investment returns are measured in bps. Credit risk is insurer i's credit portfolio value-weighted average credit rating, with bonds assigned a number from 1-6 dependent on their credit risk (as assigned by the insurance regulator, NAIC). The sample consists of quarterly observations from March 2001 through December 2017. t-statistics are reported in the brackets and are calculated using standard errors clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Cash Allocation (perc.)			Credit Assets × Risk			Investment Return (bps)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Underwriting Volatility (i,t-1)	0.22***		0.06*	-0.26***		-0.09***	-0.16***		-0.06***
	(7.56)		(1.79)	(-8.91)		(-2.97)	(-7.18)		(-2.66)
Size (t-1)		-0.34***	-0.30***		0.36***	0.31***		0.21***	0.17***
		(-12.57)	(-9.40)		(11.61)	(8.95)		(9.80)	(7.22)
Reinsurance Activity (t-1)			0.08***			-0.00			-0.04**
			(2.75)			(-0.13)			(-2.25)
Risk Based Capital (t-1)			-0.14***			0.03			0.05**
			(-5.28)			(1.07)			(2.43)
Asset Growth (t-1)			0.05***			-0.03***			-0.02**
			(4.63)			(-2.71)			(-2.29)
Unearned Premia (t-1)			-0.05*			0.01			-0.00
			(-1.76)			(0.47)			(-0.11)
Date FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Adj R-sq (Within)	0.048	0.114	0.146	0.067	0.128	0.135	0.036	0.065	0.075
Observations	25,091	25,091	25,091	25,091	25,091	25,091	25,091	25,091	25,091

Table V. Investment returns drive the time series of premiums: life insurance

This table shows the time series relation between insurance premiums, as measured by the markups on annuities issued by life insurers, and credit spreads. It reports the parameter estimates from the following regression:

$$m_{ikt} = \beta_{CS} \cdot CS_t + \beta_{GFC} \cdot \mathbb{1}_{GFC} + \beta_{csGFC} \cdot CS_t \times \mathbb{1}_{GFC} + B' \cdot X_t + FE_i + FE_k + \epsilon_{ikt}$$

where m_{ikt} is the annualised markup set by insurer i at time t for an annuity which is in sub-product k. Sub-products vary depending on age, sex and maturity of the annuities. CS_t is Moody's credit spread of 10 year BAA corporate bonds yields over treasuries, and $\mathbb{1}_{GFC}$ is an indicator variable set to one over the global financial crisis (November 2008 through February 2010). We include a vector of time series controls X_t which includes the risk-free rate, the slope of the yield curve, the TED spread, the CAPE ratio and US unemployment rate. Columns 1-3 report the parameter estimates from time series regressions where $\overline{m}_t$ is the average markup across insurers and sub-product categories in each time period. Columns 4-5 report full panel specifications. Panel A, B and C show the results for markups on life, guarantee and fixed-term annuity products respectively. The sample consists of biannual observations from January 1989 through July 2011. The t-statistics in the time series regressions are calculated using Newey and West (1987) standard errors with automatic bandwith selection. The panel regression also includes firm and fixed effects and standard errors clustered by date and firm. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Panel A: Life Annuity Markups and Credit Spreads

	$\overline{m}_t$			m_{ikt}	
	(1)	(2)	(3)	(4)	(5)
Credit Spread	-0.44***	-0.47***	-0.57***	-0.50***	-0.66***
	(-11.55)	(-8.52)	(-6.60)	(-9.24)	(-7.91)
$\mathbb{1}_{GFC}$			-1.22**		-1.12***
			(-2.65)		(-3.09)
Credit Spread × $\mathbb{1}_{GFC}$			0.26**		0.30***
			(2.26)		(2.89)
Time Series Controls Vector		yes	yes	yes	yes
Entity FE				yes	yes
Product FE				yes	yes
Adj R-sq (Within)	0.804	0.862	0.872	0.433	0.444
Observations	73	73	73	13,663	13,663

[table continued on next page...]

Panel B: Guarantee Annuity Markups and Credit Spreads

	$\overline{m}_t$			m_{ikt}	
	(1)	(2)	(3)	(4)	(5)
Credit Spread	-0.46***	-0.41***	-0.52***	-0.45***	-0.63***
	(-12.96)	(-8.20)	(-6.45)	(-7.04)	(-7.05)
$\mathbb{1}_{GFC}$			-1.07***		-1.15***
			(-3.19)		(-3.49)
Credit Spread × $\mathbb{1}_{GFC}$			0.24**		0.32***
			(2.43)		(3.09)
Time Series Controls Vector		yes	yes	yes	yes
Entity FE				yes	yes
Product FE				yes	yes
Adj R-sq (Within)	0.803	0.873	0.880	0.530	0.551
Observations	54	54	54	16,469	16,469

Panel C: Fixed-Term Annuity Markups and Credit Spreads

	$\overline{m}_t$			m_{ikt}	
	(1)	(2)	(3)	(4)	(5)
Credit Spread	-0.55***	-0.46***	-0.67***	-0.44***	-0.66***
	(-9.09)	(-3.08)	(-4.65)	(-4.50)	(-6.45)
$\mathbb{1}_{GFC}$			-1.05*		-1.47***
			(-1.76)		(-4.41)
Credit Spread × $\mathbb{1}_{GFC}$			0.39**		0.47***
			(2.43)		(4.49)
Time Series Controls Vector		yes	yes	yes	yes
Entity FE				yes	yes
Product FE				yes	yes
Adj R-sq (Within)	0.864	0.859	0.872	0.328	0.348
Observations	46	46	46	2,921	2,921

Table VI. Investment returns drive the time series of premiums: P&C Insurance

This table shows the time series relation between insurance premiums, as measured by P&C insurer's underwriting profitability, and credit spreads. It reports the parameter estimates from the following time series regression:

$$u_{it} = \beta_{cs} \cdot CS_t + \beta_{GFC} \cdot \mathbb{1}_{GFC} + \beta_{csGFC} \cdot CS_t \times \mathbb{1}_{GFC} + B' \cdot X_t + FE_i + \epsilon_{it}$$

where u_{it}, is the underwriting profitability for insurer i in quarter t. Underwriting profitability is defined as underwriting profits (premiums earned minus losses and expenses) divided by the premiums earned. c_t is the 1-year rolling average of Moody's credit spread of BAA corporate bonds, $\mathbb{1}_{GFC}$ is an indicator variable set to one over the financial crisis (November 2008 through February 2010), and X_t is a vector of time series controls including 1-year rolling averages of investment returns and macroeconomic variables. Columns 1-3 report parameter estimates from the time series regression where the dependent variable, $\overline{u}_t$, is the average underwriting profitability in quarter t across all insurers. Columns 4-5 report parameter estimates from panel regressions with insurer fixed effects. The sample consists of quarterly observations from March 2001 through December 2017. t-statistics are reported in the brackets and are calculated using Newey and West (1987) standard errors in the time-series specifications, and standard errors clustered by date and firm in the panel specifications. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	$\overline{u}_t$			u_{it}	
	(1)	(2)	(3)	(4)	(5)
Credit Spread	-0.44***	-0.83***	-1.08***	-0.74***	-1.06***
	(-2.71)	(-3.32)	(-4.85)	(-2.94)	(-4.73)
$\mathbb{1}_{GFC}$			-1.80		-1.64
			(-1.28)		(-0.80)
Credit Spread × $\mathbb{1}_{GFC}$			0.85**		0.87*
			(2.57)		(1.72)
Time Series Controls Vector		yes	yes	yes	yes
Entity FE				yes	yes
Adj R-sq (Within)	0.119	0.222	0.293	0.031	0.039
Observations	67	67	67	41,589	41,589

Table VII. Investment returns drive the cross section of premiums: Life Insurance

This table shows the cross section relation between insurance premiums, as measured by the markups on annuities issued by life insurers, and firm-specific expected investment returns. It reports the parameter estimate from the following panel regression:

$$m_{ikt} = \beta_y \cdot y_{it} + \beta_{yGFC} \cdot y_{it} \times \mathbb{1}_{GFC} + B' \cdot X_{it-1} + FE_i + FE_k + FE_t + \epsilon_{ikt}$$

where m_{ikt} is the annualised markup set by insurer i at time t for an annuity which is in sub-product category k, y_{it} is the insurer's investment return, $\mathbb{1}_{GFC}$ is an indicator variable set to one over the global financial crisis (November 2008 through February 2010), and X_{it} is a vector of lagged variables that capture balance sheet strength (leverage, risk-based capital, asset growth and deferred annuities). The control vector includes squared variables to capture non-linear effects of capital constraints. We additionally control for date fixed effects, product fixed effects and firm fixed effects, and report within group r-squared. Panel A, B and C show the results for markups on fixed-term, guarantee and life annuity products respectively. The sample consists of quarterly observations from March 2001 through March 2018. t-statistics are reported in bracket and calculated using standard errors clustered by date and firm. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Panel A: Fixed Term Annuities

	(1)	(2)	(3)	(4)	(5)
Investment Return	-0.03***	-0.03***	-0.01	-0.03***	-0.01
	(-2.63)	(-2.86)	(-1.31)	(-2.77)	(-1.20)
Investment Return × $\mathbb{1}_{GFC}$				-0.06	-0.10*
				(-0.99)	(-1.74)
Firm Controls Vector		yes		yes	
Firm FE			yes		yes
Date FE	yes	yes	yes	yes	yes
Product FE	yes	yes	yes	yes	yes
Adj R-sq (Within)	0.010	0.078	0.007	0.078	0.009
Observations	955	955	955	955	955

Panel B: Guarantee Annuities

	(1)	(2)	(3)	(4)	(5)
Investment Return	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***
	(-3.86)	(-4.35)	(-3.21)	(-4.34)	(-2.72)
Investment Return × $\mathbb{1}_{GFC}$				0.00	-0.05***
				(0.20)	(-4.70)
Firm Controls Vector		yes		yes	
Firm FE			yes		yes
Date FE	yes	yes	yes	yes	yes
Product FE	yes	yes	yes	yes	yes
Adj R-sq (Within)	0.121	0.229	0.165	0.229	0.168
Observations	5,989	5,989	5,989	5,989	5,989

[table continued on next page...]

Panel C: Life Annuities

	(1)	(2)	(3)	(4)	(5)
Investment Return	0.00	-0.02***	-0.02***	-0.02***	-0.02***
	(0.37)	(-2.97)	(-3.15)	(-3.48)	(-3.31)
Investment Return × $\mathbb{1}_{GFC}$				0.08***	0.03
				(3.55)	(1.54)
Firm Controls Vector		yes		yes	
Firm FE			yes		yes
Date FE	yes	yes	yes	yes	yes
Product FE	yes	yes	yes	yes	yes
Adj R-sq (Within)	0.001	0.069	0.004	0.072	0.005
Observations	3,410	3,410	3,410	3,410	3,410

Table VIII. Investment returns drive the cross section of premiums: P&C Insurance

This table shows the cross section relation between insurance premiums, as measured by P&C insurer's underwriting profitability, and firm-specific expected investment returns. It reports the parameter estimate from the following panel regression:

$$u_{it} = \beta_y \cdot y_{it} + \beta_{yGFC} \cdot y_{it} \times \mathbb{1}_{GFC} + B' \cdot X_{it-1} + FE_i + FE_t + \epsilon_{it}$$

where u_{it} is the underwriting profitability for insurer i at time t, and y_{it} is the insurer's investment return. We additionally control for date fixed effects, firm fixed effects and X_{it}, which is a vector of lagged variables that capture balance sheet strength (leverage, risk-based capital, asset growth and unearned premiums). This includes variables squared to control for non-linear effects of capital constraints. We also include a control for the level of reinsurance activity insurance company i engages in at time t. The samples consist of quarterly observations from Q1 2001 through Q4 2017. In columns 4-5 we interact investment return with an indicator variable $\mathbb{1}_{GFC}$ set equal to one during the global financial crisis (Q4 2008 through Q1 2010). t-statistics are reported in bracket and calculated using standard errors clustered by date and firm. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)
Investment Return	-0.10**	-0.12***	-0.11***	-0.13***	-0.12***
	(-2.37)	(-3.09)	(-5.19)	(-3.37)	(-5.70)
Investment Return × FC				0.10	0.12**
				(1.52)	(2.56)
Firm Controls Vector		yes		yes	
Firm FE			yes		yes
Time FE	yes	yes	yes	yes	yes
Adj R-sq (Within)	0.001	0.071	0.001	0.071	0.001
Observations	37,044	37,044	37,044	37,044	37,044

Table IX. P&C Insurance cross section: instrumented variable estimation

This table shows the cross section relation between insurance premiums, as measured by P&C insurer's underwriting profitability, and the instrumented expected investment returns of individual insurance companies. Columns (3) and (4) report the parameter estimate from the following instrumental variable panel regression:

$$u_{it} = \beta_y \cdot y_{it} + B' \cdot X_{it-1} + FE_t + \epsilon_{it}$$

where u_{it} is the underwriting profitability for insurer i at time t, and y_{it} is the instrumented investment return of insurer i at time t. Columns (1) and (2) report the first-stage results from the regression

$$y_{it} = \beta_{vol} \cdot \mathit{Volatility}_{i,t-1} + \beta_{Size} \cdot Size_{i,t-1} + B' \cdot X_{it-1} + FE_t + \epsilon_{it}$$

where the instruments are the historical 5-year volatility of insurer i's underwriting profitability up to and including time $t-1$, $\mathit{Volatility}_{i,t-1}$, and the insurers size (log assets) at $t-1$. First stage results in Columns (1) and (2) correspond to the second-stage results in Columns (3) and (4) respectively . We control for date fixed effect in all specifications, and in (2) and (4) we include an untabulated vector, X_{it-1}, of lagged variables that capture balance sheet strength (leverage, risk-based capital, asset growth and unearned premiums), and the level of reinsurance activity insurance company i engages in at time t. The samples consist of quarterly observations from Q1 2001 through Q4 2017. For the second stage, we report the Cragg-Donald Wald F-statistic, and in the case where we have two instrumental variables (Column 4), we report the p-value from the Sargan's χ^2 test of overidentifying restrictions. t-statistics are reported in bracket and calculated using standard errors clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	First Stage:		Second Stage:	
	(1)	(2)	(3)	(4)
Underwriting Volatility (t-1)	-0.16***	-0.07***		
	(-7.47)	(-2.63)		
Size (t-1)		0.17***		
		(6.69)		
Investment Return			-0.35***	-0.27**
			(-3.41)	(-2.36)
Control Vector		yes		yes
Date FE	yes	yes	yes	yes
Adj R-sq (Within)	0.040	0.075		
Cragg-Donald F-stat			101.576	2042.461
Sargan test p-value				0.478
Observations	25,091	25,091	25,091	25,091

Table X. Life Insurance Cross Section: evidence from mergers and acquisitions

This table shows the relation between the annuity markups and investment returns using a difference-in-differences approach around merger events. The treatment group is the life insurance companies involved in a merger and acquisition event over our sample, and the control group is all other life insurance companies. The control time period is the two years pre-mergers, and the treatment is the two years following merger. The table reports the parameter estimate from the following regression:

$$m_{ikt} = \beta_D \cdot D_{it} + FE_i + FE_k + FE_t + \epsilon_{ijt}$$

where m_{ikt} is the markup set by insurer i at time t on product k, and D_{it} is a variable set equal to zero for all observations except for treatment group insurance companies in the treatment period (the two years following their merger or acquisition event). For these observations, the variable is set equal to the treatment group insurance company's investment return minus the investment return of the other insurance company involved in the transaction (i.e. it is the investment return differential). For each individual mergers, we select the two years either side of the event for our sample, with our total sample made up of the union of the individual merger samples. This leads to 941 observations across 20 quarterly dates, with 5 treatment group entities and 48 control group entities. We use one annuity product type for each of our three broad categories of annuity - 20yr fixed term annuity, life annuity for males aged 50, and 10 year guarantee life annuity for a male aged 50. We control for time, company and product fixed effects. Standard errors are clustered by insurance company and date. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	markup (ikt)
Δ Investment Return(it)	-0.22***
	(-3.44)
Firm FE	yes
Date FE	yes
Product FE	yes
Adj R-sq (Within)	0.007
Observations	2318

Table XI. Evidence from excess bond risk premium

This table shows the relation between the markups on annuities issued by life insurers and the expected return component of credit spreads. It reports the parameter estimate from the

$$m_{jt} = \beta_e \cdot EBP_t + \beta_{df} \cdot DF_t + \beta_{eGFC} \cdot EBP_t \times \mathbb{1}_{GFC} + \beta_{dGFC} \cdot DF_t \times \mathbb{1}_{GFC} + FE_i + FE_k + \epsilon_{jt}$$

where $j = (i, k)$ and m_{jt} is the annualised markup set by insurer i at time t for an annuity which is in sub-product category k. Sub-products vary depending on age, sex and maturity of the annuities. EBP_t is the Gilchrist and Zakrajšek (2012) credit spread attributed to excess bond risk premium, DF_t is the credit spread attributed to default losses, and $\mathbb{1}_{GFC}$ is an indicator variable set to one over the global financial crisis (November 2008 through February 2010). We include a vector of time series controls X_t which includes the risk-free rate, the slope of the yield curve, the TED spread, the CAPE ratio and US unemployment rate. We also include lagged markups in the control vector. Columns 1-2 report the parameter estimates where markups, $\overline{m}_t$, are averaged across insurers and sub-products in each time period. Columns 3-4 report full panel specifications. Panel A, B and C show the results for markups on life, guarantee and fixed-term annuity products respectively. The sample consists of biannual observations from January 1989 through July 2011. t-statistics in the time series regressions are calculated using Newey and West (1987) standard errors with automatic bandwith selection. The panel regression also includes firm and product fixed effects and standard errors clustered by date and firm. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Panel A: Life Annuities

	(1)	(2)	(3)	(4)
Excess Bond Risk Premia	-0.36***	-0.61***	-0.31***	-0.46***
	(-4.35)	(-5.39)	(-4.20)	(-5.07)
Default Risk	-0.10	0.27	-0.03	0.18
	(-0.73)	(1.45)	(-0.39)	(1.22)
$\mathbb{1}_{Fin.Crisis}$		0.71		1.21**
		(1.39)		(2.31)
Excess Bond Risk Premia × $\mathbb{1}_{Fin.Crisis}$		0.48***		0.42***
		(4.11)		(4.35)
Default Risk × $\mathbb{1}_{Fin.Crisis}$		-0.43**		-0.48***
		(-2.51)		(-2.75)
Entity FE			yes	yes
Product FE			yes	yes
Time Series Controls	yes	yes	yes	yes
Adj R-sq (Within)	0.871	0.895	0.600	0.618
Observations	72	72	12460	12460

[table continued on next page...]

Panel B: Guarantee Annuities

	(1)	(2)	(3)	(4)
Excess Bond Risk Premia	-0.27***	-0.45***	-0.27***	-0.33***
	(-4.21)	(-10.08)	(-4.75)	(-5.08)
Default Risk	-0.17	-0.06	-0.10	-0.21
	(-1.56)	(-0.29)	(-1.22)	(-1.52)
$\mathbb{1}_{Fin.Crisis}$		0.12		0.18
		(0.20)		(0.34)
Excess Bond Risk Premia × $\mathbb{1}_{Fin.Crisis}$		0.37***		0.23***
		(4.25)		(2.92)
Default Risk × $\mathbb{1}_{Fin.Crisis}$		-0.15		-0.05
		(-0.72)		(-0.27)
Entity FE			yes	yes
Product FE			yes	yes
Time Series Controls	yes	yes	yes	yes
Adj R-sq (Within)	0.884	0.914	0.670	0.685
Observations	53	53	14529	14529

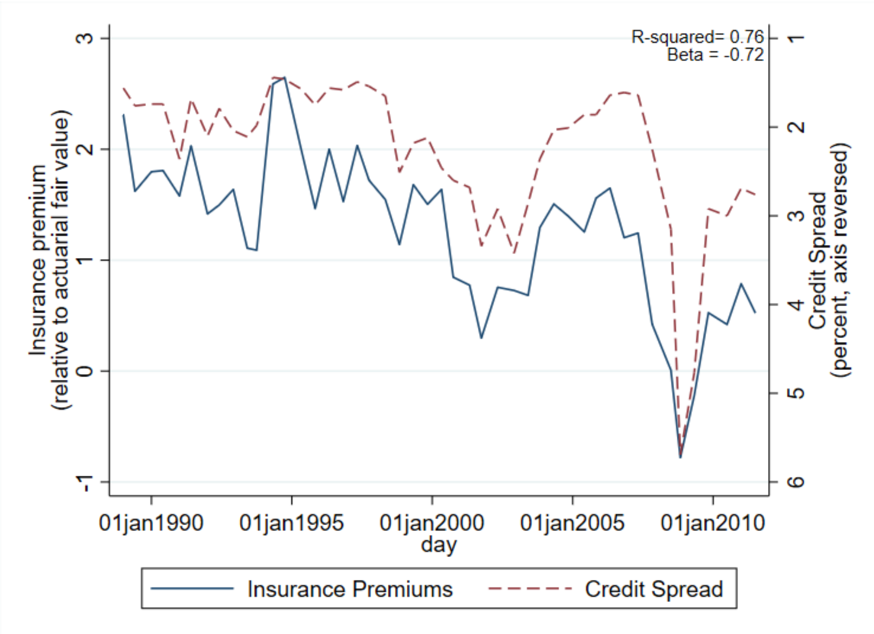
Panel C: Fixed Term Annuities

	(1)	(2)	(3)	(4)
Excess Bond Risk Premia	-0.63***	-0.68***	-0.52***	-0.56***
	(-4.97)	(-5.01)	(-6.60)	(-6.59)
Default Risk	0.35*	0.69*	0.27***	0.37**
	(2.00)	(1.78)	(3.32)	(2.09)
$\mathbb{1}_{Fin.Crisis}$		0.60		1.34**
		(0.70)		(2.41)
Excess Bond Risk Premia × $\mathbb{1}_{Fin.Crisis}$		0.26*		0.58***
		(1.85)		(5.25)
Default Risk × $\mathbb{1}_{Fin.Crisis}$		-0.41		-0.55***
		(-1.22)		(-3.08)
Entity FE			yes	yes
Product FE			yes	yes
Time Series Controls	yes	yes	yes	yes
Adj R-sq (Within)	0.910	0.911	0.472	0.475
Observations	45	45	2557	2557

Figure 1. Expected investment returns drive the time series of insurance premiums.

This figure shows the relation between insurance premiums and insurer expected investment returns as proxied by credit spreads. Panel A plots the two time series in levels. Panel B plots a scatter plot of the two time series in changes. Insurance premiums are measured as the percent deviation of the quoted price from actuarially fair value. We use the industry average 10 year fixed term annuity markup of Koijen and Yogo (2015). The credit spread variable is Moody's BAA 10-year corporate bonds yield over 10-year treasury yield (fred.stlouisfed.org).

(a) Time-Series Graph (Levels)



(b) Scatter Plot (Changes)

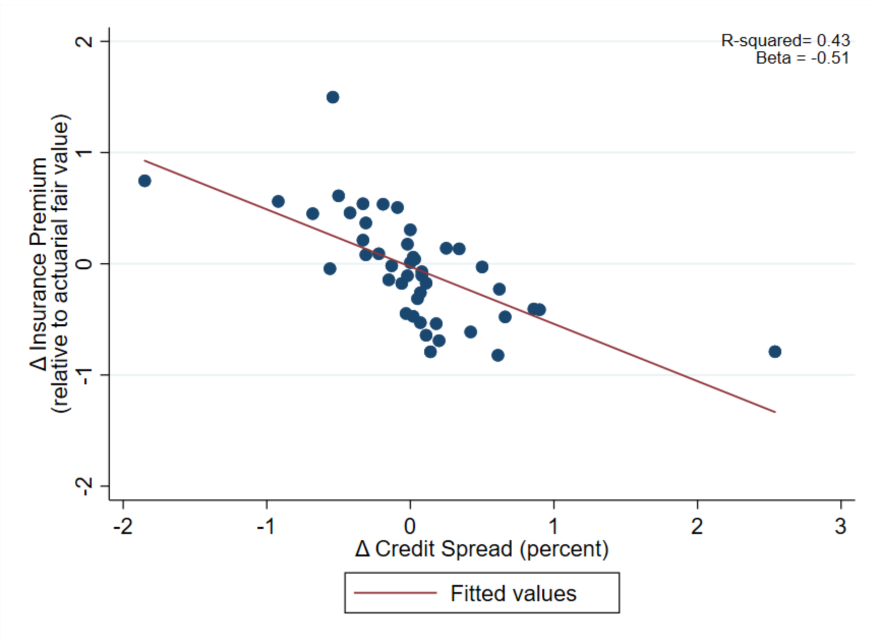
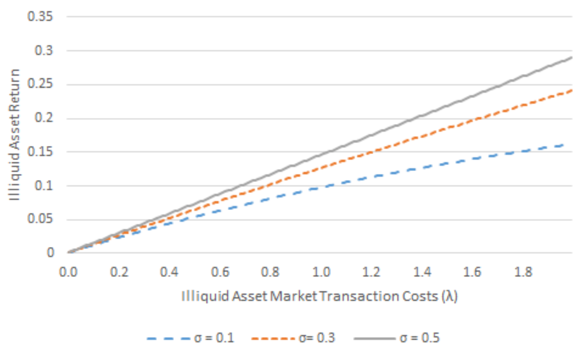


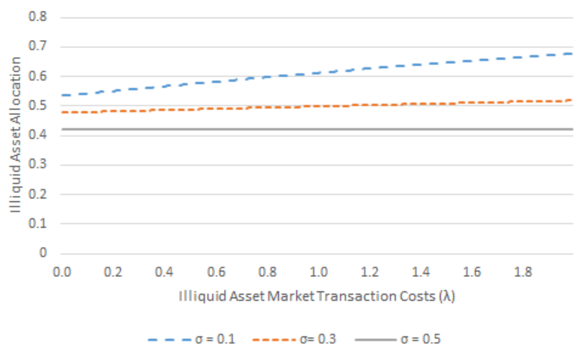
Figure 2. Model predictions.

This figure presents numerical solutions of the model with the parameters: asset supply $S = 1$, investors have $\omega = 0.2$ probability of being early consumers, insurance claims arrive at $t = 1$ with probability $\bar{\tau} = 0.5$, elasticity of insurance demand is $\epsilon = 15$, the fixed parameter in the demand function is $k = 1$, claims are $\tilde{C} = 1$, and the insurer is endowed with equity capital $E = 0.25$. Panel A, B and C plot the expected return on the illiquid asset, R, the insurance company's share in illiquid asset, Θ/S, and the premium markup relative to the expected claim, $P/\bar{C} - 1$, respectively. In each panel the variable is plotted as a function of of the asset market illiquidity, λ, with three choices of funding stability, σ.

(a) Return on the Illiquid Asset



(b) Insurer Illiquid Asset Allocation



(c) Premium Relative to Actuarial Fair Price

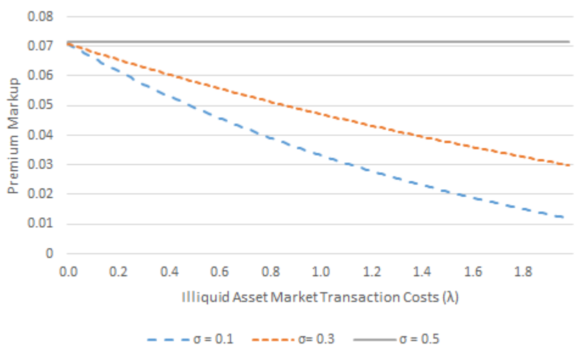
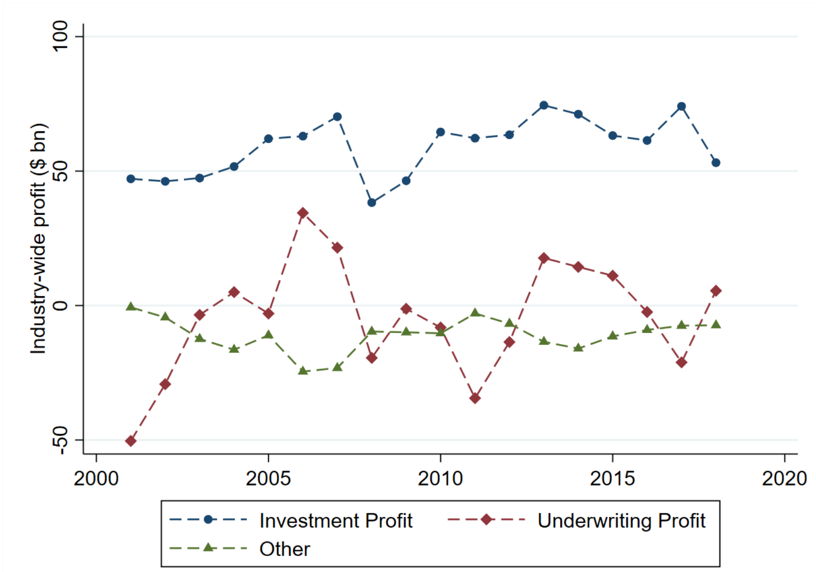


Figure 3. Investment income drives total net income.

This figure plots the P&C industry's aggregate net income split between the main contributing sources. The three components are earnings generated from i) insurance underwriting, ii) investment portfolios, iii) other. Together they constitute the total net income of the industry. In Panel A, the profits on insurance underwriting are the premiums earned minus losses and expenses. As per the industry reporting standard, it does not include any adjustment for the time-value of money of underwriting. In Panel B, we increase (decrease) underwriting (investment) income by the value of insurance liabilities multiplied by the risk-free rate. The data comes from US insurance company statutory filings and is provided by SNL Global. Individual company data has been aggregated to show the industry-wide net income.

(a) Net Income as reported by insurance companies



(b) Adjusting for the time-value of money of underwriting funding

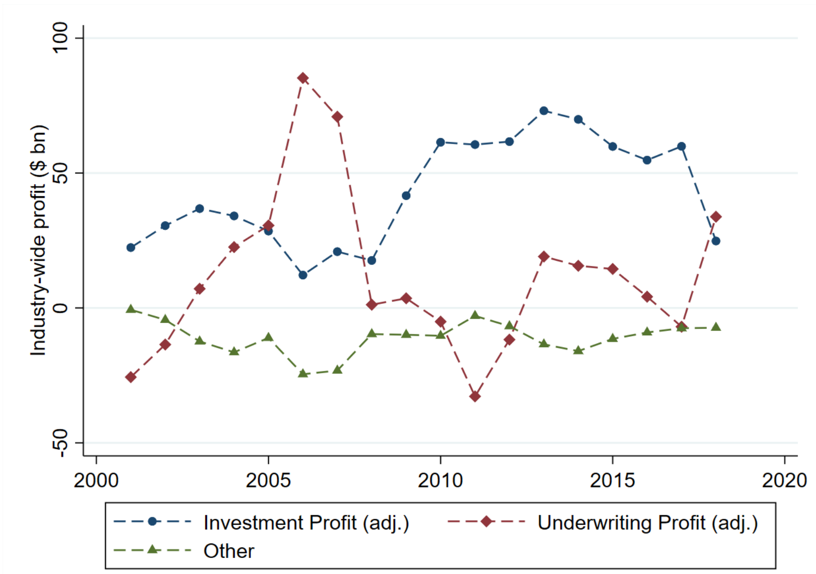


Figure 4. Variation in the expected investment returns of insurance companies.

This figure illustrates variation in the expected investment returns of insurance companies in both the time series and cross section. In each reporting quarter of our sample, the figure presents a boxplot of expected investment returns. Our sample includes firm-level data for 1,104 P&C insurers in total. Expected investment returns are measured as the net yield on invested assets, as reported in insurance company financial accounts. The data comes from US insurance company statutory filings and is provided by SNL Global.

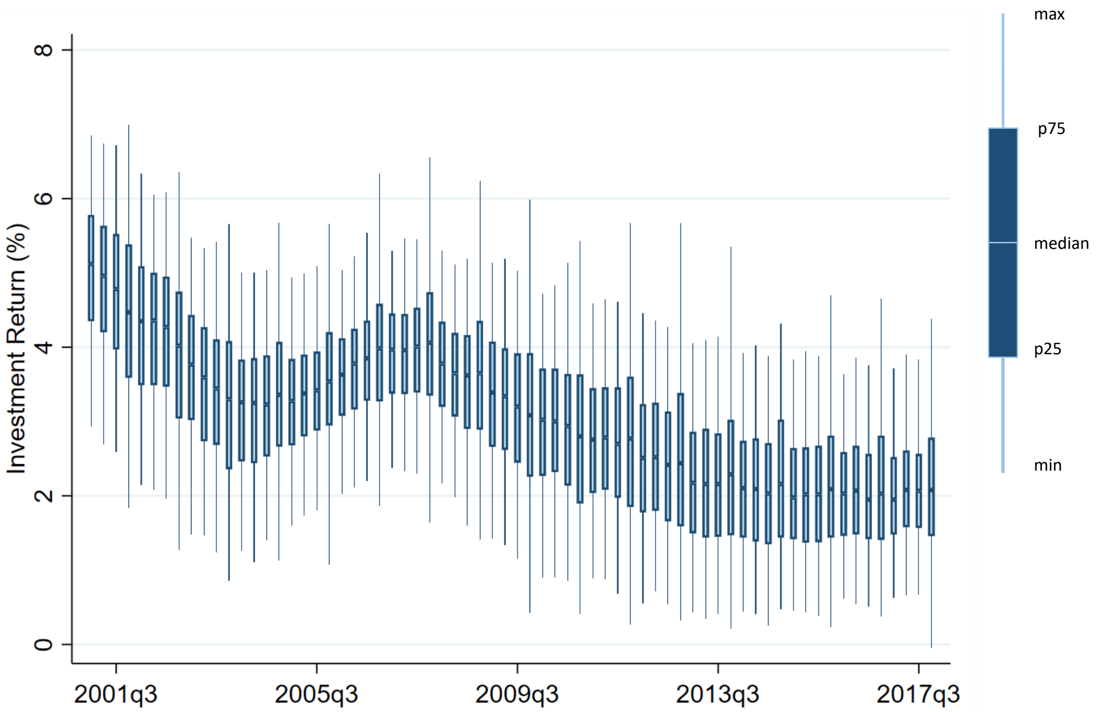


Figure 5. Expected investment returns drive the cross section of insurance premiums.

This figure presents a binned scatter plot of insurer's insurance premiums against their expected investment returns. Insurance companies have been grouped into 20 equal sized portfolios based on the ranking of their investment portfolio returns. The figure plots each portfolio's average premium against its average investment return. Insurance premiums are measured as the ratio of an insurer company's insurance underwriting profit to their insurance liabilities. The sample includes firm-level data for 1,104 Property & Casualty (P&C) insurers over the period Q1 2001 to Q4 2017, with a total of 44,780 observations. The data is reported in US insurance company statutory filings and is provided by SNL Global.

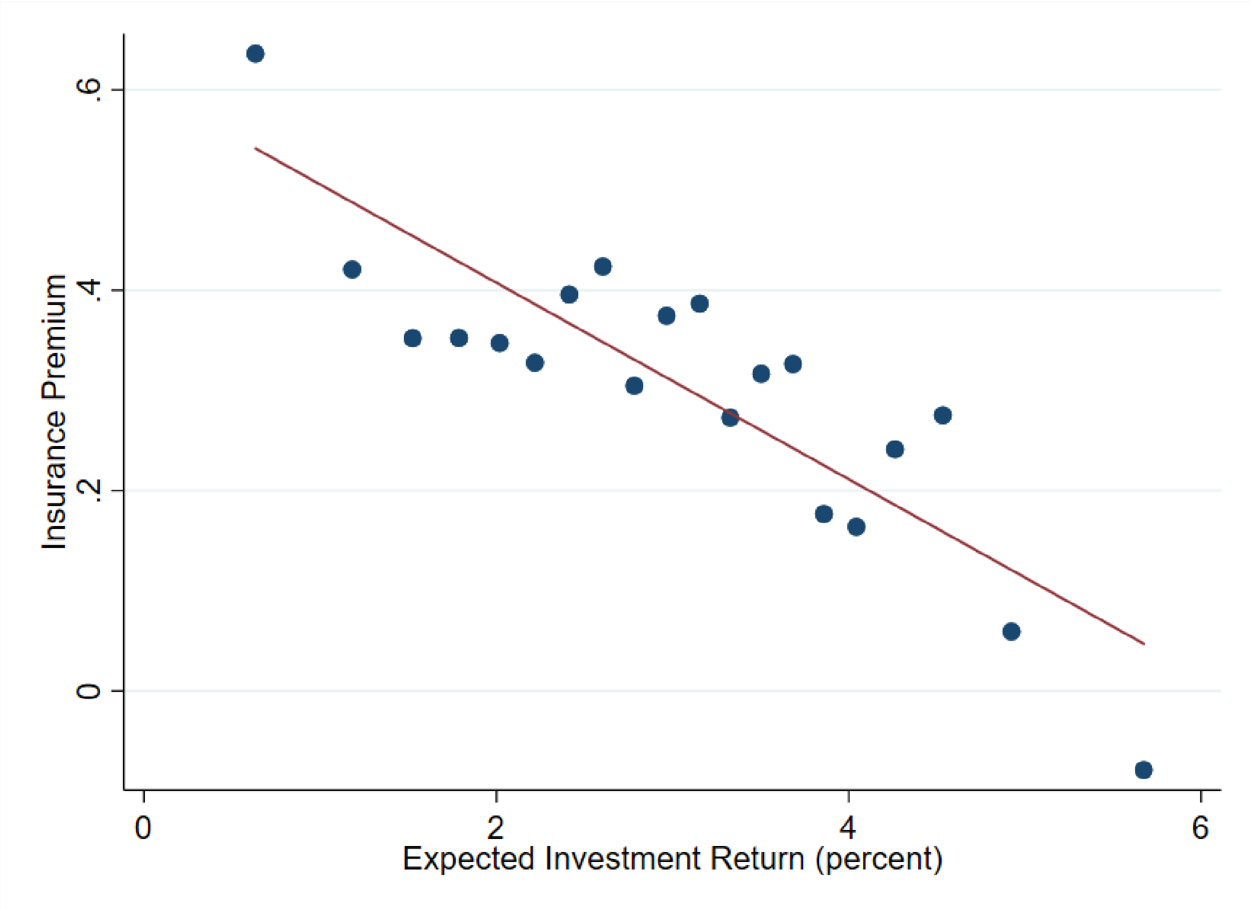
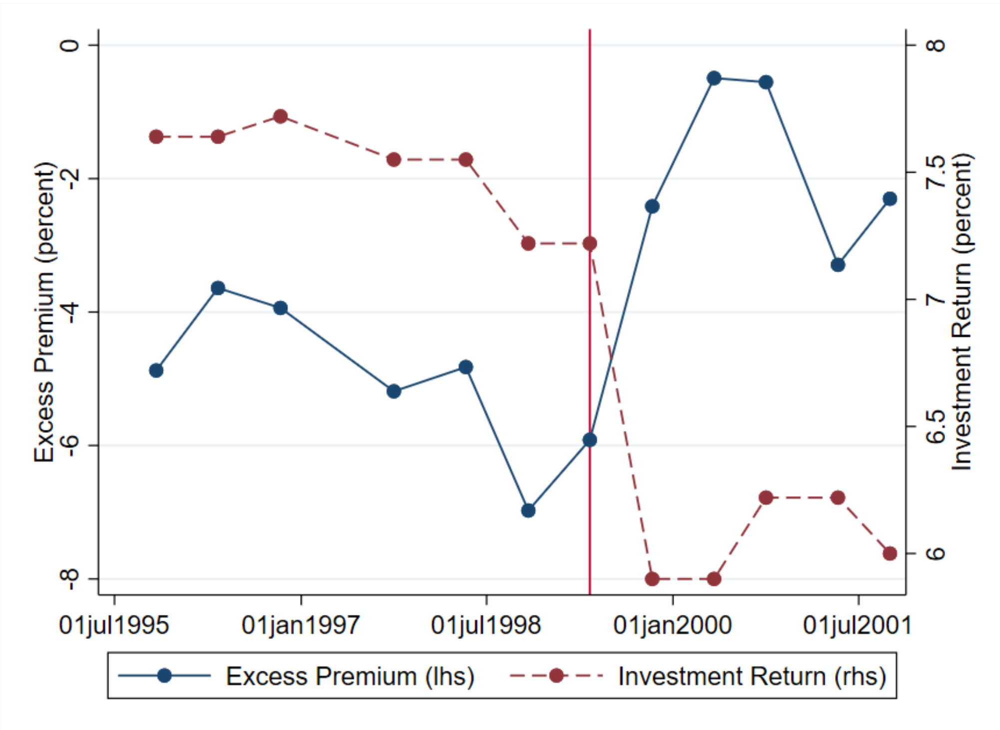


Figure 6. Mergers & acquisitions evidence - american heritage acquisition case study.

This figure plots American Heritage's excess markup on a 10yr annuity and their investment portfolio return. The sample period is 1995/2001. On October 1999 American Heritage was acquired by AllState Insurance. The acquisition is denoted by vertical line in the figure. A markup m_{ikt} for insurer i at time t on product k is the percentage deviation of the insurer's quoted price relative to the actuarial fair price. The excess markup $m^{ex}_{ikt} = m_{ikt} - \bar{m}_{kt}$ is the insurer's markup minus the industry average markup at time t on product k. The investment return is the investment portfolio income over the total value of invested assets. Markup data is provided by Koijen and Yogo (2015) and investment returns are collected this from insurer financial statements.



10 Institutional Background

10.1 Underwriting Profit in Life Insurance

Mitchell, Poterba, Warshawsky, and Brown (1999) and Koijen and Yogo (2015) have documented markups an average of 6 to 10 percent on specific life insurance products, which is after adjusting for a time value of money (assumed to be the risk-free rate). While these markups make life insurance underwriting look profitable at first glance, it is important to note that they are gross of operating expenses and commissions. Expenses on the specific products of their studies are not available to make a direct net of expenses assessment. However, on an aggregated basis, the life insurance industry reported commission and expense costs that were 20% of premiums in 2018 (SNL Statutory Files). It is therefore not unreasonable to assume that life insurance, like P&C, is dependent on asset returns for overall profitability.

Indeed, for comparision, in figure A1 we plot P&C underwriting income between its three main components - claims and expenses (outflows) and earned premium (inflows). It shows that expesnes are significant fraction of premiums, ranging from 25%-30% across the sample. P&C underwriting performance gross of expenses looks extremely profitable. In other words, expenses are critical for an overall understanding of underwriting performance.

10.2 Accounting Treatment of the Investment Returns of Insurance Companies

For cross sectional comparisons of insurer expected investment return, we use their self-reported *Net Yield on Invested Assets*. This is their accounting return on assets, and is defined as dollar net income from investments over the dollar book value of invested assets. Anecdotally, we know from market participants that it is the key metric from which insurance companies assess their expected investment portfolio performance.

For fixed income assets, which are the average insurers' main asset allocation, net yield on any asset is simply the amortisation of the purchase yield. Such treatment of assets reflects that insurers are buy and hold investors and can weather mark to market fluctuations. If the insurer does sell a bond before maturity, in the reporting period of sale the realised mark to market gain/loss is also included in the net yield measure. Further, if there are significant revisions to the prospects for a bond (i.e. default appears likely), adjustments may also be made in reported investment income. For equity investments, the net yield is the dividend rate, with mark to market fluctuations once again realised at the point of sale.

To capture insurers' expected returns at an industry-level we use the credit spread on corporate bonds. This is the average insurers' main source of investment risk and thus is our best proxy for industry wide investment opportunities. We also use the excess bond risk premium portion of credit spreads as provided in (Gilchrist and Zakrajšek (2012)), which is a way to strip out expected default loss from the credit spread.

11 Appendix Figures and Tables

Figure A1. P&C Insurance - Industry Wide Insurance Underwriting Cashflows.

This figures plots the industry-wide insurance underwriting cashflows in Property & Casualty markets. Total income from insurance underwriting are the premiums received minus the claims paid and the operating expenses associated with the running of an insurance underwriting business (pricing, reserving, marketing, operations etc.). The data comes from quarterly US insurance company statutory filings 2001:2018 and is provided by SNL Global. Individual company data has been aggregated to show the industry-wide net income.

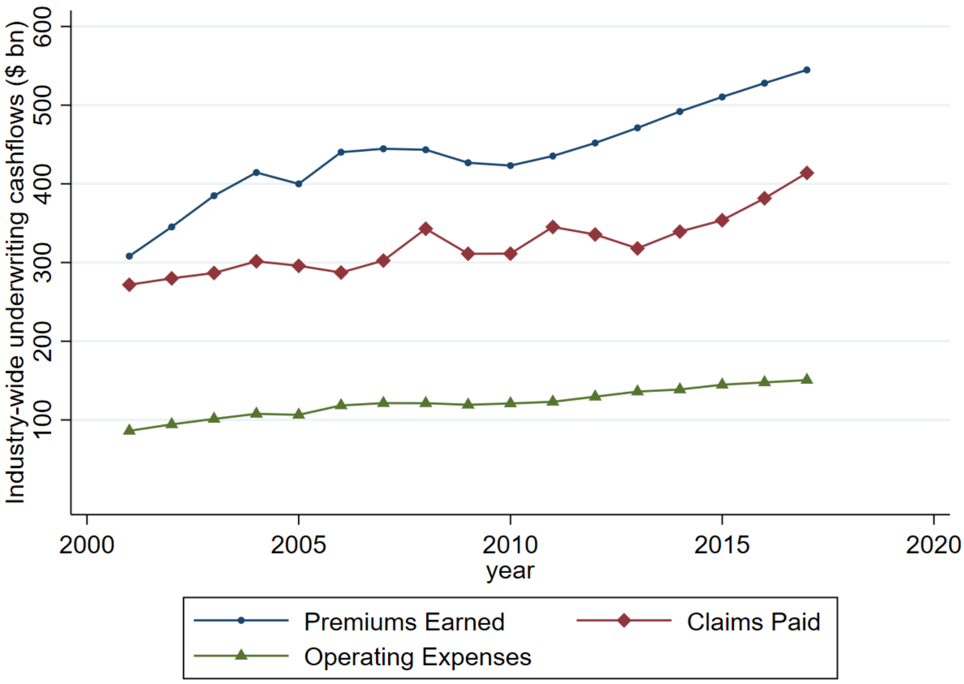
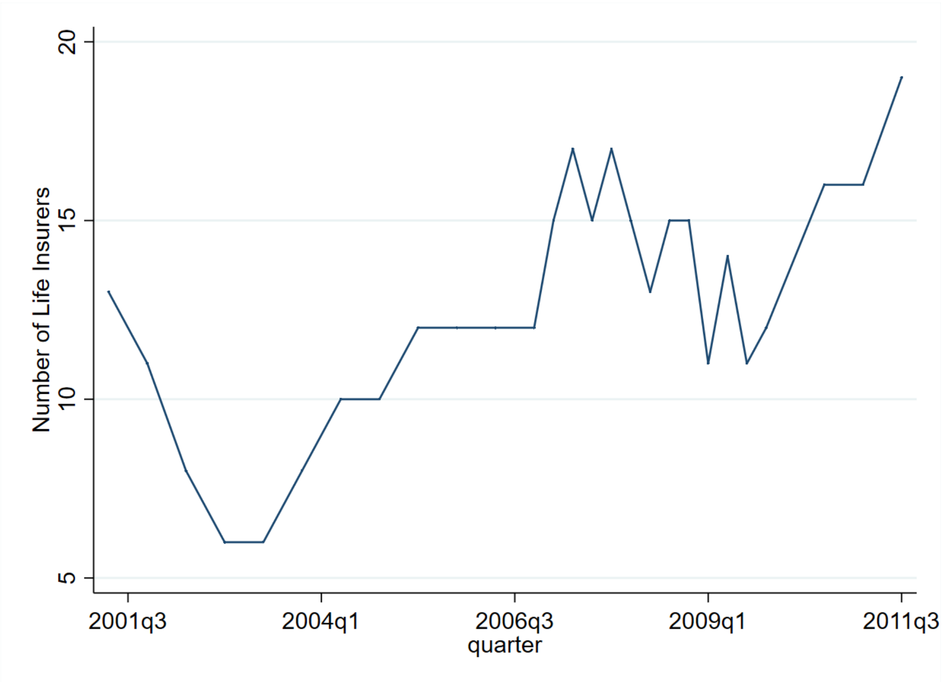


Figure A2. Entities in the Cross-Section

This figures plots the number of entities observed in the cross-section for each time-period. Panel A plots the number of life insurance companies in annuity cross-sectional regressions. Panel B plots the number of Property & Casualty entities.

(a) Life Insurers (annuities)



(b) P&C Insurers

Table AI. Mergers and Acquisitions Sample

This table shows the sample of mergers and acquistions that exist for our life insurance company dataset. The insurance companies underlined are those for which we have markup data for both pre and post the event.

Company A	**Company B**	**Deal Type**	**Date of Completion**
<u>American Heritage</u>	AllState Insurance	Acquisition	October 1999
<u>General Electric Capital Assurance</u>	Genworth Financial	Acquisition	January 2003
<u>John Hancock</u>	ManuLife	Acquisition	April 2004
<u>Jefferson-Pilot</u>	<u>Lincoln National</u>	Merger	April 2006

Table AII. Life Insurance Time Series - Full Specification Estimates

This table shows the relation between the markups on annuities issued by life insurers and credit spreads. It reports the parameter estimates from the following regression:

$$m_{ikt} = \beta_c \cdot c_t + \beta_{GFC} \cdot \mathbb{1}_{GFC} + \beta_{cGFC} \cdot c_t \times \mathbb{1}_{GFC} + B' \cdot X_t + FE_i + FE_k + \epsilon_{ikt}$$

wherem_{ikt} is the annualised markup set by insurer i at time t for an annuity which is in sub-product category k. Sub-products vary depending on age, sex and maturity of the annuities. c_t is Moody's credit spread of BAA corporate bonds, and $\mathbb{1}_{GFC}$ is an indicator variable set to one over the global financial crisis (November 2008 through February 2010). We include a vector of time series controls X_t which includes the risk-free rate, the slope of the yield curve, the TED spread and US unemployment rate. Columns 1-3 report the parameter estimates from time series regressions where for the dependent variable, $\overline{m}_t$, we have averaged across insurers and sub-product categories in each time period. Columns 4-5 are full panel specifications. Panel A, B and C show the results for markups on fixed-term, guarantee and life annuity products respectively. The sample consists of biannual observations from January 1989 through July 2011. The t-statistics in the time series regressions are calculated using Newey and West (1987) standard errors with automatic bandwith selection. The panel regression also includes firm and fixed effects and standard errors clustered by date and firm. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Panel A: Life Term Annuities

	$\overline{m}_t$			m_{ikt}	
	(1)	(2)	(3)	(4)	(5)
Credit Spread	-0.44***	-0.47***	-0.57***	-0.50***	-0.66***
	(-11.55)	(-8.52)	(-6.60)	(-9.24)	(-7.91)
$\mathbb{1}_{GFC}$			-1.22**		-1.12***
			(-2.65)		(-3.09)
Credit Spread × $\mathbb{1}_{GFC}$			0.26**		0.30***
			(2.26)		(2.89)
Risk Free (5yr)		0.12	0.13*	0.13***	0.10***
		(1.24)	(1.81)	(4.50)	(3.49)
Slope (5yr - 1yr)		0.14	0.20*	0.07	0.14**
		(1.04)	(1.79)	(1.33)	(2.51)
Ted Spread		-0.09	-0.04	0.04	0.10
		(-0.91)	(-0.34)	(0.49)	(1.19)
CAPE ratio		0.02***	0.02***	0.01	0.01**
		(2.67)	(3.59)	(1.20)	(2.29)
Unemployment Rate		0.12**	0.17***	0.17***	0.18***
		(2.38)	(3.41)	(5.31)	(5.49)
Duration (j,t)	-0.34***	0.02	0.13		
	(-3.17)	(0.08)	(0.64)		
Constant	5.06***	0.19	-1.07		
	(5.79)	(0.07)	(-0.48)		
Time Series Controls Vector		yes	yes	yes	yes
Entity FE				yes	yes
Product FE				yes	yes
Adj R-sq (Within)	0.804	0.862	0.872	0.433	0.444
Observations	73	73	73	13,663	13,663

[table continued on next page...]

Panel B: Guarantee Annuities

	$\overline{m}_t$			m_{ikt}	
	(1)	(2)	(3)	(4)	(5)
Credit Spread	-0.46***	-0.41***	-0.52***	-0.45***	-0.63***
	(-12.96)	(-8.20)	(-6.45)	(-7.04)	(-7.05)
$\mathbb{1}_{GFC}$			-1.07***		-1.15***
			(-3.19)		(-3.49)
Credit Spread × $\mathbb{1}_{GFC}$			0.24**		0.32***
			(2.43)		(3.09)
Risk Free (5yr)		0.13*	0.16	0.10*	0.08
		(1.69)	(1.49)	(2.00)	(1.06)
Slope (5yr - 1yr)		0.05	0.12*	0.07	0.16***
		(0.64)	(1.91)	(1.07)	(2.92)
Ted Spread		-0.07	-0.01	-0.04	0.02
		(-0.69)	(-0.13)	(-0.48)	(0.24)
CAPE ratio		0.01*	0.01	0.01	0.01
		(1.71)	(1.35)	(1.38)	(1.63)
Unemployment Rate		0.11**	0.16***	0.14***	0.15***
		(2.51)	(3.50)	(4.19)	(3.84)
Duration (j,t)	-0.04	-0.09	-0.14		
	(-0.42)	(-0.91)	(-1.53)		
Constant	2.08**	0.85	1.18		
	(2.25)	(0.81)	(1.04)		
Time Series Controls Vector		yes	yes	yes	yes
Entity FE				yes	yes
Product FE				yes	yes
Adj R-sq (Within)	0.803	0.873	0.880	0.530	0.551
Observations	54	54	54	16,469	16,469

Panel C: Term Annuities

	$\overline{m}_t$			m_{ikt}	
	(1)	(2)	(3)	(4)	(5)
Credit Spread	-0.55***	-0.46***	-0.67***	-0.44***	-0.66***
	(-9.09)	(-3.08)	(-4.65)	(-4.50)	(-6.45)
$\mathbb{1}_{GFC}$			-1.05*		-1.47***
			(-1.76)		(-4.41)
Credit Spread × $\mathbb{1}_{GFC}$			0.39**		0.47***
			(2.43)		(4.49)
Risk Free (5yr)		0.07	0.07*	0.18***	0.15***
		(1.32)	(1.72)	(4.29)	(4.48)
Slope (5yr - 1yr)		0.02	0.07	0.04	0.08
		(0.21)	(0.70)	(0.48)	(1.18)
Ted Spread		-0.14	-0.25*	-0.08	-0.18
		(-0.71)	(-1.82)	(-0.43)	(-1.46)
CAPE ratio		0.01	0.01	0.01**	0.02***
		(1.29)	(1.59)	(2.13)	(3.46)
Unemployment Rate		0.01	0.01	0.10**	0.11***
		(0.26)	(0.14)	(2.62)	(3.27)
Duration (j,t)	-0.28***	-0.26***	-0.23***		
	(-6.34)	(-5.59)	(-4.88)		
Constant	4.25***	3.31***	3.45***		
	(18.21)	(4.48)	(4.38)		
Time Series Controls Vector		yes	yes	yes	yes
Entity FE				yes	yes
Product FE				yes	yes
Adj R-sq (Within)	0.864	0.859	0.872	0.328	0.348
Observations	46	46	46	2,921	2,921

Table AIII. P&C Time Series - Underwriting Profitability and Credit Spreads

This table shows the relation between quarterly P&C insurance underwriting profitability and credit spreads. Columns 1-3 report the parameter estimate from the following time series regression:

$$\overline{u}_t = \alpha + \beta_c \cdot c_t + \beta_{cFC} \cdot c_t \times \mathbb{1}_{FC} + B' \cdot X_t + \epsilon_t$$

where $\overline{u}_t$ is the average underwriting profitability in quarter t across all insurers. Underwriting profitability is defined as underwriting profits (premiums earned minus losses and expenses) divided by the premiums eared. c_t is the 1-year rolling average of Moody's credit spread of BAA corporate bonds, $\mathbb{1}_{FC}$ is an indicator variable set to one over the financial crisis (November 2008 through February 2010), and X_t is a vector of time series controls with 1-year rolling averages of investment returns and macroeconomic variables. we also run the regression in the full panel of insurance companies by estimating the model:

$$u_{it} = \beta_c \cdot c_t + \beta_{cFC} \cdot c_t \times \mathbb{1}_{FC} + B' \cdot X_t + FE_i + \epsilon_{it}$$

where u_{it}, is the underwriting profitability for insurer i in quarter t. Reported adjusted r-squared are within groups for panel specifications. The sample consists of quarterly observations from 2001Q1 through to 2018Q3. T-statistics are reported in the brackets and are calculated using Newey and West (1987) standard errors in the time-series specifications when possible, and standard errors clustered by date and firm in the panel specifications. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	$\overline{u}_t$			u_{it}	
	(1)	(2)	(3)	(4)	(5)
Credit Spread	-0.44***	-0.83***	-1.08***	-0.74***	-1.06***
	(-2.71)	(-3.32)	(-4.85)	(-2.94)	(-4.73)
Risk Free (1yr)		-0.35**	-0.34***	-0.17*	-0.18*
		(-2.63)	(-2.81)	(-1.70)	(-1.97)
Ted Spread		1.10***	0.05	0.76*	-0.36
		(2.71)	(0.10)	(1.67)	(-0.73)
Slope (5yr - 1yr)		-0.26	-0.35**	0.12	-0.02
		(-1.24)	(-2.08)	(0.65)	(-0.09)
Unemployment Rate		-0.05	-0.07	-0.11	-0.12
		(-0.56)	(-0.75)	(-1.36)	(-1.47)
Reinsurance Activity (t-1)		0.28	0.63	-0.10*	-0.10
		(0.16)	(0.39)	(-1.68)	(-1.65)
Risk Based Capital (t-1)		-0.51*	-0.42	0.22***	0.22***
		(-1.69)	(-1.56)	(12.33)	(12.60)
FC			-1.80		-1.64
			(-1.28)		(-0.80)
Credit Spread × FC			0.85**		0.87*
			(2.57)		(1.72)
Constant	1.52***	5.69***	6.35***		
	(3.54)	(3.30)	(3.85)		
Time Series Controls Vector		yes	yes	yes	yes
Entity FE				yes	yes
Adj R-sq (Within)	0.119	0.222	0.293	0.031	0.039
Observations	67	67	67	41,589	41,589

Table AIV. Life Insurance Time Series - Estimates in Changes

This table shows the relation between the markups on annuities issued by life insurers and credit spreads. It reports the parameter estimates from the following regression:

$$\Delta m_{jt} = \beta_c \cdot \Delta c_t + \beta_{FC} \cdot \mathbb{1}_{FC} + \beta_{cFC} \cdot \Delta c_t \times \mathbb{1}_{FC} + B' \cdot \Delta X_t + FE_i + FE_k + \epsilon_{ikt}$$

where $j = (i, k)$ and Δm_{jt} is the change in the annualised markup set by insurer i at time t for an annuity which is in sub-product category k. Sub-products vary depending on age, sex and maturity of the annuities. Δc_t is the change in the Moody's credit spread of BAA corporate bonds, and $\mathbb{1}_{FC}$ is an indicator variable set to one over the financial crisis (November 2008 through February 2010). We include a vector of time series controls ΔX_t in changes, which includes the risk-free rate, the slope of the yield curve, the TED spread and US unemployment rate. Columns 1-3 report the parameter estimates from time series regressions where for the dependent variable, $\overline{m}_t$, we have averaged across insurers and sub-product categories in each time period. Columns 4-5 are full panel specifications. Panel A, B and C show the results for markups on fixed-term, guarantee and life annuity products respectively. The sample consists of biannual observations from January 1989 through July 2011. The t-statistics in the time series regressions are calculated using Newey and West (1987) standard errors with automatic bandwith selection. The panel regression also includes firm and fixed effects and standard errors clustered by date and firm. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Panel A: Life Annuities

	(1)	(2)	(3)	(4)	(5)
Credit Spread	-0.51***	-0.22**	-0.32***	-0.32***	-0.41***
	(-3.73)	(-2.22)	(-2.82)	(-5.37)	(-4.66)
$\mathbb{1}_{Fin.Crisis}$			0.16**		0.12
			(2.47)		(1.43)
Credit Spread × $\mathbb{1}_{Fin.Crisis}$			0.16		0.11
			(1.11)		(1.16)
Entity FE				yes	yes
Product FE				yes	yes
Time Series Controls		yes	yes	yes	yes
Adj R-sq (Within)	0.239	0.521	0.527	0.420	0.426
Observations	72	71	71	11388	11388

[table continued on next page...]

Panel B: Guarantee Annuities

	(1)	(2)	(3)	(4)	(5)
Credit Spread	-0.41***	-0.31***	-0.49***	-0.32***	-0.47***
	(-4.23)	(-3.37)	(-3.82)	(-4.64)	(-5.46)
$\mathbb{1}_{Fin.Crisis}$			0.09		0.14*
			(1.25)		(1.76)
Credit Spread × $\mathbb{1}_{Fin.Crisis}$			0.21*		0.16**
			(1.78)		(2.03)
Entity FE				yes	yes
Product FE				yes	yes
Time Series Controls		yes	yes	yes	yes
Adj R-sq (Within)	0.302	0.404	0.387	0.397	0.415
Observations	53	52	52	12927	12927

Panel C: Fixed-Term Annuities

	(1)	(2)	(3)	(4)	(5)
Credit Spread	-0.49***	-0.34***	-0.39**	-0.36***	-0.45***
	(-4.76)	(-3.46)	(-2.32)	(-4.24)	(-4.75)
$\mathbb{1}_{Fin.Crisis}$			0.38**		0.33***
			(2.35)		(3.14)
Credit Spread × $\mathbb{1}_{Fin.Crisis}$			0.05		0.12
			(0.41)		(1.18)
Entity FE				yes	yes
Product FE				yes	yes
Time Series Controls		yes	yes	yes	yes
Adj R-sq (Within)	0.343	0.657	0.662	0.373	0.383
Observations	45	44	44	2247	2247

Table AV. Investment returns drive the cross section of premiums: P&C Insurance

This table shows the relation between quarterly returns to P&C insurance underwriting and firm-specific expected investment returns. It reports the parameter estimate from the following panel regression:

$$u_{it} = \beta_y \cdot y_{it} + \beta_{yFC} \cdot y_{it} \times \mathbb{1}_{FC} + B' \cdot X_{it-1} + FE_i + FE_t + \epsilon_{it}$$

where u_{it} is the underwriting profitability for insurer i at time t, and y_{it} is the insurer's investment return. We additionally control for date fixed effects, firm fixed effects and X_{it}, which is a vector of lagged variables that capture balance sheet strength (leverage, risk-based capital, asset growth and unearned premiums). This includes variables squared to control for non-linear effects of capital constraints. The samples consist of quarterly observations from March 2001 through March 2018. In columns 4-5 we interact investment return with an indicator variable $\mathbb{1}_{FC}$ set equal to one during the financial crisis (Q4 2008 through Q1 2010). t-statistics are reported in bracket and calculated using standard errors clustered by date and firm. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)
Investment Return	-0.10**	-0.12***	-0.11***	-0.13***	-0.12***
	(-2.37)	(-3.09)	(-5.19)	(-3.37)	(-5.70)
Size (t-1)		-0.07***		-0.07***	
		(-2.94)		(-2.93)	
Reinsurance Activity (t-1)		-0.22*		-0.22*	
		(-1.95)		(-1.95)	
Risk Based Capital (t-1)		0.41***		0.41***	
		(6.38)		(6.37)	
Asset Growth (t-1)		0.01***		0.01***	
		(4.16)		(4.15)	
Unearned Premia (t-1)		-0.01		-0.01	
		(-0.15)		(-0.15)	
(Risk Based Capital)^2		-0.01*		-0.01*	
		(-1.69)		(-1.68)	
(Asset Growth)^2		0.00**		0.00**	
		(2.26)		(2.27)	
(Leverage)^2		-0.00		-0.00	
		(-1.00)		(-0.99)	
Investment Return × FC				0.10	0.12**
				(1.52)	(2.56)
Firm Controls Vector		yes		yes	
Entity FE			yes		yes
Time FE	yes	yes	yes	yes	yes
Adj R-sq (Within)	0.001	0.071	0.001	0.071	0.001
Observations	37,044	37,044	37,044	37,044	37,044

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