Financial Crises and Risk Premia*

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Abstract

I analyze the behavior of risk premia in financial crises, wars, and recessions in an international panel spanning over 140 years and over 14 countries. I document that risk premia increase substantially in financial crises, but not in the other episodes. However, drops in consumption and consumption volatility are fairly similar across financial crises and recessions and are largest during wars, so standard macro asset pricing models will have trouble matching this variation. Comparing crises to "deep" recessions strengthens these findings further. I also find the equity of the financial sector forecasts returns. Taken together, the results suggest that the health of the financial sector is important for understanding why aggregate risk premia vary. I calibrate an intermediary asset pricing model and show it can match the data.

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1 Introduction

Why do risk premia vary over time? This paper explores the behavior of risk premia across financial crises, recessions, and wars and uses variation in the data to understand the economic forces behind time varying risk premia and to distinguish between asset pricing models. I use data on consumption, dividend yields, stock returns, and credit spreads for over 140 years and 14 countries, yielding 209 recessions, 71 financial crises, and 24 war disasters. First, I document that risk premia spike dramatically in financial crises – defined specifically as a banking panic or banking crisis – but rise only slightly in recessions or wars. The large increase in risk premia during financial crises puts explaining these episodes to the forefront of the asset pricing literature. To my knowledge, this is the first paper to study and characterize the behavior of risk premia across financial crises, and is the first to compare risk premia in financial crises to these other events. Second, I examine the ability of leading macro asset pricing models to explain these facts. I find the overall drop in consumption and increase in consumption volatility across financial crises, recessions, and wars is either relatively small or has the wrong sign, meaning the variation in risk premia is difficult to reconcile with standard consumption based asset pricing models. In contrast, theories where risk premia are a function of the health of the financial sector seem to fit the patterns in the data well.[1] The evidence points to the health of the financial sector as being important for aggregate asset price fluctuations. I then calibrate an intermediary asset pricing model and show that the model can replicate the main features of risk premia during financial crises.

Figure 1 plots the increase or decrease of variables of interest across each of the events and provides the main results of the paper. The details, data description, and formal statistical analysis are all left to the main text. Panel A documents large increases in dividend yields and credit spreads, both typical measures of risk premia, during financial crises. Throughout the paper I use the term high risk premia to mean an asset with high expected return, high discount rate, or low price relative to fundamentals or expected cash flows. While these measures spike in financial crises, other episodes show only minor movements in risk premia. Later sections give these same results via regressions and trace out the impulse responses to risk premia and consumption moments across these episodes. Panel B shows that the key state variables implied by leading macro asset pricing models – the drop in consumption and the conditional volatility of consumption – have difficulty accounting for the behavior of risk premia across episodes. These variables do not vary drastically across financial crises and

[1] For example, He and Krishnamurthy (2012a), Brunnermeier and Sannikov (2012), Geanakoplos (2012), among others.

typical recessions, and each changes the most during wars. I show this further by comparing financial crises to "deep recessions" – those for which consumption in the first year of the recession fell by the most. While consumption falls by more and consumption volatility increases by more than during financial crises, these deep recessions do not have higher risk premia. The challenge posed to the standard consumption based models can not likely be overcome by changing parameters in their calibrations because the relationship between state variables and risk premia is either relatively small (across financial crises and recessions) or has the wrong sign (across financial crises and wars or financial crises and deep recessions). This poses a major challenge for consumption based asset pricing models and in later sections I show that the calibrated versions of these models (Campbell and Cochrane (1999), Bansal and Yaron (2004), and Barro (2006)) have difficulty matching the behavior of risk premia in financial crises. The facts instead appear more consistent with models where risk premia depend on the health of the financial sector. In these models, risk premia will naturally be significantly higher in financial crises compared to typical recessions because intermediary balance sheets are more strained.

There are several potential objections to the results that financial crises have much higher risk premia than other events. The first objection is that the conclusions are tautological. Of course prices fall and risk premia rise during financial crises if a "crisis" is defined ex-post as a large decline in asset values. In fact, the financial crisis dates are defined as a systemic event – a major bank run or bank failure – and are not defined based on what happened to prices. Therefore, they are not defined ex-post based on drops in asset values. However, this objection also partly misses the point. Regardless of the dating convention, the fact remains that models should explain these episodes. For example, if the habits model of Campbell and Cochrane (1999) is a good description of the world, we can define changes in prices ex-post, but it must still be the case that consumption (or "surplus consumption," which is consumption relative to habit) drops substantially whenever prices drop substantially. Worries that low market returns simply coincide with the crisis are also misguided. Market crashes do occur around recessions and wars as well, but these drops in market values are accompanied by drops in fundamentals, so that valuation ratios do not move drastically. The key feature of financial crises relative to recessions is the change in the discount rate, not the change in cash flows. One should think of the exercise of comparing crises to recessions and wars as a "difference in difference" type approach where in both cases the economy faces similar drops in cash flows and fundamentals, but in one episode the financial sector is particularly affected.

The second main objection is that dividend yields and credit spreads are poor measures of risk premia. Maybe the spike in dividend yields in crises is really about expected dividend growth in those episodes, even though unconditionally we don't see dividend yields strongly forecast future dividend growth. I show that dividend yields are valid measures of expected returns because they forecast returns and not cash flows, both *conditional* on financial crises as well as unconditionally. The results show that the standard result that dividend yields forecast future returns and not dividend growth hold during crises and recessions as well. These results are shown in the appendix which conducts a number of other robustness checks. Moreover, I show that *realized* returns after financial crises are very large at around 20%, which is a non-parametric way of showing that risk premia in these episodes are indeed large. During crises asset prices show a "V-shape" pattern of collapse and recovery. This confirms that the key feature of financial crises relative to typical recessions is the discount rate effect or spike in risk premia. In contrast, in the other events subsequent realized returns are not abnormally high. In fact, the extra drop in return in financial crises vs. recessions is completely reversed several years out, so there is very little difference in long term cash flow news but substantial difference in discount rates across these episodes.

Finally, one may worry about the long lasting effects of financial crises and whether they are indeed far worse than the other events in the long term. While these effects are difficult to estimate, I find the long term effects of financial crises on consumption to be slightly worse than recessions, slightly better than deep recessions, and much better than war related disasters. The difference in long term effects compared to recessions remains modest in comparison to the difference in risk premia across the events. I find long term effects of financial crises on consumption to be on the order of 2% lower than those in typical recessions. While not trivial, from the perspective of standard models this difference is again relatively small to explain the much larger differences in risk premia across the events. Next, if one is still worried about this difference as explaining the results, I compare crises to "deep recessions" where the drops in consumption are larger than those around financial crises. Even in these deep recessions, risk premia do not move substantially.

It is also important to note that this paper says nothing about the causality of the macroeconomic outcomes during recessions, crises, and wars. In particular, I am silent as to whether the drop in consumption around financial crises is caused by a collapse in lending in the financial sector or whether it reflects, say, shocks to TFP. The underlying shocks in any episode are difficult to observe and consumption is the endogenous outcome of these shocks along with potential amplification from the financial sector. Therefore, one can not conclude from the findings in this paper that financial crises do not have severe macroeconomic effects. It may well be the case that the entire drop in consumption around financial crises is caused by the financial sector and that a recession would not have otherwise occurred, so one can not simply compare the drop in economic activity between recessions and crises to conclude causality. However, the broader point in this paper is that for the standard asset pricing models, the causes of the drop in consumption are irrelevant and can be taken as exogenous. Similar changes in consumption – regardless of their cause – should produce similar changes in risk premia based on equilibrium relationships in those models.

I next calibrate a simple intermediary asset pricing model and show that it can largely match the behavior of risk premia in financial crises. The model is based on He and Krishnamurthy (2012a) and Brunnermeier and Sannikov (2012). The model features intermediation frictions so that the stochastic discount factor (SDF) depends on intermediary equity rather than aggregate consumption. When intermediary equity is high, prices are high and risk premia are low. However, when intermediary equity is low and the equity capital constraint is more binding, risk premia are high as the risk-bearing capacity of intermediaries declines. This generates a "financial crisis." I calibrate the model to match unconditional moments and study the resulting asset pricing dynamics. The model quantitatively matches the spikes in risk premia associated with financial crises as well as the average decline of stock prices in financial crises. I also show that the model generates recessions with and without financial crises, and that, as in the data, risk premia are significantly higher in the latter. The calibrated model matches unconditional risk premia and volatility and generates time-varying risk premia that are tied to the health of the financial sector. Specifically, the model ties movements in risk premia to the equity capital or net worth of the financial sector, and I confirm this prediction in US data. As in the model, the equity of the financial sector divided by GDP has strong forecasting power for both stock and corporate bond returns, predicting around 17% of the variation in annual returns. The model also has several main short comings, the most important of which is a single aggregate shock. This limits the comparison to wars since there are no large disasters in the model. This is mainly for tractability, and one could extend the model to have multiple shocks. A second shock could also help disentangle fundamental shocks from shocks to intermediation, however, such a model is beyond the scope of this paper, which simple tries to demonstrate that models with financial intermediation are promising for asset pricing.

While I can not distinguish between whether the high risk premia during financial crises are rational or irrational, my findings still speak to behavioral theories of asset pricing as well. In particular, if one believes that sentiment is the key driver of risk premia, then the facts in this paper suggest that financial crises are uniquely important as being episodes with low sentiment. Behavioral theories would have to explain why recessions and wars do not feature equally large changes in sentiment despite the fact that investors would have many reasons to be pessimistic in these episodes. Finally, much recent work in behavioral finance has focused on investors forming incorrect expectations based on over weighting past returns or experiences (Barberis *et al.* (forthcoming), Malmendier and Nagel (2011)). In these models drops in asset prices are exacerbated by investors forming pessimistic forecasts of future returns and cause prices to fall below fundamentals and therefore measured risk premia to rise. These theories would have to explain why risk premia do not rise during all market crashes, but only the ones associated with financial crises. In other words, there must be a drop in sentiment only during financial crises for reasons beyond poor past returns. Recent work is starting to explore the link between financial cycles and risk premia in a behavioral context (see Baron and Xiong (2014)).

The main takeaway of this paper is that risk premia spike dramatically in financial crises, but *not* in other episodes which feature similar or larger movements in consumption. These facts support the idea that the health of the financial sector is key to understanding movements in risk premia and aggregate asset prices. This adds to previous work that focuses on the increase in expected returns over the business cycle (Fama and French (1989), Lustig and Verdelhan (2012), see also Cochrane (2011) for a comprehensive review of the behavior of expected returns). However, this is the first paper to systematically document the behavior of risk premia during financial crises. The paper provides an explicit link between aggregate risk premia and the financial sector that is related to similar findings by Adrian *et al.* (2011) and Adrian *et al.* (2012) who find intermediary balance sheets help explain the time-series and cross-section of asset returns. However, this paper goes farther in showing why a "financial crisis" state variable is necessary to explain risk premia because of the differential response of risk premia in crises and recessions. In a related subsequent paper, Baron and Xiong (2014) find risk premia to be abnormally low in the boom years *before* a crisis and take this as evidence of behavioral asset pricing theories where prices are driven by sentiment. Further, the evidence in this paper links financial crises, asset prices, and the credit cycle as in Geanakoplos (2012) and Kiyotaki and Moore (1997). It shows that during financial crises when credit contracts and there are runs on short term debt, asset prices fall by much more than their fundamental value. My findings are also related to Greenwald *et al.* (2014) who show that changes in risk premia or risk aversion explain a large fraction of asset price fluctuations in US data, but these changes are uncorrelated to consumption and fundamentals. This paper shows that financial crises are times when these shocks to risk premia are highest, meaning they are uniquely important to understanding risk premia. Thinking of recessions, deep recessions, and wars as control groups with similarly bad or worse macroeconomic outcomes, this paper shows the additional large increase in risk premia during financial crises despite no additional increase in typical measures of macroeconomic risk. The results show that financial crises are important for understanding variations in risk premia and strongly support models where the health of the financial sector influences risk premia.

2 Data and Empirical Results

2.1 Data Description

The main data spans from 1870-2009 across 14 countries and consists of the following: real per capita consumption and GDP data, dividend yields, real dividend growth, real stock returns, and credit spreads. The countries included in the main sample are the United States, Canada, Australia, Denmark, France, Germany, Italy, Japan, the Netherlands, Norway, Spain, Sweden, Switzerland, and the United Kingdom. Consumption and GDP data are from Barro and Ursua. Dividend yield, stock price, and return data are from Global Financial Data (and these are used to construct the dividend growth series) and are converted to real US dollars. I use 1 year real interest rates in the US from Robert Shiller when constructing excess returns. Credit spreads are from Investor's Monthly Manual which published bond prices from 1860-1930. I also add the Moody's BaaAaa default spread from 1930 onwards for US data. Therefore, for countries outside the US, credit spreads are only available from 1860-1930 and this is my most limited data series. Stock market data (dividend yield data and return data) begin at various times across these countries, but are typically continuous once they begin (the main exception is a few countries during major world wars and I return to this issue later). The data are described in greater detail in the online appendix.

Crisis and event dates come from several sources. Business cycle dates are from Jorda, Schularick and Taylor (Jorda *et al.* (2010)) Table 1 who document business cycle peaks for these 14 countries and document whether each was associated with a financial crisis or not. I will refer to the latter as "non-financial recessions" and I will refer to "recessions" as containing *both* financial and non-financial recessions. Finally, I define "deep recessions" as non-financial recessions for which the initial drop in consumption exceeds -2%. This cutoff represents the lowest 30% of recessions in terms of the initial drop. However, this criteria does not condition on anything beyond the first year of the recession, hence it does not imply a look ahead bias. Overall, my sample contains consumption data for 209 non-financial recessions, 63 of which are considered "deep recessions", and 71 financial crises. These numbers reduce to 135 recessions (43 of which are deep recessions) and 41 financial crises when I consider events that have non-missing dividend yield data. Missing data is primarily due to dividend yield series starting significantly later in many countries, although some countries have missing data during the major world wars as markets shut down (particularly Germany and France). These are my primary dates because they allow me to compare the behavior of asset prices across recessions which contain a financial crisis and those which do not, for a balanced panel of countries. This allows me to estimate the *differential* response of each variable in a recession versus a financial crisis. One can loosely think of the financial crisis group as the treatment group and normal recessions as the control. I will show that both are hit with similar declines in consumption and dividends (fundamentals) but have different responses in asset prices.

I also use dates from Reinhart and Rogoff (2009) (RR) which only contain dates for financial crises but not recessions in general and the appendix shows robustness to using these dates. The main difference with the RR dates are that they date the crisis when a major bank run or bank failure occurs, rather than using the preceding business cycle peak as in Schularick and Taylor. However, they are also more extensive and cover far more countries with data on 70 countries starting as early as 1800. The main disadvantage of the RR dates is that they do not allow me to directly compare asset price responses in financial crises to those in a typical recession. I analyze the results using the RR dates in the appendix. For both dating conventions, the occurrence of a financial crisis is due to a major bank run or bank failure – therefore financial crisis and banking panic are used synonymously. The crises are not dated ex-post by aggregate stock market declines.

I also run a standard VAR of returns and dividend yields to decompose unexpected returns into discount rate news and cash flow news (see Campbell (1991)). When doing so, I demean the dividend yield and return series within each country and run a single pooled VAR. One major caveat of this approach is that I only have dividend yields historically and no other predictor variables, hence I likely assign too little of unexpected return variation to discount rate news. This allows me to distinguish return shocks based on changes in dividend yields or dividend growth.

2.2 Empirical Results

I plot the raw data in Figure 1 and give corresponding numbers in Table 1. I plot the five year change in dividend yields and credit spreads one year after the start of the event since this is when risk premia typically peak for both financial crises and recessions. For wars, I compute the five year change at the beginning of the event rather than one year after because this is when risk premia are typically highest, but the results are robust to using the highest possible dividend yield in a five year window around each event as shown in Table 1. The increases in risk premia during crises in this flexible window are over 35% whereas the other episodes are under 25%. Picking a completely random window in my same gives a peak change of 22%. I compute consumption volatility over a forward looking 10 year window beginning at the start of the event to try to pick up persistent increases in consumption volatility. This window does not contain the current year so does not condition on the fact that consumption drops in the current year. It instead computes volatility going forward after the event has occurred. Finally, for drops in consumption I compute the peak to trough change in real consumption over each event in a 10 year window. This window does not affect the results, but guards against conflating multiple events (as an example, one would not want to assign part of the drop in the Great Depression to the occurrence of World War II). Using peak to trough consumption is natural because consumption often responds with a lag to asset price changes in these events and this captures the overall severity of the event in terms of consumption loss but avoids imposing perfect timing between consumption and asset price changes. In every event, I use the corresponding series for the country experiencing the event (i.e. if Spain experiences a financial crisis or a civil war, I look at changes in asset prices, consumption, etc. in Spain at that time). One can easily see the main patterns in the data: financial crises are associated with large spikes in measures of risk premia, whereas wars and recessions are not. However, drops in consumption and consumption volatility are about the same across financial crises and non-financial recessions. Therefore, we can almost immediately see that consumption based models will struggle to fit the behavior of risk premia. This basic point illustrates the main results of this paper and the rest of this section simply makes this point more rigorously.

2.2.1 Empirical Strategy

Table 2 runs regressions of each of outcome variables on dummies that indicate whether a recession, financial crisis, or war related disaster occurred. My outcome variables are (log) consumption growth, stock returns, and dividend growth, as well as log changes in dividend yields and surplus consumption ratios and changes in consumption volatility. Consumption volatility is computed using a GARCH(1,1) model but is robust to simply using rolling windows. The recession dummy is equal to one if a recession occurs for any reason (i.e. it includes both financial *and* non-financial as well as wars). The financial crisis dummy therefore picks up the differential effect of financial crises *relative* to recessions. I include several lags of each dummy variable to account for the fact that the dating is about the business cycle peak and asset prices typically respond after the business cycle peak (Gorton (1988)). Including more lags does not change the results. I also include country fixed effects in every regression to account for differences in returns, growth rates, etc., across countries and I include the lag of each variable as well.[2] Standard errors are clustered by year. Finally, I follow Barro *et al.* (2011) and include a dummy for post war data to account for a trend break in growth and volatility for the roughly 30 years following WWII.[3]

$$\begin{aligned} y_{i,t} \;=\; & \alpha_i + \sum_{k=1}^{K} \phi_k y_{i,t-k} + \sum_{j=0}^{J} a_j 1_{fin,i,t-j} + \sum_{j=0}^{J} b_j 1_{recession,i,t-j} \\ & + \sum_{j=0}^{J} c_j 1_{war,i,t-j} + \gamma_1 1_{(t \geq 1946)} + \gamma_2 1_{(t \geq 1973)} + \varepsilon_{i,t+1} \end{aligned} \quad (1)$$

Figure 2 takes the coefficients from these regressions and plots the cumulative response for each variable of interest to a financial crisis, recession, war, and to a deep recession and also plots bootstrapped 90% confidence bands, which gives a sense of the joint significance of the coefficients in (1).[4] The impulse response for a deep recession adds dummies to (1) for whether the recession was deep or not in its first year. Following this, Figure 3 plots the response to financial crises with confidence bands and the responses to other events overlayed. Graphically, we can evaluate whether the responses, which depend on all coefficients jointly, are statistically different.

2.2.2 Financial Crises and Recessions

We first see a large increase in dividend yields immediately after financial crises relative to typical recessions. Dividend yields increase 4% and 20% after years 1 and 2, respectively. The 20% increase is highly statistically significant. Again it is worth emphasizing this is over and above typical recessions. In typical recessions, dividend yields increase by 9% on

[2] One issue that comes up is potential bias when using fixed effects and lagged dependent variables because country fixed effects are correlated with the lagged dependent variables. First, it should be noted that the order of the bias is $1/T$ hence is small in this case when T is large (in other words, this is typically a "small T large N problem"). Second, using the Arellano and Bond (1991) estimator which takes first differences to remove country fixed effects then uses lagged values of the dependent variable as instruments does not give results which differ meaningfully from those presented in the main text. Therefore, I choose to stick to the basic OLS estimates with fixed effects.

[3] Barro *et al.* (2011) argue for this both because of the structural break in growth after the second world war and also because of changes in data collection practices following this period as well. An alternative way to account for changes in these variables over time is time fixed effects. However, these seem inappropriate for my setting especially if financial crises tend to have more global effects compared to recessions.

[4] I do not account for cross-correlation when sampling via bootstrap as I do not find strong cross-correlation in residuals. Further, a very conservative approach which groups all observations by year and bootstraps by year does not yield substantially different conclusions.

impact and then slowly decline. Dividend yields in crises are therefore significantly higher than in typical recessions, and much higher than "normal" times. The cumulative increase in dividend yield in a financial crisis is around 30%. For reference, the standard deviation of log changes in dividend yields is around 20%. Credit spreads show similar patterns. In financial crises, credit spreads increase by around 5%. This is larger than a 1 standard deviation change (the standard deviation in credit spreads is about 4%). There is no meaningful change in credit spreads in recessions.

But are these changes in dividend yields actually risk premia or just changes in expected dividend growth? We know it must be one of the two based on the work of Campbell and Shiller (see e.g., Campbell (1991)). To answer this, I study the behavior of returns and dividend growth. First, I show that future returns increase dramatically while future dividends do not fall dramatically. The coefficient on the dummy for a crisis at time t gives the contemporaneous effect on returns and dividend growth relative to recessions. Contemporaneously, returns fall by around 20% in a financial crisis. After three years, returns rebound by gaining around 20% above their mean. The drop in returns is presumably a "shock" due to the fact that we are conditioning on the business cycle peak. The rebound, however, is forecastable by an event several years in the past. This shows that financial crises are associated with large price declines that are subsequently reversed, meaning the crisis is largely about a change in discount rates not in cash flows. This intuition is supported by Figure 2 which shows large differences in discount rate news between the episodes, but not large differences in cash flow news. Further, dividend growth is actually higher in a financial crisis initially compared to a typical recession, which also supports that the change in dividend yield is due to discount rate news and not changes in expected dividend growth rates. In untabulated results, I find no effect on changes in longer term 10 year averages of dividend growth rates. Later, I further confirm this intuition by running standard predictive regressions of returns and dividend growth on dividend yields both unconditionally and conditional on a financial crisis. I find that the standard relationship that dividend yields forecast returns and not dividend growth also holds during financial crises.

Turning next to macro variables, we see the drop in consumption growth in recessions is around 1.1%, 3.7%, 2.0%, and 1.4% in years 0, 1, 2, and 3 after a recession, showing persistent declines in consumption. It is worth remembering that these are relative to each country's long run average of around 2% as there are country fixed effects. For financial crises, there is no drop in consumption relative to recessions on impact, but an extra 1.5% and 1.1% drop 1 and 2 years out. This is the sense in which financial crises are deeper and longer than normal recessions. It seems unlikely that this relatively small extra drop in consumption alone would generate the large spike in risk premia. The cumulative loss in these recessions is around 5% depending on the horizon and the cumulative loss in financial crises is estimated around 7%. The response in recessions is not statistically significantly different from the response in a financial crisis.

The next column of Table 2 looks at the log surplus consumption ratio of Campbell and Cochrane (1999) (CC) using their long run calibration and I also plot the impulse response in Figure 2. Surplus consumption is essentially consumption relative to a slow moving average of past consumption. The patterns look fairly similar to consumption with one key difference. The habit function is non-linear so that a bad shock in bad times decreases the log surplus consumption ratio more than in good times – as you get closer to habit you become more sensitive to drops in consumption. Does this mean the small extra drop in consumption in financial crises can generate the spike in risk premia because it comes when consumption has already fallen? No, for two reasons. First, I look at the *log* surplus consumption ratio, which has a roughly linear relationship with risk premia in their calibrated model. The log surplus consumption ratio declines by only around 10% extra in financial crises relative to recessions. In the CC calibration, that corresponds to an increase in risk premia of up to 6%, which can not match the magnitude of the increase that we observe (around 20%). But there is more convincing evidence. The log surplus consumption ratio in the non-financial recession drops over 18%. The model would imply a spike in risk premia in recessions that would be much *larger* than what we observe in the data. Therefore, the model is not able to *jointly* match the lack of variation in risk premia in recessions and the large variation in risk premia in financial crises. In this case, the lack of variation in risk premia during recessions is nearly as important as the strong increase in risk premia during financial crises.

I next look at the 10 year forward looking variance of consumption growth. This is the key state variable in Bansal and Yaron (2004) for movements in risk premia. Increases in the volatility of consumption growth increase the volatility of the stochastic discount factor. The recession dummies indicate that indeed consumption becomes more volatile following a recession, though the numbers are fairly small. Compared to recessions, financial crises actually see a *lower* consumption variance with an initial decrease of -0.2% relative to recessions. Therefore, the difference in risk premia clearly can not be accounted for by a change in consumption volatility. This is not a matter of calibration because the point estimate has the wrong sign. The long run risks model would therefore predict a spike in risk premia during recessions, but no additional increase in risk premia during financial crises.

To summarize, purely consumption based models are faced with the following challenge in matching these episodes: first, relying on changes in consumption volatility can not work because volatility does not meaningfully change across episodes. The only potential way to match the data is using the extra decline in consumption in financial crises of 2%. But this has two complications. First, if drops in consumption lead to changes in risk premia, one has to explain why there is no substantial increase in risk premia during recessions despite the 8% drop in consumption, and why there is no substantial increase in risk premia during wars when consumption drops can reach 30%. Deep recessions make this point even more clearly.

2.2.3 Deep Recessions

To strengthen the comparison of financial crises to recessions I also compare crises to "deep recessions," defined as those having an initial drop in consumption below -2% during the *first* year of decline. There are 63 such episodes, roughly comparable to the number of financial crises in my sample. I do not condition on any forward looking information beyond the first year, similar to the definition of a recession which conditions on an initial decline in growth. Deep recessions make the point of this paper even more clearly because relative to financial crises, consumption falls by larger amounts, consumption volatility increases by larger amounts, yet risk premia again do not increase. In deep recessions, consumption falls by more than it does during financial crises, at all horizons, and consumption volatility increases by more as well.

It is worth pointing out whether conditioning on the drop in consumption to define deep recessions leads to a bias. Most importantly, I do not define these episodes by the ultimate drop in consumption, simply on the drop in the first year of the recession, so there is no guarantee these episodes will ultimately be worse. Further, for the habits model conditioning on ex-post declines in consumption is a valid exercise. Risk premia in that model respond to realized declines in consumption, not expected ones. For long run risk, where the key variable is the volatility of consumption, a measured bias would only potentially occur in the first year, where volatility would be measured as large because realized consumption fell by a large amount. However, I find a large persistent increase in consumption volatility many years out, far beyond the initial year. The only model for which the dating convention here is potentially a problem is the rare disasters model where it is the probability of disaster, not the realization, that matters most (though these recessions are still too mild to be considered "disasters").

2.2.4 Wars

So far I have shown that financial crises and recessions are fairly similar among consumption variables but vary greatly in terms of risk premia. I next compare financial crises and recessions to war related disasters. These dates are from Barro and are post 1900. The results are given in Table 2.

There are advantages and disadvantages to looking at the war related disasters. The advantages are that they generate huge drops in consumption and huge increases in the volatility of consumption. This provides good testing grounds for models because it generates large changes in consumption moments. In other words, the increases in the consumption state variables are stark in these episodes. There are also downsides. First, there are relatively fewer of these episodes overall. But the biggest concern is market shut downs during some of the major world wars that prevent dividend yields from being measured. Therefore, data availability is a problem. The markets that shut down are also those that were typically hit the hardest. I will therefore only use consumption data on the countries for which markets did not shut down so my data is balanced. Another approach is to measure dividend yields in a flexible window both before and after markets shut down. According to the rare disasters story, the probability of a disaster should affect the dividend yield, and the probability is higher both before and after the realization of a disaster. Even looking in a window around the event, I find no increase in dividend yields.

Looking at Table 2, there are virtually no increases in risk premia around wars. In fact changes in dividend yields are negative. Returns are also large and negative, and dividend growth is negative. Returns are more negative than dividend growth, meaning prices decline as well as dividends, but dividends fall by more than prices, making the dividend yield decline overall. The evidence from returns and dividend yields suggests a lack of increase in risk premia.

Consumption, however, falls dramatically by 1%, 17%, and 10% in years 1, 2, and 3, respectively. The surplus consumption ratio naturally collapses while the variance of consumption increases dramatically. Notice the drops in magnitude in consumption, habits, and consumption variance are all drastically larger than in recessions by a factor of 5 or more. Again, the data strongly show that despite massive changes in consumption, risk premia as measured by dividend yields do not change. As mentioned, there are of course data issues with wars, but one has to consider the economic magnitude here. Cumulative consumption losses of near 25% and an increase in consumption variance of several standard deviations produces no measurable increase in risk premia. Dividend yields must be related to expected returns or dividend growth. The only way risk premia could have been high in these wars is if expected dividend growth was equally high, so that price dividend ratios remained constant. Yet, if anything we see (and would expect) negative expected dividend growth rates.

There is one possible defense of the rare disasters model: that these are just the realizations of the disaster, but maybe the probability of disaster did not increase and therefore the risk premium not increasing is natural. However, this explanation does not ultimately work. First, war related disasters are very likely forecastable. There is usually a "build up" period to wars in which events occur that substantially increase the probability of a disaster. In the appendix, I show that events which almost surely increased the probability of a war related disaster (i.e., the Cuban Missile Crisis, Hitler invading Poland, the attack on Pearl Harbor), do not feature large increases in risk premia. More generally, as shown in Table 1, when using a flexible window five years before the disaster and looking for the maximum changes in risk premia, I still find very little evidence of any increase. It is hard to imagine that in the five year window before these major war disasters there was no change in the likelihood of a major disaster at any point. Further, when a war actually starts consumption has not yet fallen, but clearly the probability that it will fall has gone up. In the disaster calibrations, even very small increases in the probability of the disaster occurring will have very large implications for risk premia. This is the entire foundation of these models. Even if the probability does not increase before the disaster, it should certainly increase during and after the disaster as these events tend to be clustered. Further, an agent who updates the probability of a disaster in a Bayesian way will typically expect a higher probability of disaster after one has occurred. But risk premia are not elevated during those times either. Finally, one might still argue that maybe the disasters are not forecastable, so that the probability is a constant. But that would imply constant dividend yields, meaning these models wont be able to match time-variation in risk premia. In any case, the standard consumption disaster model is not likely to fit the data.

One may also worry that the data are poorly measured around wars. For some countries, markets completely shut down during the major world wars. First, there are enough war related episodes without this issue that clearly show large declines in consumption and no change in dividend yield. While there are definitely data issues, the magnitudes of the discrepancies appear too large to be attributed to poorly measured data. However, as mentioned, risk premia in the rare disasters model should increase *before* the war begins and markets shutdown as risk premia depend on the probability of the disaster not its occurrence. These probabilities would increase leading up to wars as the wars became more and more likely. I see no change in risk premia in the lead up to wars or just after wars. Therefore, wars do not seem to be associated with large spikes in risk premia of the magnitude implied by standard disasters models.

The war evidence is consistent with what we found in recessions: large drops in consumption and increases in consumption variance do not seem to be associated with risk premia. Even with potential objections to the data and small sample, the message seems to be clear given the enormous magnitudes.

2.3 Robustness and additional tests

Figure 4 provides robustness checks. First, I re-do all of these results on different dimensions of the data. The general pattern in results qualitatively hold when looking only at post war data (i.e., after 1950), when using the Reinhart Rogoff dates, when looking at US data, and when using a balanced panel of macro and financial market data. When using the RR dates, I define recessions using the Bry and Boschan (1971) algorithm and deep recessions as those having less than -2% consumption growth in the first year as above. In general, we see financial crises as having the only meaningful spikes in dividends (ranging from 30-50% meaning huge declines in prices relative to fundamentals). Typically, in each case, financial crises are somewhat worse than recessions, but not worse than deep recessions, in terms of either consumption declines or consumption volatility. Yet the increases in risk premia are substantially larger in financial crises. Thus the main results hold in post war data, ruling out measurement issues in the data in the pre-WWII era and ruling out other arguments including different regulatory regimes on the financial sector. The results in the US show crises as being significantly worse than recessions, but about the same as deep recessions. Here the drop in prices relative to dividends, however, is around 50% during crises, a massive amount. The confidence intervals using US data only are wide reflecting that there are only around six crises in US data.

The appendix contains additional robustness checks, which I will describe briefly here. The appendix confirms that movements in dividend yields correspond to changes in risk premia both unconditionally and during financial crises by running standard predictive regressions of returns on dividend yields with dummies for financial crises and recessions. The unconditional relationship that dividend yields predict returns is unaffected during these times. The appendix also discusses data sources in more detail.

3 Models

3.1 Unifying Framework

This section briefly reviews the state variables that drive risk premia in leading asset pricing models. All asset pricing models specify a stochastic discount factor (SDF) M. The main pricing equation is

$$E_t\left[R_{t+1}\right] - R_f = -R_f cov_t\left(M_{t+1}, R_{t+1}\right) \tag{2}$$

The SDF, M, is typically a function of a state variable S. Therefore, the covariance and risk premia will also depend on S and therefore we end up with an equation of the form[5]

$$E_t\left[R_{t+1}\right] - R_f = f\left(S_t\right) \tag{3}$$

where f is some generic function. Each model proposes a different state variable S that determines risk premia. I will review how each model specifies S and discuss the calibrations of each model. We have already seen variation in the left hand side (risk premia) in the data between financial crises and other episodes. The key question is whether that variation can be reasonably explained by variation in the state variables.

3.2 Consumption Based Models

3.2.1 Habits

Habit models specify utility as $U(C) = (C - X)^{1-\gamma}$ where X is the habit level. I will focus on the external habit model of Campbell and Cochrane (1999) where X depends on past consumption. Here the state variable is the surplus consumption ratio $H_t = (C_t - X_t)$.

$$E_t\left[R_{t+1}\right] - r_f \approx \sigma_t\left(M_{t+1}\right)\sigma_t\left(R_{t+1}\right) \tag{4}$$

$$E_t\left[R_{t+1}\right] - r_f \approx \sigma_t\left(\left(\frac{H_{t+1}}{H_t}\frac{C_{t+1}}{C_t}\right)^{-\gamma}\right)\sigma_t\left(R_{t+1}\right) \tag{5}$$

Consumption growth is i.i.d., and habit is based on past consumption, so the key state variable is H. Therefore high risk premia should be associated with drops in consumption (relative to habit). As noted in Campbell and Cochrane (1999) the dividend yield is nearly linear in the log surplus consumption ratio, which is the state variable I work with empirically.

[5] The link is clearest in continuous time where the main pricing equation is

$$E_t\left[dR_{t+1} - rdt\right] = -\lambda\left(s_t\right)\sigma_{R,t}$$

where $\lambda\left(s_t\right)$ is the volatility of the pricing kernel and $\sigma_{R,t}$ represents the factor loadings.

To get a sense of magnitudes, I calibrate the habit model based on Campbell and Cochrane (1999). The calibration is difficult because different countries have different expected growth rates and different volatilities of consumption. Campbell and Cochrane (1999) have two calibrations – one based on postwar data and one over a longer sample. In the calibration geared to match the recent sample, habits play a larger role in the results because consumption volatility is much lower (1.2% vs. 3%), and because the Sharpe ratio is larger in the recent sample. Therefore, habit must be "cranked up" dramatically to account for higher volatility of the discount factor (to match the higher Sharpe ratio) with lower consumption volatility. Therefore, in this calibration, the slope coefficient of expected return on log habit is about -3. In the model calibration, risk premia are non-linear in the level of habit, but nearly linear in log habit level. In the long sample parameterization, the sensitive of risk premia to log habit is only about -0.6. This would be further reduced if calibrated to international data because international consumption volatility tends to be even higher. However, I will use the long sample calibration as it best applies to the data I have and is taken directly from their original study. The estimated coefficient and estimated increase in habit in financial crises would imply an increase in expected return of around 5% in financial crises relative to recessions. Moreover, the estimated increase in risk premia during recessions imply that expected returns would rise by around 9%, whereas they would increase by around 35% during wars and around 20% in deep recessions. All in all, recessions and financial crises should not be drastically different in terms of increases in risk premia according to the habit model, while risk premia in wars and deep recessions should be dramatically higher than both. Therefore the model has difficulty matching the data on this dimension.

3.2.2 Long Run Risks

Long run risks models (Bansal and Yaron (2004)) feature Epstein-Zin-Weil utility and slow persistent movements in consumption and consumption volatility. Future consumption enters the SDF and hence

$$E_t\left[R_{t+1}\right] - R_f = f\left(\sigma_{C,t}\right) \tag{6}$$

The model is lognormal, so more specifically we have

$$E_t\left[r_{t+1}\right] - \frac{1}{2}\sigma^2\left(r_{t+1}\right) - r_f = \alpha + \lambda\sigma^2_{C,t} \tag{7}$$

for constants α and λ. Therefore high risk premia should correspond to high consumption volatility. Return volatility also depends on consumption volatility, therefore expected excess returns are only a function of consumption volatility.

Empirically, I measure consumption volatility in two ways. I look at 10 year rolling estimates of consumption volatility and also estimate consumption volatility in each country as a GARCH(1,1) process. The estimated consumption volatility at time t uses the forward 10 years of annual data. I choose to use volatility instead of variance because units are more easily interpreted, but using variance produces similar results. In the data, consumption volatility is similar across recessions and financial crises, and is much larger in both wars and deep recessions. Regardless of magnitudes, this model is not able to fully account for the variation in risk premia across episodes. Here the calibration is not correctly suited to the data because the original BY study focuses on US data after WWII when consumption volatility is small. Therefore, rather than using that calibration, or re-calibrating the model to past data, I will simply point out that the model will struggle to match the facts under any parameters.

3.2.3 Rare Disasters

The rare disasters literature (Barro (2006), Rietz (1988), and Gabaix (2012)) argues that asset prices and risk premia can be explained by rare disasters which are defined as any large decline in consumption and/or GDP. Empirically, most of these disasters are major wars or financial crises. In these models the equity premium is only a function of the probability of the rare disaster, and a 1-2% probability of disaster can match the equity premium with low risk aversion. Gabaix (2012) shows that the expected no-disaster equity premium is approximately given by

$$E_t\left[R_{t+1}\right] - r_{f,t} = p_t E_t\left[B_{t+1}^{-\gamma}\left(1 - R_{t+1}^{dis}\right)\right] \tag{8}$$

where p_t is the probability of disaster, B_{t+1} is the size or severity of the disaster (i.e. a 30% loss in output means $B_{t+1} = 0.7$), R_{t+1}^{dis} is the gross return conditional on disaster, and γ is risk aversion. Therefore the equity premium moves one-for-one with an increase in the probability of disaster, and increases exponentially with the size and potential severity of the disaster where the sensitivity depends on the risk aversion parameter γ. Typically, the rare disasters literature exogenously specifies a process for p_t to generate both high unconditional risk premia and time-varying risk premia. In calibrated disaster models, a 2% increase in the probability of disaster would double the equity premium, so even small changes in p will have large changes in risk premia (in fact, this is the point of these models).

My findings indicate that consumption disasters can not explain variation in risk premia because the most severe consumption disasters – wars – show little increases in risk premia while financial crises, which are comparably not nearly as severe, have much larger increases in risk premia. Consumption drops an average of 25% in a war related disaster, compared to about 8% in a financial crisis. Therefore, B_{t+1} is clearly highest in wars.

Of course measuring the probability of a consumption disaster is difficult and my analysis so far relies on the idea that the probability of a disaster increases right before the beginning of a disaster. I think this is a reasonable assumption for wars because usually at the start of a war, or just before a major war is lost, it seems reasonable that there is an increased likelihood of consumption falling. My results show that in years right before consumption is about to fall drastically, there is no substantial increase in risk premia, so one would have to believe that the probability of a disaster is constant over that period. However, I also look at the data from several other angles and reach the same conclusion. I find that the results are robust to using the peak dividend yield in a five year window before the disaster, which only assumes that the probability of the disaster increased at some point leading up to the event. These results are given in Table 1. Lastly, for US data where I have higher frequency, I find that risk premia do not change substantially in events that clearly increased the probability of a war related disaster such as the attack on Pearl Harbor, Hitler invading Poland, or the Cuban Missile Crisis. These results are in the appendix.

3.3 Intermediary Based Models

In intermediary based theories the SDF depends on the health of the financial sector through. This is typically related to how constrained the financial sector is in raising debt and/or equity financing. The constraints affect the risk bearing capacity of the financial sector and therefore affect risk premia. Naturally, these theories imply risk premia will be highest in financial crises because these are the episodes where the financial sector is hardest hit.

Generically,

$$E_t\left[R_{t+1}\right] - R_f = f\left(e_t\right) \tag{9}$$

where one can think of e_t as the health of the financial sector. Times when e are low constitute financial crises when the risk bearing capacity of the financial sector is particularly low and when their balance sheets are weakened. Therefore the central prediction of these models are that risk premia are highest in financial crises, consistent with what we see in the data. Examples of these models include He and Krishnamurthy (2012a), Brunnermeier and Sannikov (2012), Danielsson *et al.* (2011), and Adrian and Boyarchenko (2012). The next section goes in depth into an intermediary asset pricing model then calibrates the model to the data.

4 Intermediary-based Model

The model is based on the growing literature on intermediaries, asset pricing, and macroeconomics and is most closely related to He and Krishnamurthy (2012a) and Brunnermeier and Sannikov (2012).[6] Relative to these papers, I use a simplified framework. My goal is to calibrate the model to aggregate asset price data and see how well it can explain the facts presented thus far. My goal is not to focus on micro foundations for where these frictions come from or to fully estimate the model. I also do not claim that this is the only model one can write down where the financial sector plays a role for asset prices. Instead, the goal is simply to show that a plausible calibration of these models provides a good way to interpret the data. This allows me to compare the model to the calibrated consumption based models described earlier. As a result, however, the model takes short cuts in the interest of space.

4.1 Model of Financial Crises and Risk Premia

There are two agents in the economy: households who consume and intermediaries who make investment decisions. The key assumptions are that intermediaries are better at making investment decisions than households, but that households can only contribute a limited amount of equity to intermediaries. The first assumption makes it more efficient for households to give funds to intermediaries while the second assumption implies asset prices will depend on the amount of capital households can contribute due to frictions. I refer to intermediary equity capital as the amount of equity households provide to intermediaries at any given time.

Time is continuous and there is a tree which bears fruit, or output, Y that evolves according to:

$$\frac{dY_t}{Y_t} = \mu dt + \sigma dB_t \tag{10}$$

where B_t is a Brownian motion. The growth rate of output, μ, and output volatility, σ, are constant and output shocks are the only source of uncertainty in the model.

Let P denote the (endogenous) price of the tree which is a claim to the stream of dividends $\{Y\}$. The market return is defined as:

$$dR_t = \frac{dP_t + Y_t}{P_t} \tag{11}$$

[6] See also Rampini and Viswanathan (2012), Danielsson *et al.* (2011), and Moereira and Savov (2014). These also build on earlier work on financial frictions by Holmstrom and Tirole (1997) and Bernanke *et al.* (1996).

Given the process for output and definition of returns, I next describe in detail the decisions of households and intermediaries.

4.1.1 Households

Households are risk neutral and discount the future at rate ρ. Households make decisions to maximize

$$E\left[\int_0^\infty e^{-\rho t} C_t dt\right] \tag{12}$$

Households make decisions over consumption and investment. They can invest in a risk free asset which earns r_t or they can invest in intermediaries and earn $dR_{\varepsilon,t}$. Households are bad at managing the tree themselves and if they hold the tree directly it depreciates at constant rate δ forever and they are not able to sell back the tree to intermediaries. Because of this, households would be willing to pay at most $\underline{P} = \frac{Y}{\rho+\delta}$ which follows from the Gordon growth formula. Provided $P \geq \underline{P}$, households will not hold any of the risky asset. This sets a lower bound on the price dividend ratio. Lastly, if households invest in the intermediary, they can invest at most ε units of capital where ε is taken as given by households and will be discussed in the next section. One can loosely think of this as a moral hazard constraint that limits the amount of equity households can contribute to the intermediary (see He and Krishnamurthy (2012c), He and Krishnamurthy (2012b)).

Households' wealth evolves according to:

$$\frac{dW_t}{W_t} = -\frac{C_t}{W_t}dt + \frac{\varepsilon_t}{W_t}dR_\varepsilon + \frac{W_t - \varepsilon_t}{W_t}r_t dt \tag{13}$$

where I am assuming households give the maximal amount to intermediaries (equivalently the expected return on the intermediaries portfolio is at least as high as the risk free rate: $E\left[dR_\varepsilon\right] \geq r$). I will show that this condition always holds.

4.1.2 Intermediaries

Intermediaries can only raise a certain amount of equity capital from households. Once intermediaries raise capital from households, they make a portfolio choice decision over the risky asset and the risk free asset. Thus, their liabilities will be made up of equity from households and any risk free borrowing while their asset side will typically be made up of risky assets. After returns are earned, a fraction ψ of intermediaries die in each period.

There is a continuum of intermediaries who can each raise equity ϵ_t from households. Intermediaries have log preferences over their consumption which is a constant fraction of the equity raised from households $C_t^I = \lambda\epsilon_t$. We should think of λ as an infinitesimal fee intermediaries charge households as a fraction of equity they manage. That is, the fee is small enough that it does not affect the return intermediaries offer households and so that $\lambda\epsilon_t$ does not affect aggregate consumption. He and Krishnamurthy (2012b) instead interpret this as the intermediary's "reputation" instead of their consumption so that it has no affect on aggregate consumption

Given their preferences and the stochastic death rate ψ, intermediaries maximize

$$E\left[\int_0^\infty e^{-\psi t}\ln\left(\lambda\epsilon_t\right)dt\right] \tag{14}$$

The amount of equity capital intermediaries can raise, ϵ, evolves as

$$\frac{d\epsilon_t}{\epsilon_t} = \alpha_t\left(dR - rdt\right) + rdt \tag{15}$$

where α_t is the portfolio choice of the intermediary. Intuitively, this says that intermediaries can raise more capital when past returns are high. It captures the idea that households will be less willing or able to invest in the intermediary when past returns are poor. This can be due to informational reasons, or to a moral hazard argument (see He and Krishnamurthy (2012c) for a model which formalizes this) and results in a performance flow relationship. In this paper, I take this constraint as given.

Given the log objective function, the intermediaries' problem is reduced to a simple mean-variance portfolio choice problem

$$\max_{\alpha_t}\alpha_t\left(\mu_{R,t} - r_t\right) - \frac{1}{2}\left(\alpha_t\sigma_R\right)^2 \tag{16}$$

That is, intermediaries behave "as if" they have preferences over the equity given to them by households directly and optimize the return of this equity in a mean-variance fashion. The first order condition is:

$$\mu_{R,t} - r_t = \alpha_t\sigma_R^2 \tag{17}$$

Define ε as the *aggregate* equity raised by intermediaries. ε evolves as

$$\frac{d\varepsilon_t}{\varepsilon_t} = \alpha_t\left(dR - rdt\right) + \left(r - \psi\right)dt + d\gamma_t \tag{18}$$

Where α_t is given by the above equation and ψ reflects the death rate. The term $d\gamma_t \geq 0$ reflects entry, which I describe when describing the boundary conditions. Entry happens very rarely when the price falls to the households private value.

The return to households holding a unit of equity in the intermediary is thus:

$$dR_\varepsilon = \alpha_t \left(dR - rdt \right) + rdt \tag{19}$$

It is clear that $\mu_{R_\varepsilon} \geq r$; hence the households will give maximum possible equity to the intermediary due to risk neutrality of households. Without this assumption, there are regions where the capital constraint doesn't bind and households contribute less capital than the constraint allows. These add additional non-linearities to the model but do not change the basic conclusion. Since the tightness of the constraint essentially determines risk premia, the assumption here provides a direct link between intermediary equity and risk premia. Moreover, risk neutrality results in a constant risk free rate, whereas the interest rate in He and Krishnamurthy (2012c) can be highly negative and volatile in crises.

4.1.3 Equilibrium and Solution

An equilibrium consists of prices and allocations such that agents' decisions are chosen optimally given prices and the market clears. Given risk neutrality of households, we must have $r = \rho$, which implies the risk free rate is constant. As long as $\varepsilon > 0$, so that intermediaries are able to raise capital, the risky asset is held entirely by the intermediary sector, meaning $\alpha_{t\varepsilon t} = P_t$. For this to hold, it must be that $P \geq \frac{Y}{r+\delta}$, where $\frac{Y}{r+\delta}$ is the households valuation of the risky asset if held directly. I discuss this more fully below.

We must also have that households consume all output $C_t = Y_t$ and own all wealth $P_t = W_t$. Recall that this requires that the fraction λ of households' equity that intermediaries consume is arbitrarily small or that we interpret intermediaries as maximizing "reputation" rather than consumption as in He and Krishnamurthy (2012b). This assumption is mainly for tractability and greater ease in solving the model without substantially changing the results.

Equilibrium

I conjecture a price function $P_t = p(e_t)Y_t$, where I define $e_t = \frac{\varepsilon_t}{Y_t}$, the ratio of intermediary equity to total output, as the main state variable. Given our assumption on $p(e_t) \geq \frac{1}{r+\delta}$, the intermediary holds the entire risky asset. By market clearing

$$\alpha_t = \frac{P_t}{\varepsilon_t} = \frac{p(e_t)}{e_t} \tag{20}$$

Then using market clearing and intermediary optimality

$$\left(E_t\left[dR_t\right]-r_t\right)\frac{1}{dt}=\mu_{R,t}-r_t=\frac{p(e_t)}{e_t}\sigma_{R,t}^2 \tag{21}$$

We can think of the term $\frac{p(e_t)}{e_t}$ as the risk aversion of a fictitious representative agent with mean-variance preferences so that "aggregate risk aversion" depends on intermediary capital. We can see two main features of risk premia, $E_t\left[dR_t\right]-r$. First, risk premia depend on intermediary capital so that low capital implies high risk premia and vice versa. This will make financial crises, defined as times when e_t is low, the times when risk premia are highest. Second, these effects are non-linear due to the $\frac{1}{e_t}$ term – when intermediary capital is high, changes in capital will have small effects on risk premia, but when it is low risk premia will spike and be particularly sensitive to further changes in intermediary capital. This means volatility will be high as small changes in intermediary capital can lead to large changes in prices.

Solution

Given the conjecture that the price dividend yield depends only on e, we can calculate the market return using Ito's Lemma as

$$dR_t=\frac{dP_t+Y_t}{P_t}=\frac{dY_t}{Y_t}+\frac{p'}{p}de_t+\sigma\sigma_e\frac{p'}{p}dt+\frac{1}{2}\sigma_e^2\frac{p''}{p}dt+\frac{1}{p}dt \tag{22}$$

We can combine the return equation (22) with optimality (21) to derive the ODE:

$$\mu+\frac{p'}{p}\mu_e+\sigma\sigma_e\frac{p'}{p}+\frac{1}{2}\sigma_e^2\frac{p''}{p}+\frac{1}{p}-r=\frac{p}{e_t}\sigma_R^2 \tag{23}$$

The Appendix goes through the details of solving the ODE and specifies the boundary conditions.

5 Calibration and Comparison to Data

5.1 Calibration and Basic Moments

Table 3 contains the calibrated parameters. I assume standard parameters where available. I set the volatility of aggregate output or consumption growth, σ, to 5%, which is consistent with historical data from Barro *et al.* (2011). In the model there is no difference between consumption and output (GDP) because it is an endowment economy. I will therefore try to calibrate to consumption data, but should note that using GDP instead is not meaningfully different. The parameter μ is chosen at 1.8% to match average real economic growth. The intermediary death rate ψ is set to 8%. This parameter ensures well behaved dynamics and a stationary distribution but is also chosen to match the (unconditional) equity premium. By having a high death rate, the economy will be more likely to be in the crisis region and this will increase unconditional risk premia. Finally, the parameter ρ is set at 3% to roughly match the real interest rate and also to match the average price dividend ratio in the data. The model has only five parameters and these are either pinned down by the data or chosen to match unconditional moments.

The depreciation rate δ governs entry on behalf of households and determines how low the price dividend ratio will fall. I choose a depreciation rate of 13% so that the implied lower bound on the price dividend ratio is about 6. I calibrate this parameter to roughly match the lower bound on the price dividend ratio in the data. For the U.S. the lowest value in the past 100 years is around 10, while when using international data this value fell to as low as 4. If I simulate the model, the average minimum price dividend ratio observed in 100 years of annual data is just over 9, which is close to the lowest value observed in U.S. data.

I plot the model solution in Figure 5. As we can see risk premia and volatility are increasing as intermediary equity falls. These effects are non-linear and the sensitivity of these variables to intermediary equity is significantly higher in bad times. For reference, I plot a dashed vertical line which represents the 7th percentile of the state variable, which will represent the cutoff for a crisis in the economy as I describe later. I also plot the stationary distribution of the state variable (I exclude the high end of the distribution on the plot because all variables are essentially flat there). As we can see in normal times when e is very high, negative shocks will not have large effects on risk premia, but in crisis times (to the left of the dashed line), small shocks will have very large effects.

Basic Moments

Table 4 compares moments in the model to the data. I simulate the model monthly then aggregate all simulated data to the annual frequency to match my sample which contains annual data. The model calibration matches average moments quite well. By design the model matches average economic growth, the volatility of consumption growth, and the equity premium. Given the parameters chosen to match these moments, the model also matches equity volatility (20% vs.. 19%), and hence the market Sharpe ratio.[7] The model also matches the "volatility" of volatility (10.3% in the model vs.. 9.2% in the data) so

[7] Note that the Sharpe ratio is computed as the unconditional average return over unconditional volatility of returns, which in the model is somewhat different than the average conditional Sharpe ratio because of the co-movement between expected returns and volatility. The average conditional Sharpe ratio is 0.42 vs an unconditional Sharpe ratio of 0.35, which reflects this co-movement in the model.

volatility in the model is strongly time-varying. The model is too low on the log price-dividend ratio (2.8 in the model vs.. 3.3 in the data). The model has a reasonable real risk free rate at 3%. The real risk free rate is less than 1% in post war US data, but is 2.9% over a longer sample in US data (see Campbell and Cochrane (1999)) and is around 1.5% using an international sample (Barro (2006)). The biggest challenge for the model is the persistence of the dividend yield (0.5 vs.. 0.8 in the data), which also results in low volatility of dividend yields. However, the value from the model is much closer to Lettau and Van Nieuwerburgh (2008) who use trend breaks in the dividend yield and find a persistence of 0.6 and volatility of 0.2. In my setting, I could likely add low frequency persistence in the mean dividend growth rate to generate higher dividend yield persistence. This would likely not change risk premia dynamics much due to log utility, but would generate more persistent price dividend ratios. However, this isn't pursued in this paper. Taken as a whole, Table 4 suggests that the model does a good job of matching standard unconditional asset pricing moments.

5.2 Crises and Recessions

Defining a crisis in both the model and data is a challenge. Empirically, there is not widespread agreement on what exactly constitutes a financial crisis. In the model it is clear that a crisis should be defined by low realizations of the state variable e_t, but e_t takes on a continuum of values so deciding on the exact cutoff is potentially arbitrary.

I choose to base my cutoff to target the average probability of a financial crisis. Reinhart and Rogoff (2009) estimate the share of years spent in a banking crisis since 1945 to be 7.2% for advanced economies and 11% for emerging markets. I choose the cutoff of e_t that defines a crisis so that the economy spends 7% of its time in the crisis region to match the percentage of time spent in a crisis for advanced economies which make up my sample. My definition of a crisis should not be seen as crucial, but rather a good way to illustrate the effects of a crisis and compare to the data. The results aren't sensitive to a slightly different cutoff.

Given this definition of a crisis, I show that the model produces declines in consumption and increases in dividend yields during a crisis that are in line with severe crises in the data. I plot this in Figure 6. First, the model matches the data extremely well in the response of dividend yields both in terms of levels and dynamics. In terms of timing, we see in the data dividend yields increasing a year after the onset of the business cycle peak associated with the financial crisis. Therefore in the model, I plot the response of all variables assuming the crisis begins the following year so that the timing of the dividend yield peak matches the data. The model also matches the total drop in consumption in the data well, though this is a sharp decline in the model vs. a more persistent decline in the data. In terms of returns, the model matches the initial drop in stock returns and the reversion, though the reversion happens faster in the model than in the data. Some of this could be due to timing in the data as it is hard to measure precisely when things occur, and some could be due to the starkness of the model. Overall, Figure 6 shows that the model dynamics for risk premia and economic growth in a crisis match the data very well.

Table 5 runs regressions of dividend yields, returns, and consumption growth on indicators for financial crises and recessions as in the data. In the model, I define a recession as having occurred if annual economic growth (consumption growth) is negative. I use the timing assumption as mentioned above where both events in the model occur in year 1. We can see that the model does well in matching the data. Dividend yields spike by about 20% more in financial crises than recessions in the model and data. In recessions, dividend yields spike by around 8.6%. Consumption drops also match well across episodes. In the model consumption is about 4% lower than in recessions, which is close to the data. Moreover, recessions generate around an 8-10% decline in consumption in the data and around 8% in the model. One caveat is that the timing in the model is very stark: consumption and asset price drops happen simultaneously and immediately whereas consumption in the data is perhaps slower to respond. For returns, the model generates a large loss in crises and recessions. Notice in the model only the crisis return is substantially reversion in the following period (this is due to the high risk premia). The return two years out is 22% above the unconditional average return, so prices fully rebound. In the data this takes longer, but we do see the exact same effect with returns close to 20% four years out. The bottom panel of this Table reports the results when only considering financial crisis dummies and shows similar results. Overall, the model does a good job capturing the difference between recessions and financial crises, as well as the behavior of consumption, returns, and risk premia during financial crises.

What explains the difference between typical recessions and financial crises in the model? Risk premia are very high in financial crises because the equity of the financial sector is very low and their risk bearing capacity is reduced (equivalently, their balance sheets are weakened). In times when e is low even small shocks have amplifying effects through the fact that volatility is very high (see Figure 5). In contrast, in normal times, when equity is relatively high, even large negative economic shocks (i.e. a recession) will not change risk premia drastically. Suppose the economy is near the largest possible state for e. A negative economic shock will reduce output Y, but will also reduce equity ε. Risk premia and volatility are very low in this state, as can be seen by the model solution, so the market return will be close to dividend growth that period which is equal to the drop in Y. Loosely, $dR \approx dY/Y$ in normal times because there is no amplification through the financial sector. Thus $e = \varepsilon/Y$ will change very little and the shock will cause little movement in risk premia.

One major caveat of the model is that it currently only has one shock. This is for simplicity and tractability, but admittedly limits some of the analysis. For example, it generates the close timing between consumption and asset price data. It also means that the state variable only depends on the history of economic shocks which affect both consumption and asset prices. There is no way to enter a financial crisis without having negative economic shocks, though the model does amplify those shocks differently depending on the health of the financial sector. What I have shown is that the relationship between the state variable and consumption is much more complicated in this model than other work, therefore the model can generate recessions that are deep in terms of consumption loss but show little effects in risk premia. That accords with the extreme non-linearity of the models solution seen in Figure 5. However, this is also a limit of the model. In the data, it is clear that variables uncorrelated (or at least not perfectly correlated) with consumption shocks can potentially affect intermediary balance sheets and risk bearing capacity. Therefore, a natural extension of the model would be to allow for a separate shock affecting only intermediaries which could induce even more variation between low consumption episodes and high risk premia episodes. In other words, an extension of the model could easily generate independent variation in the state variable. This richer model could help explain the behavior of risk premia during wars, which is currently outside the scope of the model because of the complication it would add. Indeed we should not take the simple model here too literally, the goal is simply to show that it does a reasonably good job at matching the data despite its simplicity. It should be clear that because risk premia are tied to intermediary balance sheets, the model still matches the data in that times when intermediary balance sheets are weak correspond to high risk premia and other measures of "bad times" do not seem to matter. Therefore the core prediction of why risk premia vary in the model is consistent with what we see in the data. The next section tries to make the link between the equity of the financial sector and risk premia even more clear in the data.

5.3 The Link Between Risk Premia and Intermediary Equity

The model says that risk premia fluctuate with the health of the financial sector. While the previous sections have established the link between financial crises and risk premia, this section *directly* shows that intermediary equity measures risk premia by showing that it strongly predicts asset returns and is "priced" in the cross-section of stock returns. This supports the main channel through which risk premia operate in the model, and formalizes the observed link between risk premia and financial crises in the previous sections. One caveat to this section is that financial sector equity data is not available historically across countries and over longer time periods, so I can not systematically analyze its behavior in financial crises.

I measure intermediary equity (e_t) as the total market value of the financial intermediary sector divided by GDP in US data. I calculate market value as price times total shares outstanding of the financial sector in CRSP. I define the financial sector as having an SIC code beginning with 6, though more refined definitions work equally well. For example, one can exclude real estate firms or only focus on commercial and investment banks. A major caveat, however, is that this measure does not include private financial intermediaries such as hedge funds or private equity. I take quarterly GDP from NIPA and create a monthly series by assuming the current monthly growth rate is equal to the previous quarters growth rate so that I do not use any future data in constructing the estimated current months GDP. Monthly data is preferred in order to forecast returns at monthly horizons because in the model there are high frequency movements in risk premia. The analysis using only quarterly data is nearly identical when predicting returns at quarterly or longer horizons. I define $e_t = \ln\left(FinMktCap_t/GDP_t\right)$.

I run predictive regressions for asset returns as:

$$R^e_{t+k} = \beta_0 + \beta_1 e_t + \beta_2 t + \varepsilon_{t+k}$$

where k is the number of months ahead and R^e_{t+k} is the excess return over the risk free rate. I include a linear time trend t to account for an increasing trend in e_t over time as the financial sector has grown. Alternatively, one can linearly detrend the series, but this technically requires using future data not known at time t. Therefore I simply account for the trend by including it in the regression.

Table 6, Panel A provides the results for forecasting the market excess return for various horizons and shows that the R^2 ranges from 2% (monthly) to 17% (annually) to 44% (5 year horizon) over the 1948-2012 time period. This is a much higher degree of predictability found using the price dividend ratio alone and when I include the price dividend ratio to the regression it does not, generally, show up as significance or increase the forecasting power.[8] The sign is negative, which is consistent with low intermediary capital corresponding to high

[8] The ability of the intermediary net worth series to drive out the price dividend ratio is again somewhat

risk premia. Intermediary equity also forecasts annual excess corporate bond returns with an R^2 of 17%, and the annual excess return of the financial sector with an R^2 of 20%. I repeat these exercises in the model. All signs are consistent with the model, and many of the values are comparable. One key difference, however, is that in the model predictability is relatively stronger at shorter horizons and relatively weaker at longer horizons, and coefficients decline with horizon. This implies that movements in risk premia are less persistent in the model than in the data. In sum, intermediary equity has substantial forecasting power for asset returns over many frequencies, lending support to the view that it co-moves with risk premia. Figure 7 plots e_t (linearly detrended) in the data along with the subsequent 5-year market return and shows the high correlation between the two series. The lowest realizations of e_t occur in 2008-2009, 1990, and 1982, respectively – all times when the U.S. experienced trouble in the financial sector.

Turning to Panel B, I show that e_t is "priced" in the cross-section of stock returns. In the model e_t enters the SDF along with the market return, motivating a two factor model for expected returns:

$$E[R^e] = a + \beta_{R,mkt}\lambda_{mkt} + \beta_{R,e}\lambda_e + \varepsilon_{t+k}$$

where $\beta_{R,mkt} = \frac{cov(R_{mkt},R)}{var(R_{mkt})}$ and likewise for $\beta_{R,e}$. According to the model, we should see positive prices of risk for exposure to intermediary equity since low e_t states are ones with high marginal value of wealth. Assets that co-vary with e_t are thus risky and must offer high returns. To test this, I use 35 excess returns from Ken French's website: 25 size and book-to-market portfolios and 10 momentum portfolios. I run standard two-pass regressions where I first estimate βs in a time-series regression and then run a cross-sectional regression of average returns on these βs. Intermediary capital indeed has a positive and statistically significant price of risk at 0.43 with a t-stat of 2.76. I use Shanken (1992) standard errors which correct for first stage estimation of βs. The two-factor intermediary model is able to explain about half of the variation in average returns in these portfolios with an adjust R-squared of 49%, though only intermediary equity carries a significant price of risk. As a benchmark, I compare this to a four factor model which includes the Fama-French and momentum factors. This four factor model explains 86% of the variation in average returns. While there is no true cross-section in the model, these findings still support the implication that intermediary equity enters the pricing kernel.

at odds with the one shock model I presented here, since in the single shock model aggregate wealth and intermediary equity will be very highly correlated. A richer model with independent shocks could again help break this correlation.

These results extend previous research linking intermediary balance sheets to risk premia (Adrian *et al.* (2012), Adrian *et al.* (2011)). First, my results use market valuations of intermediary net worth, whereas previous results use book value. My measure of risk premia is explicitly implied by a large number of models, linking my results closely to theory. Second, previous results focus on subsets of the intermediary sector (e.g., broker-dealers or shadow banks) whereas this paper uses the entire sector as a whole. I also use higher frequency data and a much longer sample. Finally, I use the same measure to show both time-series predictive power and cross-sectional pricing power, while these papers study each separately. These results are meant to compliment the previous literature on intermediaries and risk premia and to show that the main implications of the model hold in the data.

6 Conclusion

This paper argues that financial crises are essential for understanding asset price fluctuations and risk premia. I first document this fact empirically by using data on consumption, dividend yields, stock returns, and credit spreads for over 140 years and 14 countries, yielding 180 recessions, 45 financial crises, and 20 major wars. First, I document that risk premia spike dramatically in financial crises – defined specifically as a banking panic or banking crisis – but rise only slightly in recessions or wars. The large increase in risk premia during financial crises puts explaining these episodes to the forefront of the asset pricing literature, but equally interesting is the lack of variation in risk premia across the other episodes. These facts add substantially to the question of why risk premia vary over time and point to the health of the financial sector as being a key determinant of asset prices. To my knowledge, this is the first paper to study and characterize the behavior of risk premia across financial crises, and is the first to compare financial crises to other events. Next, I examine the ability of leading asset pricing models to explain these facts. The behavior of consumption moments across financial crises, recessions, and wars is either roughly flat or has the wrong sign, meaning the variation in risk premia can not be explained by standard consumption based macro asset pricing models. I then study a simple model similar to He and Krishnamurthy (2012b) and Brunnermeier and Sannikov (2012) that generates financial crises that quantitatively match those in the data. The key feature of the model is that risk premia are tied to the health of the financial sector. In the model calibrated here, this is specifically equity capital, though in other models the link is more directly to leverage and the credit cycle, as in Geanakoplos (2012). Consistent with the model, I show that a measure of financial intermediary net worth forecasts annual stock and corporate bond returns with a high degree of explanatory power of around 17-20% in US data. Overall, my findings strongly support the idea that risk premia are linked to the health of the financial sector and highlight the role of financial crises for understanding risk premia.

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Figure 1: This figure computes changes in risk premia, as measured by dividend yields (left axis) and credit spreads (right axis), in Panel A across financial crises, recessions, deep recessions, and wars. Panel B plots consumption state variables argued to capture variation in risk premia: the peak to trough decline in consumption (left axis) and consumption volatility (right axis).

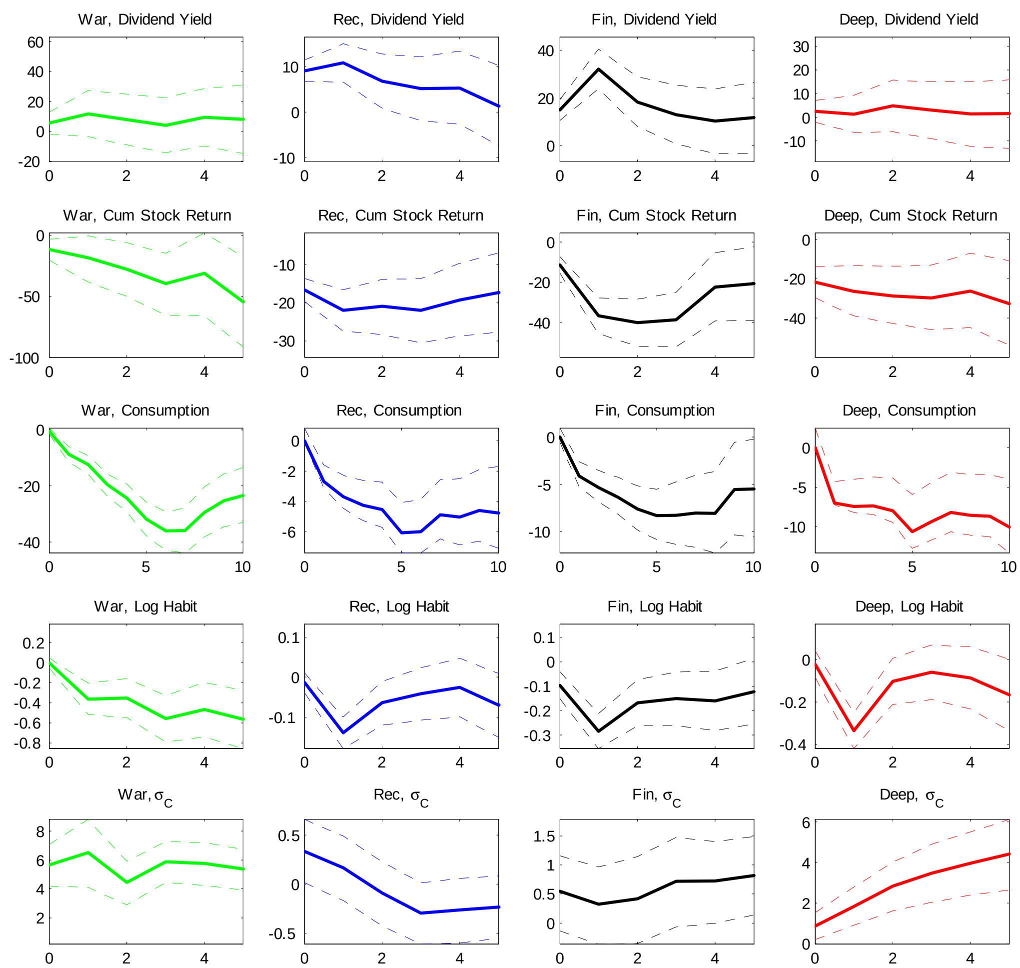

Figure 2: This figure plots the impulse responses to each event. The x-axis is in years. War denotes "war related disasters," Rec "recessions," Fin "financial crises," Deep "deep recessions" (defined as the worst 30% of recessions). I plot the dividend yield, log consumption, log habit, and volatility of consumption, all relative to means.

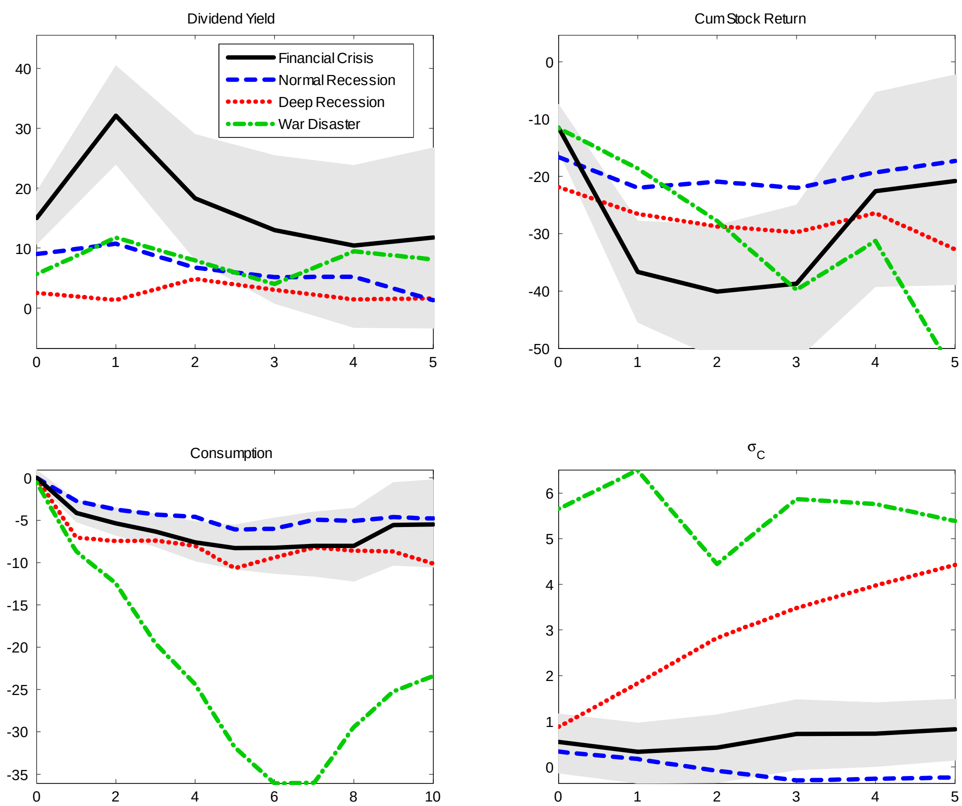

Figure 3: Impulse responses for each event are shown for key variables. I plot 90% error bands for financial crises in gray.

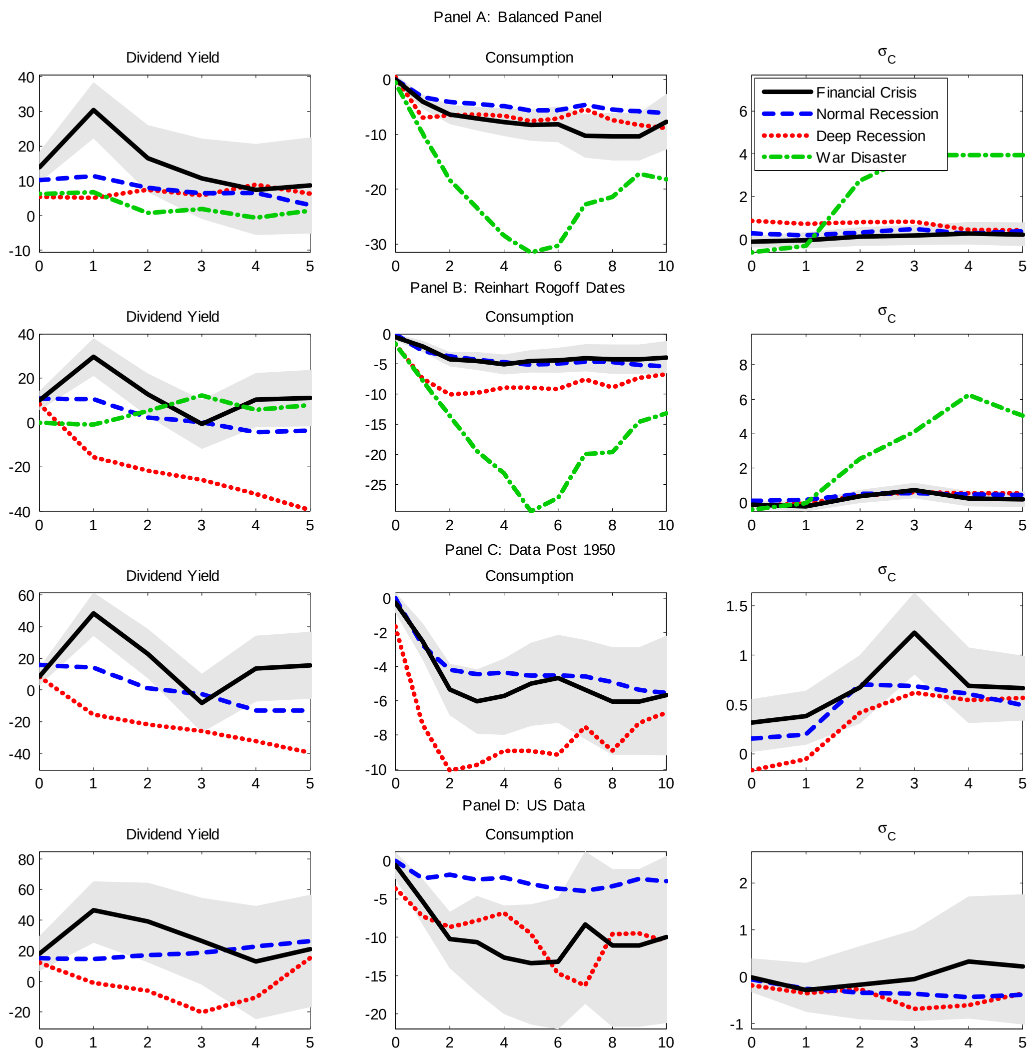

Figure 4: This figure documents robustness of the main results by showing impulse responses for dividend yields, consumption, and consumption volatility using various filters. Panel A uses a balanced panel of macro and asset price data, Panel B using Reinhart and Rogoff as an alternative way to date financial crises, Panel C shows the results using data after 1950, and Panel D focuses solely on US data. These alternatives suggest that the results are not due to pre-Fed regulatory regimes or poor measures of macro varialbes before WWII, are not due to specific dating conventions, and at least look reasonably consistent with data only from the US (though there are only 6 crises so confidence bands are wide). War disasters are omitted from the lower two panels as there are essentiall no occurences using these filters. I plot 90% error bands for financial crises in gray.

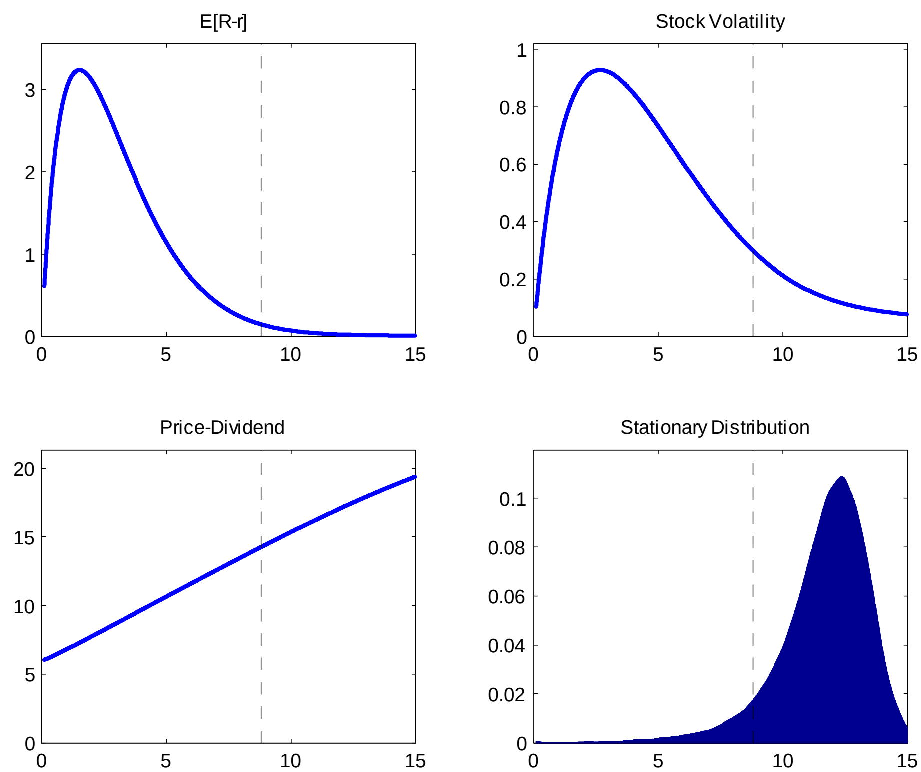

Figure 5: I plot the model solution as a function of the state variable e defined as intermediary equity divided by output. The key feature of the model solution is the spike in volatility and risk premia when e is low. The upper left panel gives the equity premium, the upper right gives equity volatility, the lower left gives the price dividend ratio, and the lower right gives the stationary distribution of the state variable e. Finally, in each panel I draw a dashed line which represents the lowest 7th percentile of realizations of the state variable which constitutes the cutoff for a financial crisis in the model.

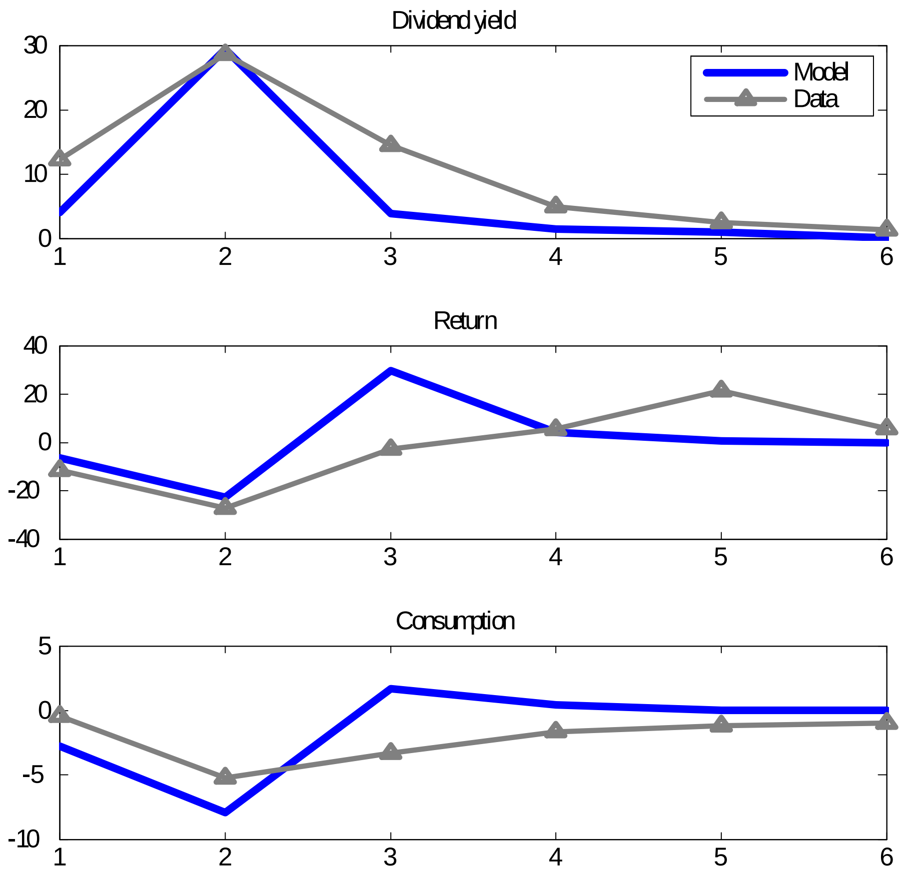

Figure 6: This figure plots the response of dividend yield and consumption growth to a financial crisis in the data and in the model. The top panel matches the timing of the peak of the crisis as occuring in year 2 in the model and data. In the middle panel I plot consumption growth in the data vs the model using the same timing convention as in the top panel. In the bottom panel I use lagged consumption growth in the model instead of current consumption growth. This allows for the fact that in the data consumption may respond with a lag rather than contemporaneously. See text for details.

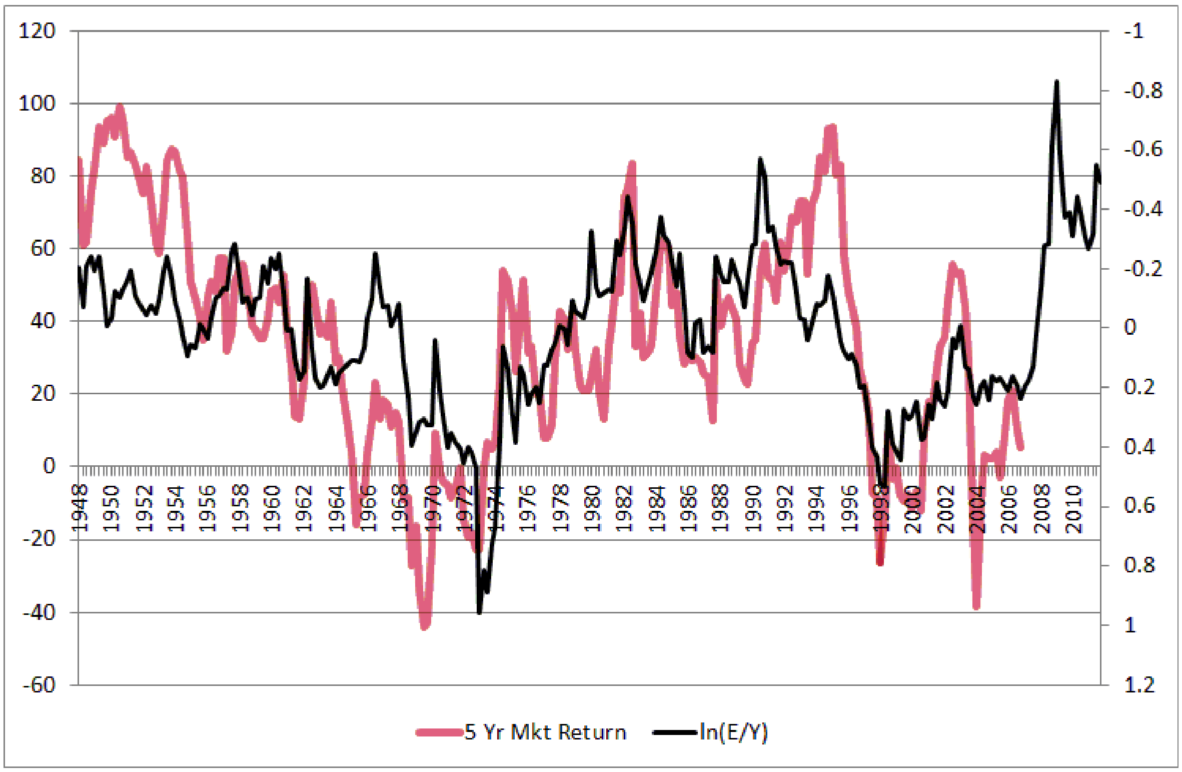

Figure 7: I plot the log of the ratio of intermediary equity to GDP (black line, right axis, decreasing scale) which is the state variable in the model, along with the subsequent 5 year excess return on the market (red line, left axis). Intermediary equity is defined as the total market capitalization of the financial sector (SIC code of 6). The intermediary equity to GDP series is linearly detrended. The model implies that intermediary equity should forecast returns.

Table 1: Summary statistics across episodes.

Risk premia:					
Variable	Description	Fin Crisis	Recession	Deep Recess	War
Δdp	5 yr change in dividend yield	26%	6%	4%	8%
$\max(\Delta dp)$	Peak dp relative to initial value*	36%	23%	17%	23%
N	#observations	41	135	43	15
spreads	Credit spreads	7%	2%	2%	1%
N		28	66	21	5

Macro:					
Variable	Description	Fin Crisis	Recession	Deep Recess	War
c	Peak to trough consumption	8%	7%	12%	24%
σ_C	Consumption volatility	4.9%	4.8%	6.7%	11.6%
N		71	209	63	24
Macro: non-missing stock market data					
c	Peak to trough consumption	8%	8%	13%	25%
σ_C	Consumption volatility	4.1%	4.8%	7.0%	9.7%
N		41	135	43	15

*Note: a random 5 year window gives an average peak dp of 22%

Robustness to alternative Reinhart Rogoff Dates:				
Variable	Description	Fin Crisis	Recession	Deep Recession
Δdp	5 yr change in dividend yield	18%	3%	-5%
c	Peak to trough consumption	7%	6%	8%
σ_C	Consumption volatility	5%	5%	7%
N		75	219	89

Table 2: I run regressions of asset prices and macro variables on event indicators. Each indicator takes on the value 1 if the event occurred at the specified lag. The variables: dp is dividend yield, r is real stock return, $r - r_f$ is excess return, Δd is dividend growth, cs is credit spread, cfn and drn are cash flow news and discount rate news extracted from a VAR as in Campbell 1991, Δc is consumption growth, sc is log surplus consumption, σ_c^2 is the variance of consumption growth. See main text for a description of these variables. All regressions include country fixed effects and some include a linear time trend as indicated to deal with decreasing dividend yields and macro volatility over time. All numbers are reported in percent per annum. I also include a lag of the dependent variable in the controls. Stars ($*$) indicate significance at $10\%, 5\%, 1\%$ levels. Standard errors clustered by year.

Response of asset prices and macro state variables to events

$y_{i,t}=\alpha_i + \sum_{j=0}^{J} a_j 1_{fin,i,t-j} + \sum_{j=0}^{J} b_j 1_{recession,i,t-j} + \sum_{j=0}^{J} c_j 1_{war,i,t-j} + \mathbf{x}_{i,t} + \varepsilon_{i,t+1}$

	y variables									
	Risk premia and cash flows							C state variables		
	dp	r	$r - r_f$	Δd	cs	cfn	drn	Δc	sc	σ_c^2
Fin Crisis										
0	4.1	3.7	1.6	11.2	5.0***	5.1	1.3	0.7	1.8	-0.2*
1	16.5***	-22.6***	-26.8***	-2.9	-0.4	-10.0**	13.3***	-1.5*	-7.0*	-0.1
2	-8.5	-0.8	-5.1	-9.0	-0.5	-7.2	-4.8*	-1.1	-6.6	-0.0
3	-5.1	8.1	2.5	8.4	-1.6	2.1	-6.0**	-0.1	0.1	0.0
4	-3.6	16.2***	15.5**	10.4	2.8**	13.5**	-2.0	-0.3	-2.4	0.1
5	3.4	0.8	-1.1	3.2*	-1.3	5.8	1.8	1.1	5.1	0.1
Recession										
0	9.3***	-15.2***	-14.4***	-9.7**	-0.2	-10.3***	5.0***	-1.1**	-4.2	0.2***
1	-0.7	-3.0	-2.9	-4.8	0.3	-6.6**	-1.7	-3.7***	-13.8	0.1**
2	-1.2	1.5	1.6	-3.3	1.3**	-2.7	-0.5	-2.0***	-6.2	0.2***
3	-0.1	-2.1	-1.1	-2.1	0.9	-3.8	-0.6	-1.4***	-4.5	0.1**
4	2.2	4.5	5.2	4.6	-0.7	3.9	-0.2	-0.8	-1.7	0.2**
5	-1.8	2.3	2.3	-4.5	-0.1	-3.3	-1.6	-2.0***	-6.7	0.1**
War										
0	3.3	-2.5	-0.8	3.7	-0.5	0.4	2.7	-1.0	-4.0	1.7***
1	-18.9**	13.7	20.5**	-3.4	-1.7	5.8	-10.4**	-17.6***	-54.8***	1.7***
2	-4.9	-33.5***	-26.5**	-29.4*	-1.2	-34.3***	-2.0	-10.0***	-22.0**	1.0***
3	-13.1	-32.7***	-22.2**	-30.7*	0.5	-33.2***	-5.4	1.6	3.0	0.4**
4	-12.5	-31.5***	-26.0**	-23.1	0.1	-23.6**	-6.0	2.9	5.3	0.2
5	-6.5	-21.4**	-19.0*	16.5	-2.0	5.9	-0.5	4.9***	16.1	0.2
N										
R^2	76%	13%	13%	16%	74%	15%	9%	21%	75%	27%

Table 3: This table provides calibrated parameters in the model. All values are annualized.

Parameter		Description	Targeted Moment
σ	5%	Volatility of output	Vol of consumption (or GDP)
ρ	3%	Time discount	Risk free rate, average price dividend
μ	1.8%	Growth rate	Average growth
ψ	8%	Intermediary death rate	Well behaved dynamics
δ	13%	Depreciation for HH	Lowest p, entry

Table 4: This table provides moments on quantities and asset prices implied by the model vs the data. In the model, I form 10,000 100 year long samples and compute corresponding statistics. Simulated data are monthly but reported in annualized numbers. dY/Y represents output or consumption growth in the model. For more details on the series, see data appendix.

Basic Moments (% per year):				
		Model		
	Data	Mean	95%	5%
$E[dY/Y]$	1.80	1.80	2.56	0.90
$\sigma[dY/Y]$	5.17	5.00	5.17	4.84
$P[crisis]$	7.2	7.0	8.3	5.8
$E[r_f]$	0.60	3.00	—	—
$E[R-r_f]$	7.36	6.94	10.24	3.67
$\sigma[R-r_f]$	18.95	19.98	22.03	18.16
$\frac{E[R-r_f]}{\sigma[R-r_f]}$	0.39	0.35	0.50	0.19
$E[\sigma_{R,t}]$	17.98	16.39	16.82	15.83
$\sigma[\sigma_{R,t}]$	9.20	10.30	11.40	9.40
$E[\ln(p/d)]$	3.28	2.84	2.85	2.83
$\sigma[\ln(p/d)]$	0.29	0.12	0.13	0.11
$AC1[\ln(p/d)]$	0.81	0.50	0.55	0.44

Table 5: I run regressions of asset prices and macro variables on event indicators in the Model and in the Data. The variables: dp is dividend yield, r is return, Δd is dividend growth and Δc is consumption growth. In the model, ΔY represents the cash flow shock, but Y represents the aggregate dividend, output (GDP), or consumption because it is an endowment economy. See main text for a description of these variables. All regressions in the data include country fixed effects and some include a linear time trend as indicated to deal with decreasing dividend yields and macro volatility over time. All numbers are reported in percent per annum. I also include a lag of the dependent variable in the controls. Stars ($*$) indicate significance at $10\%, 5\%, 1\%$ levels. Standard errors clustered by year.

Response of variables in financial crisis vs. typical recession

$y_t = \gamma_i + \sum_{j=0}^{T} a_j 1_{fin,t-1} + \sum_{j=0}^{T} b_j 1_{recession,t-1} + \varepsilon_{t+1}$

	Model			Data			
	Risk premia		CF	Risk premia		CF	
	dp	r	ΔY	dp	r	Δc	Δd
Fin Crisis							
0	2.7	-3.0	-1.2	4.1	3.7	0.7	11.2
1	21.6	-13.3	-3.1	16.5***	-22.6***	-1.5*	-2.9
2	-4.8	21.8	0.4	-8.5	-0.8	-1.1	-9.0
3	-0.9	2.9	0.0	-5.1	8.1	-0.1	8.4
4	0.0	0.0	0.0	-3.6	16.2***	-0.3	10.4
5	0.0	0.0	0.0	3.4	0.8	1.1	3.2*
Recession							
0	0.0	1.1	0.3	9.3***	-15.2***	-1.1**	-9.7**
1	8.6	-16.5	-7.5	-0.7	-3.0	-3.7***	-4.8
2	2.0	7.1	0.0	-1.2	1.5	-2.0***	-3.3
3	1.1	2.9	0.0	-0.1	-2.1	-1.4***	-2.1
4	0.7	1.4	0.0	2.2	4.5	-0.8	4.6
5	0.5	0.6	0.0	-1.8	23	-2.0***	-4.5

Response in financial crises: $y_t = \gamma_i + \sum_{j=0}^{T} a_j 1_{fin,t-1} + \varepsilon_{t+1}$

	Model			Data			
	Risk premia		CF	Risk premia		CF	
	dp	r	ΔY	dp	r	Δc	Δd
Fin Crisis							
0	4.9	-5.9	-3.0	12.0***	-8.9*	0.6	3.3
1	27.5	-21.6	-7.8	18.7***	-22.1***	-4.0***	-5.3
2	-4.7	29.3	0.0	-7.4*	2.55	-1.6*	-11.1*
3	-1.9	4.9	0.0	-5.5	6.51	-0.5	6.3
4	0.0	0.0	0.0	-0.5	20.7***	-0.6	13.8**
5	0.0	0.0	0.0	3.9	1.5	-0.6	1.2

Table 6: This table compares the predictive power of intermediary capital in the model vs the data by running predictive regressions of returns on lagged intermediary equity In the data, I use the total market valuation of the financial sector divided by GDP, analogous to the model. When forecasting asset returns, I include a linear time trend for intermediary equity as this variable is increasing over time. I compare performance to the log price-dividend ratio in the data. T-stats computed using Newey-West with lags depending on horizon. Panel B runs a cross-sectional asset pricing test using 35 portfolios (25 size and book to market portfolios and 10 momentum portfolios) to test whether intermediary equity is "priced" in the cross-section of asset returns. Shanken t-stats reported below. Data sources: $R^e mkt$ and $R^e fin$ are the market and financial sector excess returns, respectively. All stock returns are from Kenneth French's website. $R^e corp$ is an excess corporate bond return from Barclays constructed as the return on maturities between 3 and 5 years. All data are from 1948-2012 except corporate bond returns which are from 1988-2012. See appendix for additional details.

Panel A: Predicting Excess Returns: $R^e_{t+k} = \beta_1 x_t + \beta_2 t + \varepsilon_t$

	Model: $\ln(e_t)$		Data: $\ln(e_t)$		Data: $[\ln(e_t), \ln(p_t/d_t)]$		
Return	β_e	R^2	β_e	R^2	β_e	β_{pd}	R^2
$R^e mkt_{t+1}$	-0.42	3%	-0.26***	2%	-0.25***	-0.02	1%
$R^e mkt_{t+3}$	-0.39	7%	-0.27***	5%	-0.26***	-0.02	5%
$R^e mkt_{t+12}$	-0.28	21%	-0.28***	17%	-0.25***	-0.04	18%
$R^e mkt_{t+60}$	-0.10	32%	-0.27***	44%	-0.22***	-0.08*	47%
$R^e fin_{t+12}$	-0.92	51%	-0.30***	20%	-0.28***	-0.04	19%
$R^e corp_{t+12}$	-0.16	32%	-0.09***	17%	-0.08***	-0.01	17%

Panel B: Cross-Sectional Asset Pricing: $E[R^e] = a + \lambda_f \beta_f + \varepsilon_t$

	a	mkt	smb	hml	mom	$\ln(e_t)$	AdjR^2
Intermediary Model	5.96	0.63				0.43	49%
t-stat	(0.87)	(0.34)				(2.76)	
Benchmark Model	7.55	0.15	1.45	3.53	13.91		86%
t-stat	(1.99)	(0.04)	(1.01)	(2.08)	(4.55)		

Online Appendix: Financial Crises and Risk Premia

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Abstract

This appendix supplements the main text. It describes the data sources in detail and performs various robustness checks.

A0.1 Robustness

I show that the results in the main table (Table 1 in the main text) are robust to subsamples where I look specifically at data from 1950 onwards. The similarity of these results to the main results suggests that the main findings are still relevant in more modern economies. This is important because the nature of the banking sector, regulation, and government intervention in crises has changed over time. Table A1 gives these results. In fact, many of the results are stronger in this subsample. However, one caveat is that there are only 12 crises in the post-1950 sample. Next, I look at using just the Reinhart and Rogoff (2009) dates in Table A2. Again, the results are qualitatively similar. However, I can no longer control for typical recessions. Another big difference with the RR dates is the timing. Whereas my main dates come from a business cycle peak, the RR dates are at the occurrence of the crisis. Therefore, some variables may have already responded since by the time the crisis hits there has typically been bad news (crises tend to occur after business cycle peaks). This is likely also why dividend yields respond more on impact, rather than with a lag as in the main table, because we are conditioning on a later date.

Next, I assess whether dividend yields forecast returns or dividend growth during financial crises. We know that changes in dividend yields must represent either changes in expected dividend growth of changes in expected returns. Standard predictive regressions indicate that it is the latter. However, maybe in financial crises dividend yield changes are about dividend growth and not returns. Table A3 runs standard predictive regressions including an interaction term of lagged dividend yields with an indicator for whether a financial crisis or recession has occurred in the past 5 years. The coefficients on the interaction terms are small in magnitude and not statistically significant. This indicates that there is no differential effects in these times so the relationship is unchanged. It is therefore appropriate to interpret changes in dividend yields based on the standard unconditional forecasting regressions which indicate these are mostly related to expected returns.

As mentioned in the main text, the rare disasters story is perhaps the hardest to evaluate because measuring the probability of a disaster is difficult. Here I show that three events that were unexpected increases to the probability of disaster did not have significant effects on risk premia. These results are shown in Figure A1 which plots log dividend yields and the BaaAaa default spread during select episodes. In the top panel I plot a shaded indicator for Hitler invading Poland and for the attack on Pearl Harbor, both events that clearly increased the probability of a war related disaster for the US. Note in the rare disasters calibrations, even very small increases in disaster probabilities should have large effects on risk premia.

An increase in disaster probability of 1 or 2% should roughly double the conditional equity premium. Also, the model would predict a one time sharp increase in risk premia, so we want to look for a spike during only those events, rather than focus on the trends. The evidence does not point to a clear increase and risk premia: credit spreads and dividend yields appear to go down when Hitler invades Poland (the catalyst for WWII). Dividend yields barely increase during Pearl Harbor, while credit spreads are roughly flat or possibly decline. Moving to the lower panel which looks at the Cuban Missile Crisis, we also see a slight increase in dividend yields in that month (about 5%), but it is basically flat. Credit spreads are completely flat. The long slow increase in the early part of 1962 is known as the Kennedy Slide where the stock market experienced large declines after a long period of growth, but this is prior to the Cuban Missile Crisis. For the rare disasters story to work, one has to believe that during the month the Cuban Missile Crisis was occurring there was no meaningful increase in the probability of a war related disaster, which seems implausible. This evidence is therefore consistent with the main text that the war related disasters are unlikely to explain variation in risk premia. Of course one can never know exactly what investors believed at the time or exactly how much the probability of disaster would have increased in those events. Figure A2 plots the time-series of the dividend yield and BaaAaa spread monthly in US data and highlights events as financial crises, wars, or recessions. It shows that the largest increases in these series occur during financial crises (the Great Depression and 2008 crisis).

A0.2 Details on VAR

I run a VAR of returns and dividend yields following Campbell (1991). Linearizing the return equation and iterating forward yields

$$\begin{aligned} r_{t+1} &= k + dp_t - \rho dp_{t+1} + \Delta d_{t+1} \\ dp_t &= \frac{k}{1-\rho} + \Sigma \rho^j r_{t+j} - \Sigma \rho^j \Delta d_{t+j} \end{aligned}$$

Rearranging, and applying $\Delta E_{t+1} \equiv E_{t+1} - E_t$ to both sides,

$$r_{t+1} - E_t\left[r_{t+1}\right] = \Delta E_{t+1} \Sigma \rho^j \Delta d_{t+j} + \Delta E_{t+1} \Sigma \rho^j r_{t+j+1}$$

We can compute these forecasts using a VAR of returns on dividend growth. Let $x = [r_{t+1}, dp_{t+1}]$ and assume both variables are de-meaned

$$x_{t+1} = \Gamma x_t + \Psi_{t+1}$$

One can show

$$\Delta E_{t+1}\Sigma\rho^{j}r_{t+j} = e1'\rho\Gamma\left(I-\rho\Gamma\right)^{-1}\Psi_{t+1}$$

where $e1$is a vector whose first element is 1 and the rest are zeros. This equation summarizes discount rate news. Cash flow news is defined as the residual, or the movement in unexpected returns not related to discount rate news:

$$\Delta E_{t+1}\Sigma\rho^{j}\Delta d_{t+j} = r_{t+1} - E_t\left[r_{t+1}\right] - \Delta E_{t+1}\Sigma\rho^{j}r_{t+j}$$

Following Campbell (1991) I use $\rho = 0.96$ for annual data. I also de-mean price dividend ratios and returns separately for each country.

A0.3 Details of Model Solution

It remains to solve for the expressions $\mu_e, \sigma_e, \sigma_R$ in the above equation.

We know using the equation for the market return dR that

$$\sigma_R = \sigma + \frac{p'}{p}\sigma_e \tag{1}$$

Next, we can apply Ito's Lemma to get the dynamics for $e_t = \frac{E_t}{Y_t}$

$$\begin{aligned} de_t &\equiv \mu_{e,t}dt + \sigma_{e,t}dB_t \\ &= e_t\left(\mu_E - \mu + \sigma^2 - \sigma\sigma_E\right)dt + e_t\left(\sigma_E - \sigma\right)dB_t \end{aligned}$$

This gives us μ_e and σ_e in terms of μ_E and σ_E. Looking at the dynamics for E

$$\sigma_E = \frac{p}{e}\sigma_R \tag{2}$$

$$\mu_E = \frac{p}{e}\left(\mu_R - r\right) - \psi + r = \sigma_E^2 - \psi + r \tag{3}$$

Thus, we can combine these (using σ_R from above) to solve for all three volatilities

$$\sigma_R = \sigma\frac{(p - p'e)}{p\left(1-p'\right)} \tag{4}$$

$$\sigma_e = \sigma\frac{(p-e)}{(1-p')} \tag{5}$$

$$\sigma_E = \sigma\frac{(p - p'e)}{e\left(1-p'\right)} \tag{6}$$

We can therefore substitute in $\mu_e, \sigma_e, \sigma_R$ to our ODE in equation (**??**).

To solve the ODE, we need to specify the boundary conditions. As e_t becomes large, we know prices are no longer dependent on intermediary capital hence $p'(\infty) = 0$. The lower boundary condition is as follows. I assume that new intermediaries enter when the price reaches $\frac{1}{r+\delta}$, which is the households willingness to pay for the asset. I assume that at this price there is an intervention in the economy to prevent the households from buying the risky assets and thus economic growth falling permanently. This can be thought of as new capital coming in because the low price and high Sharpe ratio is attractive (**?**), or as the government injecting new capital into the economy to prevent growth from falling permanently. This means that $\underline{e}$ is a reflecting barrier and $p'(\underline{e}) = 0$ since the price will not change on entry. This condition, together with the condition, $p(\underline{e}) = \frac{1}{r+\delta}$, determines the endogenous entry point $\underline{e}$. It turns out that the economy rarely ever hits this lower bound.

The ODE to solve is then

$$p'' = \frac{2\left[\frac{p^2}{e}\sigma_R^2 - p\mu + pr - p'\mu_e - p'\sigma\sigma_e - 1\right]}{\sigma_e^2}$$

Where we can substitute in the means and volatilities (in terms of first order terms) using the expressions in the text.

I use matlabs bvp4c function to solve the ODE on a grid $[\underline{e}, \overline{e}]$ by specifying the boundary conditions. At $\underline{e}$ we have the price falling down to $\frac{1}{r+\delta}$ which is the condition for entry, hence, $p(\underline{e}) = \frac{1}{r+\delta}$. We also know that the price will not change on entry, thus $p'(\underline{e}) = 0$. I search for the endogenous value of entry $\underline{e}$ that satisfies these two boundary conditions by imposing the lower boundary $p(e^*) = \frac{1}{r+\delta}$ and running through values of e^* until $p'(e^*) = 0$. It turns out that the economy very rarely hits this boundary. The other condition is $p(\infty)$. Intuitively, we know when E goes to ∞ prices no longer depend on intermediary equity and hence $p'(\infty) = 0$. In solving the ODE numerically, I choose a finite upper bound $\overline{e}$ and ensure that the process rarely reaches this bound. For higher values of e, the drift is increasingly negative since the equity premium goes to zero, thus $\mu_e = e(\sigma^2 - \psi) < 0$. I verify that the solution is not dependent on the choice of this upper bound. Lastly, we need to verify ex-post that $p(e) \geq \frac{1}{r+\delta}$ for $e > \underline{e}$ so that the household never steps in to buy the asset. This is easily verified ex-post by showing that $p'(e) \geq 0$ for $e > \underline{e}$ which intuitively just says that prices are increasing in intermediary capital.

A0.4 Details on Data Sources

BaaAaa spread: Federal Reserve's FRED database series AAA and BAA represent Moody's corporate bond yields. I begin using this data monthly from 1930-present for the US only.

This supplements my credit spread data which end in 1930.

Credit spreads: Credit spread data provided by the International Center for Finance at Yale. The data set is constructed from the Investor's Monthly Manual from 1860-1930 and contains bond price data. I form credit spreads by taking all corporate bond yields over UK government yields.

War and War Related Disaster Dates: I use war-related disasters from Barro (2006) (see Table I Part A. I use the 20 OECD countries only due to lack of availability of historical dividend yields for any of the Latin or Asian countries). Note: in Barro (2006) every disaster is war related (WWI, WWII, or aftermath) or related to financial crises (Great Depression). Results are robust if augmented with dates the U.S. entered – or nearly entered – into a major war: 1898 (Spanish-American), 1916 (WWI), 1941 (WWII), 1950 (Korea), 1955 (Vietnam), 2001-02 (Afghanistan, Iraq), 1962 (Cuban Missile Crisis).

Financial Crisis Dates: My main dates come from Jorda *et al.* (2010) (ST) and Reinhart and Rogoff (2009) (RR) who date crises across many countries going back to the 1800's. The main difference in their dating convention is that ST date business cycle peaks whereas RR use the occurrence of the actual crisis. When focusing only on US data, Gorton (1988) and Bordo and Haubrich (2012) contain a history of US business cycles categorized as banking crises or not (much of their categorization is based on Friedman and Schwartz (1971), and the resulting dates are similar to Jorda *et al.* (2010)).

GDP and Consumption Data: Robert Barro's webiste (see, e.g., Barro *et al.* (2011)).

Country Level Price, Return, and Dividend Yield Data: All indices for all countries are from Global Financial Data. All price series are real values of stock indices in U.S. dollars. Real dividends are constructed using prices and returns.

U.S. Equity Returns: From Kenneth French's website when possible. When calculating monthly volatility of the stock market and "vol of vol," however, I use daily S&P500 observations from CRSP. Vol is computed as the standard deviation of daily returns each month, and vol of vol is the volatility of this monthly series. I also pull the momentum, size and book-to-market portfolios from Kenneth French's website.

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Table A1: I repeat the results from the main text using the sample post 1950. I run regressions of asset prices and macro variables on event indicators. Each indicator takes on the value 1 if the event occurred in any of the past three years. The variables: dp is dividend yield, r is return, $r - r_f$ is excess return, Δd is dividend growth, cs is credit spread, cfn is "cash flow news", drn is discount rate news, Δc is consumption growth, sc is log surplus consumption, σ_c^2 is consumption variance. See main text for a description of these variables. All regressions include country fixed effects and some include a linear time trend as indicated to deal with decreasing dividend yields and macro volatility over time. All numbers are reported in percent per annum. For persistent variables (dp and habits), I also include a lag in the controls. Stars ($*$) indicate significance at $10\%, 5\%, 1\%$ levels. Standard errors clustered by year.

Response of asset prices and macro state variables to events

$y_t = \gamma_i + \sum_{j=0}^{T} a_j 1_{fin,t-1} + \sum_{j=0}^{T} b_j 1_{recession,t-1} + cy_{t-1} + dt + \varepsilon_{t+1}$

	y variables								
	Risk premia and cash flows						C state variables		
	dp	r	$r - r_f$	Δd	cfn	drn	Δc	sc	σ_c^2
Fin Crisis									
0	2.4	8.2	8.8	12.0**	10.8	2.2	0.3	-0.1	-0.00
1	48.4***	-36.8***	-36.8***	-2.0	-10.6	26.5***	-1.6	-6.3**	-0.00
2	-21.2**	14.8*	17.2*	-16.9***	-4.5	-12.0***	-1.9***	-12.9***	-0.01
3	-4.7	-6.3	-6.6	7.0	-14.8	-6.6	-0.6	-2.0	-0.02
4	3.9	0.6	-0.5	0.2	4.1	4.4	-1.3	-7.0	-0.02*
5	7.6	-11.1	-10.8	-6.8	-7.3	5.2	0.1	5.0	-0.02*
Recession									
0	20.3***	-26.3***	-25.4***	-6.6**	-18.1***	9.1***	-1.8***	-7.4***	0.01**
1	-4.2	-7.3*	-7.5*	-12.9***	-14.5***	-3.7*	-3.0***	-12.9***	0.01**
2	1.2	1.5	1.5	-7.7***	-0.6	-1.9	-0.8**	-2.7*	0.01
3	3.5	-3.9	-3.8	-2.6	-3.8	1.1	-0.5	-2.6*	0.01
4	3.8	2.4	2.7	2.5	1.9	0.9	0.1	0.2	0.01
5	-2.2	9.0**	8.7**	0.7	6.0*	-2.0	-0.4	-2.1	0.00
y_{t-1}	0.74	0.04	0.04	0.14***			0.25***	0.25***	0.01***
t	Y						Y		Y
R^2	76%	14%	14%	16%	11%	15%	48%	93%	40%

Table A2: I run regressions of asset prices and macro variables on event indicators. Each indicator takes on the value 1 if the event occurred in any of the past three years. The variables: dp is dividend yield, r is return, $r - r_f$ is excess return, Δd is dividend growth, cs is credit spread, cfn is "cash flow news", drn is discount rate news, Δc is consumption growth, sc is log surplus consumption, σ_c^2 is consumption variance. See main text for a description of these variables. All regressions include country fixed effects and some include a linear time trend as indicated to deal with decreasing dividend yields and macro volatility over time. All numbers are reported in percent per annum. For persistent variables (dp and habits), I also include a lag in the controls. Stars ($*$) indicate significance at $10\%, 5\%, 1\%$ levels. Standard errors clustered by year. Dates used are from <cite>ReinRog2012</cite> (RR) and differ from those in the main text. Please read the data description for details.

Response of asset prices and macro state variables to events

$y_t = \gamma_i + \sum_{j=0}^{T} a_j 1_{fin,t-1} + b y_{t-1} + ct + \varepsilon_{t+1}$

	y variables								
	Risk premia and cash flows						C state variables		
	dp	r	$r - r_f$	Δd	cfn	drn	Δc	sc	σ_c^2
Fin Crisis									
0	15.9***	-24.6***	-30.1***	-7.1	-14.8***	11.0***	-0.2	-2.6	-0.06
1	2.6	-0.9	-2.2	0.5	-5.8	-0.8	-2.4***	-10.0***	-0.07
2	-2.4	7.6	5.5	8.6	3.5	-2.7	-0.4	1.8	-0.06
3	-2.6	3.1	0.5	4.4	6.0	0.4	-0.7	-3.5	0.06
4	-1.8	0.7	-2.2	-2.1	0.1	-1.9	-0.6	0.2	0.07
5	-1.6	1.2	0.5	7.9	3.1	0.0	0.2	0.8	0.01
y_{t-1}	0.84***	0.19***	0.18***	0.49***			0.11***	0.22***	0.12***
t	Y							Y	Y
R^2	80%	6%	7%	14%	3%	8%	3%	72%	12%

Table A3: I run predictive regressions of returns and dividend growth on lagged dividend yields. I include indicators for financial crises and recessions. The indicator takes the value 1 if the event has occurred in the past 5 years. This tests whether the relationship between dividend yields, returns, and dividend growth changes during these periods. Small and insignificant coefficients indicate that it does not. See main text for data details.

Panel A: Return predictability in crises and recessions					
$R_{t+1} - r_{f,t} = a_i + b\ln(d/p)_t + c1_{fin}\ln(d/p)_t + d1_{non,fin}\ln(d/p)_t + et + \varepsilon_{t+1}$					
	b	c	d	e	Adj R^2
Raw dp	0.06				2%
(t-stat)	(3.25)				
Raw dp	0.080	-0.003	0.018		2%
(t-stat)	(3.80)	(-0.20)	(-1.68)		
With time trend	0.096			0.12	3%
(t-stat)	(4.57)			(3.70)	
With time trend	0.11	0.00	-0.01	0.11	3%
(t-stat)	(4.70)	(0.00)	(-1.06)	(3.32)	

Panel A: Dividend growth predictability in crises and recessions					
$\ln\left(\frac{d_{t+1}}{d_t}\right) = a_i + b\ln(d/p)_t + c1_{fin}\ln(d/p)_t + d1_{non,fin}\ln(d/p)_t + \varepsilon_{t+1}$					
	b	c	d		Adj R^2
Raw dp	-0.001				3%
(t-stat)	(-4.78)				
Raw dp	-0.001	0.000	-0.001		3%
(t-stat)	(-4.07)	(0.37)	(-0.67)		
With time trend	-0.001			-0.00	3%
(t-stat)	(-4.29)			(-0.14)	
With time trend	-0.001	0.000	-0.000	-0.00	3%
(t-stat)	(-3.86)	(0.34)	(-0.69)	(-0.21)	

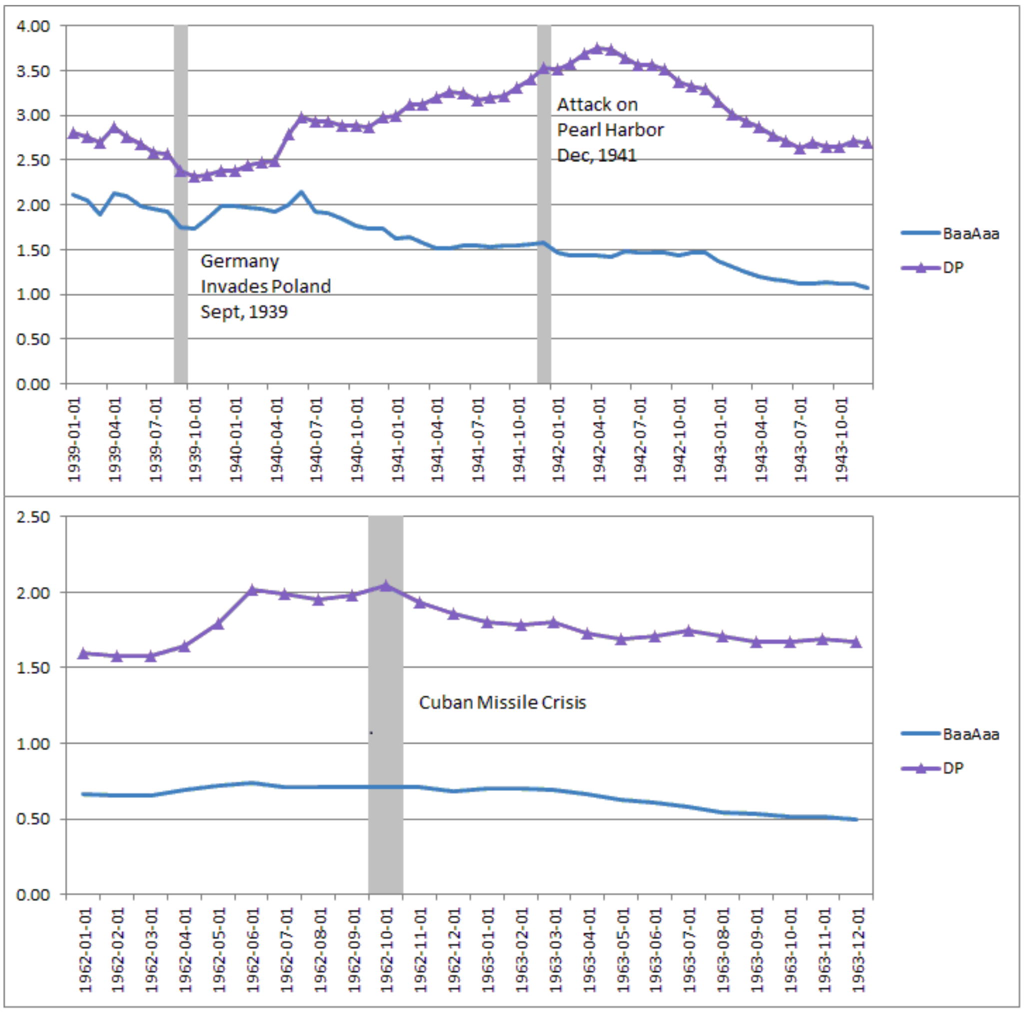

Figure A1: This figure plots the behavior of log dividend yields and the BaaAaa default spread using monthly US data. I analyze the behavior around events which were unexpected and increased the probability of a war related disaster. The top panel shows Germany invading Poland and the Attack on Pearl Harbor, while the bottom shows the Cuban Missile Crisis.

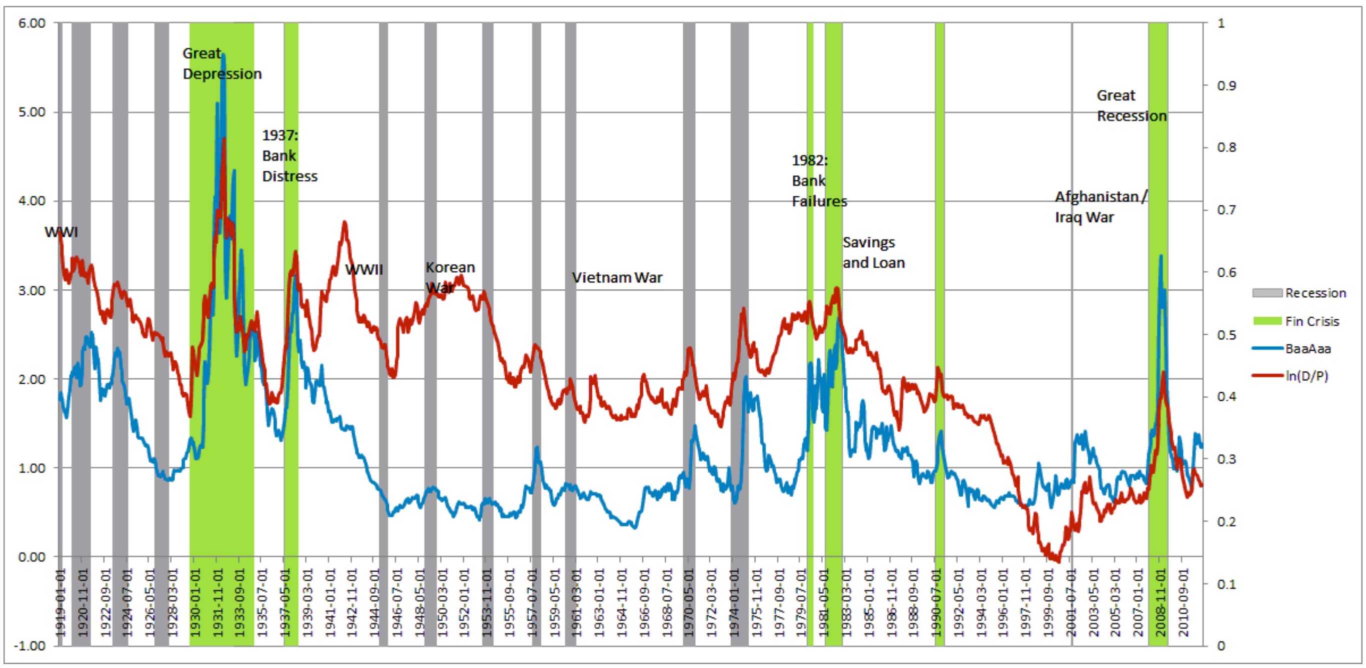

Figure A2: This figure plots the log dividend yield (red) and BaaAaa spread (blue) monthly from 1919 to 2012. Green shaded areas indicate financial crises or events considered a "credit crunch" involving bank failures. Grey areas indicate recessios and also label times the US entered into a major war.