Financial Crises, Risk Premia, and the Term Structure of Risky Assets*

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Abstract

The literature on rare disasters shows that low probability events can explain high, time-varying risk premia. I find that large spikes in risk premia occur around financial crises but not around other disasters such as wars. A model with financial intermediaries generates endogenous financial crises that quantitatively match those in the data, while also replicating high equity risk premia and volatility. Compared to a standard disasters framework, the model makes additional empirical predictions which I confirm in the data. First, the equity of the intermediary sector strongly forecasts stock returns. Second, financial crises are temporary, which implies that the term structure of risky assets is downward sloping during financial crises when risk premia are concentrated in the near term. The model explains the level and slope of the term structure of risky assets including equities, corporate bonds, and VIX, both unconditionally and in a crisis. I then use the term structure of risky assets to infer the daily probability and persistence of a financial crisis in real time, providing a useful tool to analyze policy responses in a crisis.

1   Introduction

A recent literature shows that rare disasters can theoretically explain a range of asset pricing facts. For example, Barro (2006) and Gabaix (2012) show that a small probability of a rare disaster for the representative consumer can lead to a high equity premium and time-variation in this probability can lead to return predictability.[1] In this paper I argue that we should focus on financial crises as the rare disasters of interest for asset pricing. I document the behavior of risk premia around financial crises and find that the equity premium and credit spreads increase by around three times their unconditional levels. In contrast, non-financial disasters show little movement in risk premia, despite the fact that they show larger movements in GDP and consumption. I explain these facts with a macro model that features intermediation frictions, along the lines of He and Krishnamurthy (2012b) and Brunnermeier and Sannikov (2012), and which endogenously generates financial crises as times when intermediary equity capital is low. The model generates risk premia which fluctuate only with the probability of a financial crisis because the stochastic discount factor (SDF) in the model depends largely on the equity capital of the financial sector rather than aggregate consumption.

By putting more economic structure on the idea of disasters, the model generates additional empirical implications. For example, the model implies that risk premia should depend on the equity of the financial sector, which I confirm in the data. Most importantly, crisis probabilities evolve endogenously and the model generates temporary financial crises. This is because low intermediary equity capital implies high risk premia, but high risk premia lead to higher expected growth in asset values which results in higher future equity capital. The model generates a dynamic term structure of crisis probabilities which is typically upward sloping but becomes strongly downward sloping in a crisis. Since risk premia depend on the probability of a crisis, this implies that the term structures for risky assets is downward sloping in a crisis as well, which matches empirical patterns for corporate bonds, equities, and VIX. Finally, I show how the empirical term structure of risky assets can be used to infer the daily term structure of crisis probabilities as perceived by market participants in the data in real time. These probabilities are informative for the expected duration of crises and expected path of recovery, providing a useful tool for evaluating the impact of major events such as policy responses in a crisis.

The first contribution of this paper is to show that financial crises are economically the most interesting "disasters" for asset pricing. I split historical disasters into wars and

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[1]See also Barro *et al.* (2011), Gourio (2012), and Wachter (2012).

financial crises and show that large increases in risk premia occur around financial crises but not war related disasters. Specifically, Figure 1 shows an increase in the log dividend yield of around 50% during financial crises which translates into an estimated 20% rise in the equity premium, about triple its unconditional level. However, financial crises are not worse in terms of the size of the disaster: in war related disasters GDP and consumption fall by a cumulative amount of around 47% vs. only 11% for financial crises. These facts are difficult to reconcile with the typical disasters literature where the stochastic discount factor (SDF) is based on aggregate consumption growth. In rare disasters models, both the probability and potential size of a disaster contribute to risk premia. Therefore, at the beginning of war related disasters such as the start of both world wars, we should see large increases in risk premia as the probability and severity of a war related disaster increases. The fact that large increases in risk premia occur instead around financial crises is more consistent with a model in which the SDF depends on the health of the financial sector and thus a high marginal value of wealth is tied to financial crises.[2] As further evidence of this, I also split U.S. recessions into those containing a financial crisis and those which do not. I find similar effects: recessions without financial crises result in significantly lower changes in volatility and risk premia.

I explain these facts using a model that features intermediation frictions so that the stochastic discount factor (SDF) depends on intermediary equity rather than household consumption. This means the "disasters" that matter in terms of state-pricing are financial crises which are defined to be times when the equity capital of the intermediary sector is low. I model intermediaries as sophisticated investors subject to an equity capital constraint as in He and Krishnamurthy (2012a) and Brunnermeier and Sannikov (2012). 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."

The second contribution of this paper is to show that a calibrated version of this model can quantitatively account for a range of asset pricing facts. I calibrate the model to match the annual drop in output around financial crises and study the resulting asset pricing and output dynamics. The model quantitatively matches the spikes in risk premia associated with financial crises as well as the average decline of stock prices and the duration of financial crises. Moreover, the model captures the large variation of recovery times from financial crises that can take many years. The calibrated model also matches unconditional risk

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[2]See also Adrian *et al.* (2012) for empirical evidence along these lines. The authors construct an SDF based on intermediary balance sheets to explain the cross-section of asset returns.

premia and volatility and generates time-varying risk premia that are tied to the equity of the financial sector. 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. I contribute to the literature on intermediaries and asset pricing by connecting these models to the literature on disasters, showing they can quantitatively explain many asset pricing facts, and explicitly testing their key empirical predictions. For example, the model ties movements in risk premia to the equity capital or net worth of the financial sector, and I confirm this prediction in the 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. This provides an explicit link between risk premia and the financial sector that is related to similar findings by Adrian *et al.* (2011) and Adrian *et al.* (2012). Relative to these papers, I use a measure of risk premia explicitly implied by a model and show that the predictive values quantitatively match those in the model.

The third contribution of this paper is to show how the term structure of risky assets relates to the term structure of crisis probabilities. Crises in the model are temporary and thus tend to feature risk premia which are higher in the short term. To understand this, note that crises are times when intermediary equity is low and risk premia are high. High risk premia increase the expected growth rate of intermediary equity, since they hold risky assets, implying that future equity is likely to increase. This means crises are temporary and that, conditional on being in a crisis, the probability of remaining in a crisis is high in the short term but low in the longer term as intermediary equity recovers. The term structure of crisis probabilities is downward sloping during a crisis, which implies that the term structure of risky assets will also be downward sloping.

I confirm these predictions in the data by studying the term structure of investment grade corporate bond yield spreads, equities, and VIX. Each of these term structures is typically upward sloping, but slopes downward in crises. I particularly focus on corporate bond spreads because of their longer data availability. For example, I construct the corporate yield curve during each financial crisis and recession since 1929 and show that the inverted slope is typical of financial crises, but not recessions in general. Using Moody's expected default frequency (EDF), which provides the term structure of expected default probabilities, I find that this downward slope is due to downward sloping risk premia rather than probabilities of default. I also find similar patterns in the VIX term structure. The model is able to quantitatively match both the upward slope of these term structures in good times as well as the downward slope in crisis times. My findings corroborate and extend work by van Binsbergen *et al.*

(2012b) who find similar patterns in the term structure of equity yields, but in a shorter sample from 2002-2011. I thus contribute to the term structure of risk premia literature by examining multiple asset classes jointly over longer samples, explicitly connecting these term structure facts to financial crises, and showing that a model with intermediary frictions can explain their conditional level and slope. In contrast, van Binsbergen *et al.* (2012a) argue that these facts are a major challenge to leading asset pricing models (for example, Bansal and Yaron (2004), Campbell and Cochrane (1999), and Barro (2006)).

Finally, I use the strong link between the term structure of crisis probabilities and term structure of risky assets to back out the term structure of crisis probabilities empirically. Since the term structure of risky assets by definition embeds crisis expectations at various horizons, this is a natural place to measure crisis probabilities in the model. At each point in time, I use the data to infer the term structure of crisis probabilities with striking results. Over a long sample, the model identifies the Great Depression, early 1980s and recent Great Recession as times of financial crises. The model estimates the probability of remaining in each of these crises to be around 60% at the one year horizon and 20% at the two year horizon, thus providing speeds of recovery. Next, using daily data during the recent 2008-09 financial crisis, I analyze how the daily term structure of crisis probabilities evolves and responds to major events. Most notably, I find that the equity injection into the financial sector and the Federal Reserve lowering interest rates to zero both substantially bring down the probability of remaining in a crisis in one year by around 20%. This provides a potentially useful way to evaluate policy responses designed to aid the economic recovery. I contribute to the measurement of systemic risk by using a structural model to extract a full term structure of crisis probabilities using the term structures of risky assets.

This paper proceeds as follows. Section 2 discusses why we should focus on financial crises for asset pricing. Section 3 presents the model and calibration. Section 4 calibrates the model and compares it to the data. Section 5 analyzes the term structure of risk premia surrounding financial crises and uses these term structures to measure crisis probabilities at various horizons. Section 6 concludes.

2   Why Financial Crises?

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 a linear 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

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

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 $B_t = 0.7$), 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 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.

At its core, the rare disasters literature posits that small probabilities of a state with extremely high marginal value of wealth, in this case $B_{t+1}^{-\gamma}$, can account for high unconditional risk premia. The rare disasters literature has focused on consumption disasters since they have used a representative agent approach which ties the marginal value of wealth to aggregate consumption growth.

Why Financial Crises?

I argue that we should focus on financial crises as the rare disasters of interest for asset pricing. I show that financial crises are associated with dramatic increases in risk premia, whereas other disasters are not. My dataset is based on GDP data from Barro *et al.* (2011) and dividend yields from Global Financial Data. In Barro (2006) each disaster is essentially a financial crisis, largely associated with the Great Depression, or a war related disaster, largely associated with one of the world wars. I therefore split these events and study the behavior of risk premia around each event. For financial crises, I use the dates and sample of countries given in Reinhart and Rogoff (2009), as well as the financial crises in Barro (2006), and dates for U.S. financial crises (Bordo and Haubrich (2012) and Jorda *et al.* (2010)). For war related disasters, my sample is from Barro (2006) who identifies these disasters based on GDP growth falling below 15%; each of these disasters occurs during the first and second world wars. The appendix contains further details on the data and dates used.

Figure 1 plots risk premia and GDP growth in a 10 year window around financial crises and war related disasters with the disaster occuring in year zero. I use the log dividend yield to measure risk premia, which is common in the literature. Below I also show for U.S. data how dividend yields correspond to risk premia and dividend growth both in and out of

financial crises.

The top panel shows that log dividend yields increase by around 40-50% during financial crises. Using standard predictive regressions I find a unit increase in the dividend yield during a financial crisis increases the equity premium by 40% or more, hence the increase in dividend yields in a financial crisis corresponds to an increase in the equity premium of 16-20%, around triple its unconditional level.[3] In contrast, there is no substantial spike at the start of war related disasters.[4] Table 1 presents the changes in risk premia over different horizons and uses more flexible dating by computing the peak dividend yield in a window several years around the disaster. In this case changes in risk premia around financial crises increase to 80% compared to 20% for war related disasters. The rare disasters literature would specify that as long as the probability of a consumption disaster rises, there will be a one-for-one rise in risk premia. It should be clear that at, or near, the beginning of a war the probability of a severe disaster and large drop in output would increase, particularly for large scale world wars. The above method would then pick up any increase in disaster probability at any point around the event as reflected in the dividend yield. In typical disaster calibrations, a 2% increase in this probability would result in a more than doubling of the equity premium and thus a large increase in dividend yields. Yet we see essentially no large increase in risk premia throughout these episodes.[5]

The bottom panel of Figure 1 shows GDP growth around financial crises and war related disasters and Table 1 presents peak to trough declines in GDP and consumption around these events.[6] We see much larger drops in wars with a cumulative drop in GDP of 47%, as compared to financial crises which have a cumulative drop of 11%. The numbers using consumption are similar. I also find the distribution of disasters around wars to be more extreme, meaning the potential for a very large loss is higher, which should further increase the equity premium for wars. Thus, all else equal, this should drastically increase risk premia before wars as the expected severity of a disaster is significantly larger.[7] An increase in risk

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[3]I run a predictive regression using the trend break methodology in Lettau and Van Nieuwerburgh (2008) to account for slow moving trends in $\ln(d/p)$. My results are consistent with their findings, see their Table 1. In fact, if I add a dummy for a financial crisis this coefficient increases from 0.3 to 0.5. See Table 9.

[4]However, only 11 of the 24 countries have available dividend yields over the relevant period partly due to some markets shutting down (see Barro *et al.* (2011)). The results are nearly identical if I only include countries with both price and quantity data available.

[5]One concern is price controls which were imposed in some countries during the war. I emphasize that this disaster probability should be reflected in dividend yields in a window prior to the beginning of the disaster.

[6]See also Cerra and Saxena (2008) for a discussion of GDP responses to wars vs. financial crises.

[7]A closely related issue with the typical consumption disasters literature is that consumption disasters must occur simultaneously with a stock market crash. However, correlation between consumption growth

premia and lower expected growth should both contribute to higher dividend yields. In unreported results, I also find no large increase in risk premia around such events as the Cuban Missile Crisis which increased the chance of nuclear disaster, Pearl Harbor, or the start of the U.S. Civil War. Thus the probability of war related disasters seems an unlikely candidate for explaning large variation or levels of risk premia. This finding is related to Berkman *et al.* (2011) who look at political crises that could potentially escalate into conflict or war-related disasters: "we conclude that there is no evidence to directly support the hypothesis that the expected stock market excess return is an increasing function of expected disaster risk." However, Berkman *et al.* (2011) do find higher volatility, lower realized stock returns, and higher earnings-price ratios around these events. They also find that these events do forecast future GDP and consumption growth, suggesting they affect stock prices through bad news about fundamentals and dividend growth, but not necessarily risk premia.

Figure 3 plots the time-series of dividend yields and BaaAaa default spread in U.S. data with shaded areas for wars vs. financial crises, where I plot any time the U.S. entered into a war and any time the U.S. entered, or nearly entered, a financial crisis.[8] For the period 1834-1919, I use the consumption to price ratio and, when availaible, the dividend yield. The consumption to price ratio supplements the dividend yield for the period 1834-1872 where the dividend series is not available, and both co-move strongly in the later sample suggeting the consumption to price ratio provides a good proxy for the dividend yield. During the period 1919-2012, I use monthly data on the BaaAaa spread and dividend yield. The BaaAaa spread is an additional measure of risk premia that forecasts both stock and corporate bond returns.[9] The plot shows many spikes in risk premia associated with financial crises, but very few around wars.

The above results suggest that financial crises are important events for understanding risk premia, while other disasters are less important. Intuitively, this suggests that the SDF (stochastic discount factor) is particularly high during financial crises, thus generating the large equity premium and time varying risk premia that fluctuate with the probability of a financial disaster. This conclusion has been echoed in other work, most notably empirical

and stock returns is weak, and this weakness continues to be an issue over disaster periods (Julliard and Ghosh (2012) discuss timing issues between stock declines and consumption around rare disasters).

[8] Here I use a broader definition of financial crisis that includes the dates of 1973-1975 and 1988-1991 as in Lopez-Salido and Nelson (2010). While most other work argues that this was not in fact a full financial crisis, the goal here is to show that a likely increase in the *probability* of a financial crisis can increase risk premia.

[9] Both measures forecast excess returns on stocks and corporate bonds. The dividend yield is a stronger forecaster of stocks while the BaaAaa spread more strongly forecasts corporate bonds.

work by Adrian *et al.* (2012) who find that an SDF based on intermediary balance sheets can explain the cross-section of expected returns including bonds as well as stocks sorted on size, book to market, and momentum. Also, Gandhi and Lustig (2012) find a size premium in bank stocks which they argue is compensation for financial crisis risk, supporting the idea that the SDF is particularly high during financial crises.

I show that these results are not solely due to the fact that financial crises tend to occur in recessions. Aside from disasters, recessions have also been a popular explanation for movements in risk premia (see Lustig and Verdelhan (2012) for evidence that risk premia tend to be higher in recessions and the habits model of Campbell and Cochrane (1999) which features high risk premia in recessions). I split U.S. recessions into those which contained a financial crisis and those that did not and repeat my exercise as above where I use dates from Gorton (1988) and Bordo and Haubrich (2012). The results are plotted in Figure 2. The results are striking – recessions associated with financial crises tend to feature increased dividend yields, high volatility, and high credit spreads, recessions not associated with financial crises do not. In recessions associated with financial crises, dividend yields increase by 30%, volatility increases from 15% to 50%, and the default spread increases from 1% to 3%. Each of these increases much less in non-financial recessions if at all, with dividend yields increasing to at most about 10% right after the onset of the recession, volatility increasing from 15% up to 20%, and the default spread increasing up to 1.5%. Note however in the bottom panel, that while GDP growth is lower in financial recessions, it is not drastically lower. Therefore, it seems unlikely that the higher volatility and risk premia are due to financial recessions being significantly "worse" in terms of GDP growth. This once again suggests to focus on financial crises in understanding high risk premia.

Finally, one may be concerned that the observed spikes in dividend yields during financial crises correspond to expected growth and not risk premia.[10] This might especially be a worry since financial crises often result in lower growth. However, I find that for U.S. data dividend yields actually forecast returns more strongly during financial crises. To see this, Table 9 runs standard predicitive regressions of future returns and dividend growth on dividend yields with a dummy for financial recessions and a dummy for non-financial recessions. I use two methodologies: the first uses "raw" dividend yields while the second allows for two breaks in the mean of dividend yields as advocated by Lettau and Van Nieuwerburgh (2008). We can see in the top panel that, for either method, returns are more predictable in financial recessions with the coefficient on the dividend yield ranging from around 0.4 to 0.5 in these

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[10]See Cochrane (1994), van Binsbergen and Koijen (2010) for discussions – by definition dividend yields must correspond to risk premia or expected dividend growth.

episodes, imlying that a unit increase in dividend yield during a financial crisis translates to a 40-50% increase in the equity premium. In contrast, the evidence for dividend growth is mixed: using raw dividend yields suggests a coefficient of 0.09, while using the two break method suggests a coefficient of -0.19. Therefore, we can conclude that a 30% increase in dividend yields during a financial recession corresponds to between a 12-15% rise in expected returns and, potentially, a fall in expected dividend growth of at most 8%. These findings are consistent with Lustig and Verdelhan (2012) who find that increases in dividend yields during recessions primarily correspond to risk premia and not dividend growth.

3 Model

The model is based on the growing literature on intermediaries, asset pricing, and macroeconomics and is most closely related to He and Krishnamurthy (2012b) and Brunnermeier and Sannikov (2012). I first review this literature and point out the similarities and differences of my model. A key point is that while this literature uses different micro-foundations that give rise to intermediary frictions, they generally share two main features: (1) the economy and asset prices depend on intermediary equity capital or "net worth" and (2) this effect is typically larger in bad economic times. My main goal is to capture these features in a simple framework. Readers familiar with this literature can skip directly to the model.

3.1 Literature on Intermediaries and Macroeconomics

My model is related to the recent theoretical literature on financial intermediaries and macroeconomics and is most similar to He and Krishnamurthy (2012b).[11] These models feature exactly solved dynamic frameworks with intermediary frictions that build on the earlier financial frictions literature of Holmstrom and Tirole (1997) and Bernanke *et al.* (1996). First, intermediary equity capital, also called "net worth," is the key state variable in the economy. Low intermediary equity implies high risk premia and low investment where the latter typically follows from standard q-theory: low valuations imply low investment, though some of these models do not feature production. Second, the effects of intermediary equity are non-linear and are "sharp" in bad times when intermediary equity is low. That is, in normal times fundamental shocks have minor effects, but when the intermediary sector is under-capitalized, a negative shock is amplified to have large effects.

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[11]See also Brunnermeier and Sannikov (2012), He and Krishnamurthy (2012a), He and Krishnamurthy (2012c), Haddad (2011), Maggiori (2011), Rampini and Viswanathan (2012), and Danielsson *et al.* (2011).

The model here assumes a particular micro-friction – that intermediaries are limited in their ability to raise equity based on a moral hazard argument. This should be thought of as a convenience rather than being essential to the results. For example, other models instead limit the amount of debt financing intermediaries are able to obtain (see especially Danielsson *et al.* (2011), Geanakoplos (2012), and Adrian and Boyarchenko (2012)). The difference between these assumptions is the channel through which intermediaries affect asset prices. With the equity capital constraint, intermediaries are forced to bear a larger share of the asset risk in bad times when their equity is low and hence risk premia must rise (He and Krishnamurthy (2012a), Brunnermeier and Sannikov (2012)). With the debt constraint, intermediaries are forced to liquidate assets they can no longer fund during crises and "less informed," more risk-averse, or more pessimistic agents must hold them, driving risk premia up (Danielsson *et al.* (2011), Fiore and Uhlig (2012), Geanakoplos (2012), Adrian and Boyarchenko (2012)). These models give different implications for the leverage of financial institutions, with the first featuring counter-cyclical leverage and the latter having leverage being pro-cyclical. Empirically, it appears that leverage for financial institutions depends largely on the type of institution. Intermediaries such as broker-dealers and hedge funds typically have pro-cyclical leverage due to short term debt constraints (see, e.g., Adrian *et al.* (2012) and Ang *et al.* (2011)), whereas institutions such as commercial banks, who essentially have unlimited access to short term debt financing due to deposit insurance, appear to have counter-cyclical leverage. This heterogeneity in the intermediary sector is both interesting and important, but is not a focus of this paper.

Regardless of the friciton typically modeled, the main features of interest outlined above are essentially unchanged – in particular the equity of the financial sector is the key state variable in both models, with low equity implying high risk premia. The goal of this paper is distinct from the theoretical literature on intermediary frictions: rather than seeing if a particular micro-friction can generate a model in which intermediaries affect asset pricing, I instead ask whether such a model quantitatively matches asset pricing data and data on financial crises.

To summarize, the model presented here has two main features generally shared by this literature:

Feature 1 (Risk premia): Intermediary capital affects risk premia and output

This feature can result from several possible channels: intermediaries may be "special," for example, in their abilitiy to collateralize loans (Rampini and Viswanathan (2012)), invest in risky securities (He and Krishnamurthy (2012a)), monitor projects (Holmstrom and Tirole (1997)), mitigate information asymmetry (Fiore and Uhlig (2012)), or reduce search frictions

(Duffie and Strulovici (2012)). Intermediaries may also simply be less risk averse than households in a heterogeneous agent model (Longstaff and Wang (2008)). Finally, they may face balance sheet constraints that dynamically change their effective risk aversion (Danielsson *et al.* (2011)). Therefore a large range of realistic assumptions can generate the feature that low intermediary capital is associated with high risk premia and output. As we will see, this observation also has strong empirical support.[12]

Feature 2 (Non-linear effects): The effects of intermediaries on the economy are larger when their captial is low

Feature 2 says that in good times when intermediaries are well capitalized, a negative shock to their balance sheet will have minor, if any, effects. However, when in a crisis, the economy is more sensitive to intermediary capital. This feature is consistent with models in He and Krishnamurthy (2012b), Brunnermeier and Sannikov (2012), and Danielsson *et al.* (2011) among others.

3.2 Model of Financial Crises

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:

$$\frac{dY_t}{Y_t} = (\mu - g(rp_t)) \, dt + \sigma dZ_t \tag{2}$$

where Z_t is a Brownian motion, μ is the long run growth rate of the economy, and $g(rp_t)$ is the transitory portion of growth which depends on the endogenously determined risk premium (rp) in the economy. The term $g(rp_t)$ is very small on average, but can be large in financial crises. Informally, we can imagine that investment is cut when intermediaries are

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[12] Also see Adrian *et al.* (2012) and Adrian *et al.* (2011) for studies of the link between intermediaries and aggregate asset prices and Mitchell *et al.* (2007), Koijen and Yogo (2012), and Duffie (2010) and the many references therein for evidence of intermediary frictions and/or intermediary capital effects on particular markets.

undercapitalized and risk premia are high. This approach is also consistent with a typical production economy where investment depends on risk premia by q-theory logic. In q-theory, high risk premia mean low valuations and high cost of capital which translates into lower investment, thus lowering economic growth. Output volatility, σ, is constant.

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

$$dR_t = \frac{dP_t + Y_t}{P_t} \tag{3}$$

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

3.2.1 Households

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

$$E\left[\int_0^\infty e^{-\rho t} C_t dt\right] \tag{4}$$

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 $dR_{E,t}$. I assume 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 will be important in setting a lower bound on the price dividend ratio. Lastly, if households invest in the intermediary, they can invest at most E units of capital where E 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)).

The households decisions will result in the following in equilibrium: (1) the interest rate must be equal to the time discount rate, thus $r_t = \rho$ must hold, (2) provided the expected return from equity in intermediaries is greater than or equal to r, households will give the maximal amount of funds E to intermediaries, (3) households will not buy the tree provided the price doesn't fall below $\underline{P} = \frac{Y}{r+\delta}$.

Households' wealth evolves according to:

$$\frac{dW_t}{W_t} = -\frac{C_t}{W_t}dt + \frac{E_t}{W_t}dR_E + \frac{W_t - E_t}{W_t}r_t dt \tag{5}$$

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: $E[dR_E] \geq r$). I will show that this condition always holds.

3.2.2 Intermediaries

As in He and Krishnamurthy (2012b), 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.

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

$$E\left[\int_0^\infty e^{-\psi t}\ln\left(\lambda\epsilon_t\right)dt\right] \tag{6}$$

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

$$\frac{d\epsilon_t}{\epsilon_t} = \alpha_t\left(dR - rdt\right) + rdt \tag{7}$$

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).

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

$$\max_{\alpha_t} \alpha_t \left(\mu_{R,t} - r_t \right) - \frac{1}{2} \left(\alpha_t \sigma_R \right)^2 \tag{8}$$

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 conditions are:

$$\mu_{R,t} - r_t = \alpha_t \sigma_R^2 \tag{9}$$

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

$$\frac{dE_t}{E_t} = \alpha_t \left(dR - rdt \right) + (r - \psi) \, dt + d\gamma_t \tag{10}$$

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 when the price falls to the households private value.

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

$$dR_E = \alpha_t \left(dR - rdt \right) + rdt \tag{11}$$

Note that by the intermediaries' first order condition, $\mu_{R_E} \geq r$ hence the households will give maximum possible equity to the intermediary at all times. This comes from the assumption of 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 (He and Krishnamurthy (2012b)). Since the tightness of the constraint essentially determines risk premia, the assumption here provides a direct link between intermediary equity and risk premia. Moreover, this risk neutrality assumption here results in a constant risk free rate, whereas the interest rate in He and Krishnamurthy (2012b) can be highly negative and volatile in crises.

3.2.3 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. At this interest rate households are indifferent between current and future consumption. As long as $E > 0$, so that intermediaries are able to raise capital, the risky asset is held entirely by the intermediary sector, meaning

$\alpha_t E_t = P_t$. 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 and 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. Intuitively intermediaries' consumption makes up a trivial amount of overall consumption, therefore I make this assumption for greater ease in solving the model. One could instead define "total" consumption as $Y_t^* = Y_t + \lambda E_t$. In this case, $C_t = Y_t$ holds and household wealth is the present value of the tree (Y_t) hence $P_t = W_t$.

Solution

I conjecture a price function $P_t = p(e_t)Y_t$, where I define $e_t = \frac{E_t}{Y_t}$, the ratio of intermediary equity to total output, as the main state variable. Given this conjecture, we can calculate the market return using Ito's Lemma as

$$dR_t = \frac{dP_t + Y_t}{P_t} = \frac{dY_t}{Y_t} + \frac{p'}{p}de_t + \sigma\sigma_e\frac{p'}{p}dt + \frac{1}{2}\sigma_e^2\frac{p''}{p}dt + \frac{1}{p}dt \tag{12}$$

Given our assumption on $p(e_t) \geq \frac{1}{r+\delta}$, the intermediary will hold the entire risky asset. Hence by market clearing

$$\alpha_t = \frac{P_t}{E_t} = \frac{p(e_t)}{e_t} \tag{13}$$

I define aggregate "risk aversion" as:

$$\Gamma(e_t) = \frac{p(e_t)}{e_t} \tag{14}$$

Then using market clearing and intermediary optimality

$$\mu_{R,t} - r_t = \Gamma(e_t)\sigma_{R,t}^2 \tag{15}$$

which justifies $\Gamma(e_t)$ as the risk aversion of a ficticious representative agent with mean-variance preferences. We can see two main features of risk premia, $\mu_{R,t} - r_t$. First, risk premia depend on intermediary capital so that low capital implies high risk premia and vice versa. Second, these effects are non-linear due to the $\frac{1}{e_t}$ term in $\Gamma(e_t)$ – 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.

It is further useful to define the Stochastic Discount Factor (or pricing kernel), which prices all assets:

$$\frac{d\Lambda_t}{\Lambda_t} = -rdt - \lambda_t dB_t = -\rho dt - \Gamma(e_t)\sigma_{R,t} dB_t \qquad (16)$$

This points to the failure of the CCAPM in the model, which is the major conceptual difference betwen my model and the typical disasters literature. For the CCAPM to hold the SDF would be based off of aggregate consumption growth, thus the diffusion term on the SDF (λ_t) would need to be $\lambda_t = \alpha\sigma_{C,t} = \alpha\sigma$, which would imply a constant price of risk. Instead, assets are priced off the *intermediary's* marginal rate of substitution, hence $\lambda_t = \alpha\sigma_{E,t}$ and the SDF is a function of intermediary capital. This will make financial crises, defined as times when e_t is low, the times when risk premia are highest.

Next we can combine the return equation (12) with optimality (15) to derive the ODE:

$$\mu - g(rp_t) + \frac{p'}{p}\mu_e + \sigma\sigma_e\frac{p'}{p} + \frac{1}{2}\sigma_e^2\frac{p''}{p} + \frac{1}{p} - r = \frac{p}{e_t}\sigma_R^2 \qquad (17)$$

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

We know using equation (12) for dR

$$\sigma_R = \sigma + \frac{p'}{p}\sigma_e \qquad (18)$$

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

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

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

$$\sigma_E = \frac{p}{e}\sigma_R \qquad (19)$$

$$\mu_E = \frac{p}{e}(\mu_R - r) - \psi + r = \sigma_E^2 - \psi + r \qquad (20)$$

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

$$\sigma_R = \sigma\frac{(p - p'e)}{p(1 - p')} \qquad (21)$$

$$\sigma_e = \sigma\frac{(p - e)}{(1 - p')} \qquad (22)$$

$$\sigma_E = \sigma\frac{(p - p'e)}{e(1 - p')} \qquad (23)$$

16

We can therefore substitute in $\mu_e, \sigma_e, \sigma_R$ to our ODE in equation (17).

Finally, I assume that expected economic growth takes the form $g(rp_t) = a\Gamma(e_t)$, where $a > 0$. Intuitively this specifies that economic growth is low when risk aversion $(\Gamma(e_t))$ is high so that growth depends on the risk premium in the economy. This can be justified by a q-theory argument where higher risk premia raise the cost of capital which lowers investment and output, though these effects are not explicitly modeled here for simplicity.

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 (He and Krishnamurthy (2012b)), 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. I discuss these conditions in more detail in the appendix and give details on the numerical solution.

4 Calibration and Comparison to Data

4.1 Calibration and Basic Moments

Table 2 contains the calibrated parameters. I assume standard parameters where available. I set the volatility of aggregate output growth to 5%, which is consistent with historical US GDP data. I use GDP data from 1900-2012, but results are robust to longer samples as well. This value for GDP volatility is not significantly different using an international dataset as in Barro *et al.* (2011). I specify the parameters of the conditional mean of output, $\mu - a\Gamma(e_t)$, to match several moments. The parameter μ is chosen at 2.5% to match average economic growth. The parameter a governs the amplification of output in a crisis and the role for transitory fluctuations in growth. I therefore choose a based on the average one year drop in output in a financial crisis. Time-variation in $a\Gamma(e_t)$ will represent transitory declines in the growth rate of GDP in a crisis, though most of this decline will be through the Brownian shocks. It is important to note that while a is chosen to match output growth during a crisis

year, it does not imply that the model will match the dynamic response of output to a crisis several years out.

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 price dividend ratio is 6.25. 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 can fall 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 4. 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.

Basic Moments

Table 3 compares moments in the model to the data. I simulate the model monthly but report annualized moments and aggregate the simulated data to compute annual observations when necessary. The model calibration matches average moments quite well. By design the model matches average economic growth and volatility of output. The model also matches the equity premium (6.9% vs. 7.4% in the data), volatility (20% vs. 19%), and hence the market Sharpe ratio.[13] The model also matches the "volatility" of volatility (10.3% in the model vs. 9.2% in the data). The model is low on the log price-dividend ratio (2.8 in the model vs. 3.3 in the data) and is too high on the risk-free rate (the real risk free rate is less than 1% per year in my sample). However, the risk free rate is more consistent with values from a longer sample, 1.5% in Barro (2006) and 2.9% in Campbell and Cochrane (1999). 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 volaitlity of dividend yields. However, this value is 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 slow persistence in the mean dividend growth rate to generate higher dividend yield persistence. Taken as a whole, Table 3 suggests that the model does a good job of matching standard moments on

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[13]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.

output and asset prices for U.S. data.

4.2 Definition of a Crisis and Crisis Moments

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. The United States has historically spent 18% of years in a crisis since the crisis of 1914 (when the Federal Reserve was created) and 15% since 1800. However, of the more recent crises since 1914, only the years 1930-1933 and 2007-2009 were "severe" in terms of the large number of bank failures, large loss in output, spike in unemployment, and panic in financial markets. The term severe or systemic is used to categorize crises by Reinhart and Rogoff (2009) to distinguish from less devastating crises. This would put the probability of a severe crisis at 7% for the U.S.

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 the U.S. has spent in a "severe" or systemic crisis, but one could also think of this as the average time spent in a crisis for the advanced economies. In calibrations, I will use international data, but as Reinhart and Rogoff (2009) note the impacts of crises are "an equal opportunity menace" that affect advanced and emerging countries equally. 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. In the model, most of the action in these events comes from the far left tail (events below 2%).

Given this definition of a crisis, I show that the model produces declines in GDP and increases in dividend yields during a crisis that are in line with severe crises in the data. I plot this in Figure 5. The data used is a panel of international crises from Reinhart and Rogoff (2009) (see appendix). Relative to the data, the model matches GDP with one year growth immediately after a crisis being 9% below trend, but shows a smaller increase in dividend yields (about 30% vs. 50%).Table 4, Panel C, supports these conclusions. I run a panel regression of dividend yields on crisis dummies (controlling for lagged dividend yields) in the data and find that a financial crisis increases one year dividend yields by 41% in my larger sample (24% using only historical US crises), vs. 32% in the model.

I provide average equity and GDP declines and duration of these declines from previous

peak to trough in both the model and the data in Table 4. Peak is taken as the largest value over the previous 3 year window before the crisis, while trough is taken over the subsequent 25 years. I choose 3 years based on Figure 5 which shows this is typically when GDP starts to decline going in to a crisis. The results are quite similar if I use an unrestricted window before the crisis to compute the peak, but due to the continuous time model, this can occasionally result in the model choosing peak that is extremely far away from the crisis.

The average duration of a crisis in the model is 3.3-4.5 years which is slightly longer than the 3-3.4 years in the data. Stocks decline by 40% on average in the model, compared to 56% in the data, while GDP declines by 16% in the model and 11% in the data.[14] Further, I also give the distribution of GDP declines in Panel B, by comparing the 10th and 90th percentile losses in GDP as well as the maximum loss. The depth and duration of crises has been a source of recent interest and controversy given the current U.S. experience (see Reinhart and Rogoff (2009) and Bordo and Haubrich (2012)). The 10th percentile in the model has a decline of 10% and duration of 1.6 years, whereas the data has a decline of only 1% and duration of 1 year. This is because the model has only one shock. A crisis cannot occur without a fairly large shock to output since a shock to output is needed for asset prices, and intermediary equity, to fall. This is why the model also features an average decline in GDP that is relatively too large. However, for the 90th percentile, the model has a decline of 25% in GDP and duration of 9 years, while in the data these numbers are 23% and 5 years, respectively. This suggests that the model does fairly well in replicating the distribution of crisis outcomes. Finally, I compute the maximum loss and duration at 41% and 16 years in the model vs. 50% and 15 years in the data. It is also worth noting that there are only 28 crises in my GDP data, so this distribution is meant to be suggestive rather than definitive. In the model I form simulated data from 28 crises, calculate each of these statistics, then repeat this 10,000 times and take the average, so for example "maximum loss" is interpreted as the worst outcome one is likely to see if one observes only 28 crises.

4.3   Comparing Financial and Non-financial Recessions

The model captures the difference between financial and non-financial recessions in terms of risk premia. In the model I define a recession as two quarters of negative GDP growth. I then split recessions into two categories – financial recessions (where e_t falls into the crisis range) and non-financial recessions where it does not. I plot GDP growth, the log dividend yield, and volatility in each episode and compare these to the data in Figure 6. In the data

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[14]The declines in GDP in a financial crisis are also similar to those found in Cerra and Saxena (2008).

I take all NBER recessions and split them into these groups based on whether a financial crisis occured within the recession. For non-financial recessions I use beginning of recession starting dates and for financial recessions I try to use dates as close as possible to the financial crisis. The top panel shows the data, while the bottom shows the model. As in the data, dividend yields and volatility spike during financial recessions but not non-financial ones. The model also shows that financial recessions are "worse" in terms of GDP growth. In the model, when we condition on intermediary equity being low, it is more likely that fundamental shocks to output (Y) are currently negative, and have been negative in the recent past. This is because with a one shock model the only way to get low intermediary equity is through negative shocks to output (Y). Because of this, the model features low GDP growth coming into a financial recession and therefore high GDP growth coming into a non-financial recession. However, aside from the limitation of the single shock, the model appears to do a good job in replicating the data. Table 6 provides the changes in dividend yields in the model across these episodes. As we can see, dividend yields increase by around 30% over the course of a financial recession, whereas non-financial recessions see little change.

4.4 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.

I measure intermediary equity (e_t) as the total market value of the financial intermediary sector divided by GDP. 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 7, 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 in comparison with the price-dividend ratio which ranges from 1% to 8% to 29% over the same time period, highlighting the substantial forecasting power of intermediary equity.[15] The sign is negative, which is consistent with low intermediary capital corresponding to high 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

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[15]In unreported results, I also find the forecasting power to outperform the BaaAaa spread, except on the forecasts relating to corporate bond yields and returns.

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 portoflios 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.

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. The results are also consistent with my analysis in Figure 2 on the strong link between financial crises and risk premia in the U.S. historical experience.

5   The Term Structure of Risky Assets

We have seen that the model generates high and time-varying risk premia through time-variation in the probability of a financial crisis. However, because crises in the model are endogenous and temporary, the model has specific implications for the *term structure* of crisis probabilities; that is, the probability of a crisis occuring at different horizons. Since risk premia are strongly related to crises, this in turn has implications for the term structure of risky assets. In good times, crisis probabilities are concentrated in the long term and the term structure of risky assets is upward sloping. In contrast, in bad times crisis probabilities

are concentrated in the short term and the term structure of risky assets is downward sloping.

Studying the term structure of risky asset is useful for two reasons. First, it directly tests unique predictions of the model. In fact, most standard asset pricing models imply a term structure of risk premia that is always upward sloping (Bansal and Yaron (2004) and Campbell and Cochrane (1999)) or is constant over time (Barro (2006)).[16] This distinction is important since the equity premium is the sum of the premium on the individual dividends at each horizon, so focusing only on the overall equity risk premium can be potentially misleading about a model's success. Second, the close link between crisis probabilities and the term structure of risky assets will give us a way to measure the term structure of crisis probabilities empirically, which is useful in measuring systemic risk.

I will focus on three risky asset term structures: dividend strips, corporate bonds, and VIX. Dividend strips pay off aggregate dividend growth N periods from now, corporate bonds pay off \$1 N years from now except in case of default, and VIX can be thought of as a contract that pays off the integrated variance N years from now so that it is the "risk neutral" expectation of integrated variance. For corporate bonds and dividend strips, I will focus on yield spreads – the assets' yield minus the yield of a risk free asset with identical maturity, which van Binsbergen *et al.* (2012b) call forward yields. Yields are defined in the usual way as the negative of log prices divided by maturity. See the appendix for more details of these definitions.

5.1   The Term Structure of Risky Assets in the Model

The Term Structre of Crisis Probabilities

I define the "term structure of crisis probabilities" as the probability of being *in* a crisis N years from now. Thinking about how this term structure evolves turns out to be incredibly useful to the model dynamics.

I define three regions in the model. The first are "normal" times, when the probability of a financial disaster is low, intermediaries are well capitalized, and risk premia are low. I define this region based on the highest 80% of the realizations of intermediary capital, e. The next region is the "danger" region, which I define as realizations of intermediary equity in the interval [7%, 20%]. The danger region is a weakening of the financial system, but not yet a financial crisis. In the danger region there is a non-trivial probably of ending up in a financial crisis in the near future. Finally, the lowest 7% of the realizations of intermediary

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[16]See van Binsbergen *et al.* (2012a) for the implications of these models for the term structure of risk premia.

equity make up the crisis region, characterized by a sharp increase in risk premia.

I plot the average term structure of crisis probabilities, conditional on being in a given region, in Figure 9. In the normal region, the term structure of crisis probabilities is upward sloping. This is because the probability of receiving a shock large enough to put the economy in a crisis tomorrow is essentially zero. However, as we increase maturities, the probability of a crisis in later years converge to 7% – the unconditional probability of being in a crisis. Moving next to the "danger" area, a crisis is still unlikely in the very near term, but is quite possible in a year. As we increase the maturity the probability of a crisis will again fall to the unconditional value of 7%, resulting in a hump-shaped term structure. Lastly, the term structure is deeply inverted when in the crisis state. It is unlikely that the crisis will end in the very near term, but it will almost certainly end in several years. The intuition is that high risk premia mean that intermediary equity will likely grow at a high rate in the future. As this happens and intermediary equity capital is restored, the economy will exit the crisis region and risk premia will fall drastically.

Now that we understand the term structure of crisis probabilities, we can understand the term structure of risk premia and risky assets. Financial crises are states where the marginal value of wealth is incredibly high and hence are valuable states to hedge. Therefore, assets whose payoffs fall in these states have high risk premia, and therefore high yields. Since bonds will tend to default in a crisis and dividend growth is typically poor, we can see that the term structure of risk premia on equity, corporate bonds, and VIX will essentially match the term structure of crisis probabilities. We will get "inversion" in crisis times, while in "normal" times these term structures will be upward sloping.

To formally define and study these assets in the model, note that we know the SDF (pricing kernel) and thus can price any assets by simply modeling their cash flows. The appendix goes through the details to compute VIX and dividend strips. Essentially, since the dividend process is given, and since we can simulate the volatility process, both dividend strips and VIX are straightforward to calculate. My strategy for calibrating corporate default is outlined in the next subsection. For dividend strips and corporate bonds, I will study yields (log prices divided by maturity in years) over the risk free rate which I will refer to as equity yields and corporate bond yield spreads.

Figure 10 plots the *time-series* evolution of several term structures in a 50 year sample of simulated data with a crisis occuring around year 24. I plot 1 and 5 year conditonal crisis probabilities, growth expectations, corporate bond spreads, corporate default rates, and equity risk premia. I also plot 1 and 12 month VIX, where I use months because VIX data is typically given in months. We see in each case the slopes switch sign during the

crisis – near term crisis probabilities are high, near term growth expectaions are low, and near term risk premia on corporate bonds and equities are high compared to the long term. These term structures are thus useful in capturing the expected depth and duration of the crisis.

5.1.1   Calibrating Default and Matching Corporate Yield Spreads

I calibrate the corporate bond default process and compare resulting model spreads to the data. Corporate bonds are an asset that pays 1 if default does not occur and pays $(1-LGD)$, where LGD is the loss given default, in case default occurs. Once we have the cash flow process, we can price corporate bonds using the simulated SDF. The appendix goes through these details. I will calibrate the default process to target a basket of investment grade corporate bonds.[17]

I specify default to occur if realized dividend / output growth over its long run average falls below a threshold K (which is a constant) at any time before maturity in my simulated monthly data.[18] This has several desirable features that match the empirical data (see Duffie and Singleton (2003) for a review of the empirical literature). First it implies realized default will be pro-cyclical and highly correlated with GDP. Duffie and Singleton (2003) find the correlation between realized defaults and GDP growth at around 0.8 and Chen (2010) finds that macro factors such as consumption and GDP explain 50% of the variation in realized default rates. Second, it implies expected default will be higher in bad times when e_t is low since expected growth is typically low in these times, so it is more likely that growth will be below its long run average. This will match the cyclical properties of expected default rates and make corporate bonds risky since they will tend to default in bad times. However, since low GDP does not on its own constitute a financial crisis in the model, default episodes can still occur outside financial crises. This matches observations in Giesecke *et al.* (2012) who find that default episodes distinct from financial crises, but default episodes which ocurr in financial crises have particularly severe economic consequences.

In calibrating the cutoff K for the bond to default, I use Moody's Expected Default

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[17]Note that this is different from modeling default for a single firm since firms can be downgraded and no longer considered investment grade. I will calibrate a default process that resembles the overall default probability for the basket of bonds.

[18]Specifically, we can define the process $dz_t = \frac{dY_t}{Y_t} - E\left[\frac{dY}{Y}\right] dt$ as output growth minus its unconditional mean and $Z_{t,N} = \int_t^{t+N} dz_t$. Then we can define default to occur for a time t N year bond if $Z_{t,N} < K$ at any point before maturity N. The process dz_t will have positive mean outside a crisis and negative mean during a crisis. This makes default more likely in a crisis. However, since crises are temporary, the negative mean will also be temporary. In both cases default rates will be higher in the longer term (i.e. 10 years vs. 1 year) because the process starts far away from the default boundary.

Frequency, or EDF, data from 1982-2012 to calibrate average expected default and expected default conditional on a crisis for a basket of investment grade bonds. Moody's provides 1 to 5 year annualized expected default rates. For default rates above 5 years, they set forward default rates to the forward default rate from years 4 to 5, so I will focus on matching the level and slope of the 1 to 5 year default probabilities. I take averages of expected defaults across 1 to 5 years and target this average. With my choice of K, this average is 0.52% in the model compared to 0.48% in the data. Next, I compare average default in "crisis" times since I will want to correctly match the increase in default rates during bad times. In the data, I take average probabilities of default conditional on the probability of default being above the 93 percentile because in the model crises are defined as occuring 7% of the time. This turns out to be similar to using the crisis dates from Bordo and Haubrich (2012), because the dates chosen are all either in 1982, or 2008-2010. Using crisis dates from the literature is challenging because we need to determine the exact starting and ending months of the crises and may face the problem of having too few crisis dates to base our inference on. I find the probability of default in the data to be 1.17% in a crisis and 1.48% in the model. I report these results in Panel A of Table 5.

I also compute the slope of the default curve in normal times and crises. In the data these are 0.28% and 0.20%, respectively, while in the model they are 0.67% and 0.53%. The slopes in the model are higher than in the data because there are no jumps in the model, so short term bonds are very unlikely to default. However, the key feature that I match is that the slope is positive in both normal times and crises, but becomes slightly more flat in crises.

The remaining issue is the loss given default (LGD) which can also be defined based on the recovery rate. For this, I refer to Chen (2010) who finds a mean recovery rate of 48%. I therefore use a constant LGD of 50%. However, as Chen (2010) points out, recovery rates vary over time and have a correlation of -0.77 with default rates (see his Table 4). Chen (2010) finds a volatility of recovery rates of 7%. While I will not model time-varying LGD explicitly, slightly elevated default rates during crises can compensate for this. For example, what matters essentially is the probability of default times the recovery rate in default. With slightly higher probabilities of default in bad times, it is "as if" I have a time-varying LGD, especially since default rates and LGD are highly correlated. If we assume recovery rates are normally distributed, then the mean of 48% and standard deviation of 7% estimated by Chen (2010) implies that the expected recovery rate conditional on recovery rates being in the lowest 7% of their realizations is about 35% which translates to a 65% LGD. I will use this estimate for the empirical LGD conditional on a crisis, so that $E\left[LGD|crisis\right] = 0.65$. When

comparing to the data I will compare expected default times LGD in both the model and the data. I show that in the data this value is 0.24% unconditionally and 0.76% in a crisis, while in the model this value is 0.26% unconditionally and 0.74% in a crisis. Therefore, my procedure matches the interaction of cyclical recovery rates and cyclical default probabilities.

I now compare correponding bond yield spreads. My data on these come from Barclay's Investment Grade yield spreads. Barclay's matches all promised payments to the appropriate risk-less curve to create yield spreads. The spreads are also adjusted for optionality and hence are labeled option adjusted spreads. The model implied yields spreads are 1.02% unconditionally compared to 1.33% in the data. In a crisis, spreads increase to 3.6% in the model compared to 4.1% in the data. The slightly higher yields in the data in both cases could potentially be due to the differential tax treatment of corporate bonds and Treasuries (Elton *et al.* (2001)) which is absent in my model. The volatility of yield spreads is 1.05% in the model and 0.88% in the data, therefore the model does a good job matching both the level and variation in yield spreads.

I also compare my calibrated investment grade bond to the BaaAaa spread in the data. This will be useful in the later estimation section because the BaaAaa spread has a long history which I can use to make inference about the state of the economy.[19] My goal here is simply to construct a bond that behaves similarly to the default spread and hence can be used for estimation purposes. I will use the calibrated investment grade bond to proxy for a BaaAaa spread. The results suggest the average yields, volatility of yields, and largest 7% of yields are all in line with the investment grade calibration. Again, in the data I define "crisis" as the highest 7% of realizations of the BaaAaa spread – but again *all* of these realizations occur during the Great Depression, banking crisis of 1982, or recent financial crisis, which are the three typically defined banking crises over this period, and again this calculation avoids me having the specify the exact beginning and end of each crisis. The average BaaAaa yield in the data is 1.14% with a volatility of 0.72% and level in a crisis of 3.12%. These values are fairly similar to the investment grade bond in the model. Taken together, this suggests my constructed invesment grade bond will work well as a proxy for the BaaAaa spread since they behave quite similarly.

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[19]My data for the BaaAaa spread is from FRED, 1927-2012 in accordance with the time period used later for the estimation.

5.2 The Term Structure of Risky Assets in the Data

I next explore the term structure of risky assets in the data. van Binsbergen *et al.* (2012b) study the equity yields market and find "inversion" in the term structure of equity yields during the 2008-09 financial crisis but have only 10 years of data, making it difficult to generalize the results (see Figure 15). I extend these results by also analyzing corporate bond yields and VIX, and by studying a longer sample to connect these episodes specifically to financial crises. The appendix contains details on data sources.

I plot corporate yields spreads for various maturities in the top panel of Figure 11. My data are from Barclay's and contain option-adjusted corporate yield spreads for investment grade firms from 1988-2012. I decompose corporate yield spreads into expected default and risk premia in the middle and lower panels of Figure 11 using Moody's Expected Default Frequency data.[20] As in previous research, I find the risk premium component to be the largest source of credit spread fluctuations (Collin-Dufresne *et al.* (2001), Gilchrist and Za-krajsek (2012), Giesecke *et al.* (2011)). I find that the slope of the corporate yield curve is directly related to the slope of the term structure of risk premia: the correlation between these two slopes is about 1. In contrast, the slope of the default curve does not change drastically over time. Moreover, as the model predicts, we only see the "inversion" in the corporate yield curve in financial crises (1990 and 2008),[21] but not during the 2001 recession and dot com crash. I confirm that this is a more general feature of the data by constructing corporate yield spreads during all U.S. financial crises since 1920 in Figure 8. I supplement data before 1988 with hand collected corporate bond yields over government yields from the New York Times (see appendix for details). I also plot the corporate yield curve for non-financial recessions, where I collect data from the recession mid-point. The evidence in Figure 8 suggests that the inversion in the corporate yield curve is typically a feature of financial crises, but not recessions in general. This therefore directly ties the inverted term structure of risky assets and risk premia to financial crises in U.S. data.

Finally, I plot the VIX term structure in Figure 13. I decompose the term structure into an expected volatility (or square root of expected variance) component and a risk premium component by running a VAR to forecast log variances. For VIX, the majority of the level

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[20]Previous studies that document inversion in credit spread curves typically attribute this to default risk (Arellano and Ramanarayanan (2012)). Standard structural models of default can generate downward sloping default curves, but typically only for risky firms which are close to default. However, even this is questionable as Helwege and Turner (1999) find upward sloping curves even for speculative grade firms. Here I focus only on investment grade firms which have upward sloping default rates.

[21]1990 represents the end of the S&L crisis and is considered in the window of financial crisis in, e.g, Reinhart and Rogoff (2009) and Lopez-Salido and Nelson (2010).

and slope is due to the expected volatility component. We see inversion in VIX during 2008 which corresponds mostly to higher short term expected volatility but also to higher short term risk premia. The slope of the risk premium curve again closely matches the slope of the VIX term structure – the correlation between the two is 0.80 and statistically significant, suggesting that the shape of the term structure of VIX and the shape of the term structure of volatility risk premia move together. For VIX, the slope also largely reflects the shape of the term structure of expected volatility.

The following section goes through the estimation and decomposition of each of these term structures into risk premia and cash flows in more detail.

Empirical decomposition of cash flows and risk premia

Each asset class I consider can be decomposed into a cash flow component and a risk premium component. Let rp denote the risk premium of a particular asset class, ef represent the forward equity yield, cf represent the corporate bond yield spread, $var_{t,t+n}$ denote integrated variance from t to $t+N$, $pd^{(n)}$ denote the annualized default rate,[22] LGD denote loss given default, and super-script (n) denote years to maturity. Then

$$VIX_t^{(n)} = \left(\frac{1}{n} E_t \left[var_{t,t+n} \right] \right)^{\frac{1}{2}} + rpv_t^{(n)} \tag{24}$$

$$ef_t^{(n)} = -E_t \left[\frac{1}{n} \ln \left(\frac{D_{t+n}}{D_t} \right) \right] + rpe_t^{(n)} \tag{25}$$

$$cf_t^{(n)} = \frac{1}{n} pd_t^{(n)} LGD_t^{(n)} + rpc_t^{(n)} \tag{26}$$

In words, VIX is equal to an expected variance and a volatility risk premium component, forward equity yields are equal to an expected dividend growth component and a risk premium component, and corporate bonds are equal to a default component and a risk premium component. If variance is expected to be high, growth expected to be low, or default expected to be high, the corresponding yields will naturally increase. Similarly, if the volatility, dividend, or corporate bond risk premiums increase, yields will increase. Notice in each case we observe the left hand side. My strategy is to estimate one object on the right hand side then use the equality above to obtain the remaining object of interest. For example, van Binsbergen *et al.* (2012b) estimate expected dividend growth using a predictive regression then define the risk premium as the residual using the observed forward equity yield.

I outline my strategy to do the same for both VIX and Corporate bonds.

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[22]I use default rate and probability of default interchangeably. They are approximately the same because $-\ln(1 - PD) \approx PD$. This approximation is especially close here because I work with investment grade bonds whose default rates are always close to zero. $\frac{1}{n} pd_t^{(n)}$ is then the annualized default rate.

Corporate Bond Decomposition

Corporate yield spreads are due to a default component and a risk premium component

$$cf_t^{(n)} = \frac{1}{n}pd_t^{(n)}LGD_t + rpc_t^{(n)}$$

I separate the default and risk premium components using Moody's EDF term structure. Moody's Analytics estimates default probabilities by combining a structural model of default with rigorous empirical analysis on predicting default, making their measure both theoretically grounded and highly accurate in terms of capturing default probabilities. Given these probabilities of default at each horizon, I assume a constant loss given default (LGD) of 50%. The results are not senstive to higher choices of loss given default, including assuming 100% loss given default, or assuming a time-varying LGD that is correlated with default rates. Given the default component, we can define the risk premium component as

$$rpc_t^{(n)} = cf_t^{(n)} - \frac{1}{n}pd_t^{(n)}LGD_t$$

I show that these estimated risk premiums are sensible. Specifically, I regress corporate bond returns on the estimated risk premium and find strong predictive power. Recall that the risk premium component should equal expected excess bond returns:

$$rpc_t^{(n)} = E_t\left[rc_{t+1}^{(n)} - rf_{t+1}^{(n)}\right]$$

where $rc_{t+1}^{(n)}$ is the return on a corporate bond of maturity n and $rf_{t+1}^{(n)}$ is the return on a Treasury bond of maturity n. This motivates the following predictive regression:

$$rc_{t+1}^{(n)} - rf_{t+1}^{(n)} = \alpha_n + \beta_n' rpc_t^{(n)} + \varepsilon_{n,t}$$

I find the above regression has (1) coefficients which are statistically signficant and near one in magnitude and (2) R^2 values that are large (2-5% at monthly horizon and 15-40% at annual horizons). This validates $rpc_t^{(n)}$ as an accurate measure of corporate bond risk premia. The large amount of predictability suggests that much of the variation in corporate bond yields is due to changes in risk premia, an assessment consistent with earlier results.

Finally, the results for the slope of the term structure also holds using CDS data, which does not rely on matching the appropriate Treasury curve and which is a more liquid market.[23] To decompose the CDS curve, I run regressions of average CDS on the average Moody's EDF measure, since the CDS data do not map directly to the firm / ratings in the

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[23]Results available from author.

Moody's EDF data. I define the predicted value as the default component and the residual as the risk premium component. This decomposition implicitly assumes that fluctuations in default probabilities for the CDS data are linearly related to the average default probability on investment grade bonds. Using the CDS data also allows me to rule out a selection bias critique. Despite the fact that I try to control for credit quality, one may still be concerned that in crisis times there is an increase in short term bond issuance by lower rated firms which could generate the downward slope.[24] Using the CDS data allows me to only include firms which have quoted CDS rates for all maturities, thus mitigating any selection bias in bond issuance. I use the CDS data only as robustness since reliable data is not available before 2004.

VIX Decomposition

Recall the decomposition for VIX:[25]

$$VIX_t^{(n)} = \left(\frac{1}{n} E_t \left[var_{t,t+n} \right] \right)^{\frac{1}{2}} + rpv_t^{(n)}$$

I estimate the expected variance using a standard VAR and define the risk premium component using the realized VIX. Define rv as realized volatility over the preceding month and let "hats" denote demeaned values. I estimate expected log variance as follows

$$x_t = \left[\ln \left(\widehat{rv}_t \right), \ln \left(\widehat{VIX}_t \right) \right] \tag{27}$$

$$x_{t+1} = \Gamma x_t + \eta_{t+1} \tag{28}$$

$$E_t \left[x_{t+n} \right] = E_t \left[\left[\ln \left(\widehat{rv}_{t+n} \right), \ln \left(\widehat{VIX}_{t+n} \right) \right] \right] = \Gamma^n x_t \tag{29}$$

I specify the system in logs as it is better behaved and also means we can use volatility and variance interchangeably since log volatility is half log variance. Variances can be approximated as log-normal so a linear system becomes a better fit in logs, and without logs the forecasting equation places a large amount of weight on a few observations (particularly, September-October of 2008). I can then approximate monthly variance n periods from now as:

$$E_t \left[var_{t+n-1,t+n} \right] \approx \exp \left(E_t \left[\ln \left(var_{t+n-1,t+n} \right) \right] \right)$$

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[24]For example, Helwege and Turner (1999) show empirically how selection bias can affect the observed slope of the corporate yield cruve.

[25]Many authors decompose the VIX in terms of variance as: $\left(VIX_t^{(n)} \right)^2 = \left(E_t \left[\frac{1}{n} var_{t,t+n} \right] \right) + rpv_t^{(n)}$. This is similar, but the advantage of my decomposition is that the units are more easily interpretable in terms of VIX and volatility. In the above decomposition in terms of variances, the series are dominated by infrequent spikes.

which I can compute by interating the VAR forward and adding back the average log variance. The downside of this specification is that the approximation ignores a Jensen's inequality term.

I can define the risk premium term using:

$$E_t \left[\frac{1}{n} var_{t,t+n} \right] \approx \frac{1}{n} \sum_{i=1}^{n} \exp \left(E_t \left[\ln \left(var_{t+i-1,t+i} \right) \right] \right) \tag{30}$$

$$rpv_t^{(n)} = VIX_t^{(n)} - \left(E_t \left[\frac{1}{n} var_{t,t+n} \right] \right)^{\frac{1}{2}} \tag{31}$$

The results are not substantially different using a specification without logs. I use daily data on VIX from CBOE and create a daily series of realized volatility over the past 22 trading days. Therefore, while the above system uses daily observations, I forecast at the monthly horizon, meaning I forecast realized volatility over the next trading 22 days. I use VIX data with maturity 1 month as the short end, and maturity 3 months at the long end. Technically, I can extend the analysis out to 12 months, but this requires iterating the VAR forward 12 months which is problematic if there is "long memory" in volatility which the VAR does not capture. While the system above is simple in comparison to other methods such as GARCH(1,1), Drechsler and Yaron (2011) find that simple predictive regressions along these lines actually provide accurate forecasting power, mostly due to the forecasting power of VIX.

5.3   Comparing the Model with the Data

I compare the term structure of risky assets in the data and the model. In the data, I define the crisis, danger, and normal regions based on the percentile realizations of the level of yields. That is, I take the largest 7% of realizations of corporate yields and VIX as the crisis periods, yields in the 7%-20% as the danger region, and all other yields as being in the normal region. For the crisis region these all correspond to the 2008-2009 period (except VIX which has a large but short lived spike around 2002). Therefore this definition is mostly useful in defining the danger region. Note that this definition is equally valid for the model since the level of yields corresponds one-to-one with the level of intermediary capital. Finally, defining the crisis region this way has the added advantage that it does not rely on exactly specifying crisis start and end dates. For variables like VIX and credit spreads this is crucial because these varibles spike enormously and also drop enormously when crises are over, and hence capturing the correct window is crucial.

The top panel of Figure 12 plots the term structure of corporate yield spreads in the data for the crisis, danger, and normal regions while the bottom panel plots the analagous object in the model. In the model, I form baskets of spreads based on maturity and take averages, analogous to the data I have where the baskets are 0-3, 3-5, 5-7, 7-10, and 10-15 years.[26] The two look remarkably similar in terms of level and slope in each of the three regimes. The only difference is that yields are slightly lower in the model and that slope is more negative in a crisis. During crises, the short term yiels in the model is 5.5% and about the same in the data, whereas the long term yield is only 3% in the model vs. just under 4% in the data. These numbers are reported in Table 8.

I repeat this exercise using the VIX term structure in Figure 14. I plot the VIX term structure for maturities 1, 2, 3, 6, 9, and 12 months. The model replicates the shape of the VIX term structure fairly well in each regime both in terms of level and slope. The main difference is that, in the model, the VIX level is higher in a crisis (60% vs. 45%) and the slope is more negative (-16% vs. -6%). Also, in the model the VIX level is too low in normal times at around 15% vs. 20% in the data.

Therefore, the model is able to match the key features of the term structures of risk and risk premia in the data through the temporary nature of financial crises. Because during a financial crisis, crisis probabilities are concentrated in the near term, assets paying off in the near term tend to become riskier and also tend to face higher risk premia since marginal utility is high in these times. In contrast, during normal times disaster probabilities are concentrated in longer term securities. In turn, the close link between probabilities of crises at different horizons and these term structures in the model suggests that using these term structures in the data are an ideal place to study crisis probabilities.

To further emphasize the intuition of temporary spikes in risk premia during crisis, I also show in Table 8 that dividend yields are much less persistent during crises than normal times. In the data, dividend yield persistence goes from 0.89 in normal times to 0.7 in crises. Using two structural breaks in dividend yields as in Lettau and Van Nieuwerburgh (2008), these numbers are 0.67 and 0.36, respectively. Thus the data is consistent with the implication that risk premia are less persistent during crises, meaning the spikes in crises are temporary.

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[26]By forming baskets, I mitigate the issue discussed earlier that short term (i.e. less than 1 year) default rates are extremely low, making short term yields extremely low. Averaging yields from 0 to 3 years will include bonds with non-zero probabilities of default. Thus, the model will not replicate yield spreads for very short term bonds.

5.4 Measuring Probabilities of a Crisis

I provide measurements of the probabilities of a crisis at different horizons using asset price data and data on risky asset term structures. In the model, everything is a function of the single state variable e. Therefore, my procedure follows two steps. First, choose the value of e most likely in the model given the data. Second, I map this value of e back into the implied term structure of crisis probabilities. These probabilities, once in a crisis, also correspond directly to speeds and probabilities of recovery.

Let G represent a vector of model implied variables minus counterparts in the data which we are trying to set to zero: $G_t(e) = (m_{t,\mathrm{mod}}(e) - m_{t,data})$.

Formally, at each point in time I choose $\widehat{e}_t$ to solve the following optimization problem:

$$\min_{\widehat{e}_t} G_t(\widehat{e}_t)' W G_t(\widehat{e}_t)$$

W is a weighting matrix which I set to be the inverse of the variance of $m_{t,data}$. One can simply think of this procedure as standardizing the variables since they may have drastically different levels. For example, VIX typically is a number around 20% and can increase to 80% while corporate spreads are around 1% and can increase to 10% so without accounting for the variance the procedure would focus almost entirely on VIX. This procedure is based on the procedure in Eisfeldt and Muir (2012) who use SMM at each date to uncover a hidden state variable.

In words, I choose $\widehat{e}_t$ to minimize a weighted sum of deviations of the model and the data. This provides me with an estimate of the unobserved state $\widehat{e}_t$ for every date. Given this variable, I can therefore estimate the probabilities of a crisis as:

$$p_t^k(\widehat{e}_t) = prob(e_{t+k} < \underline{e} | e_t = \widehat{e}_t)$$

where $\underline{e}$ represents the boundary at which the economy enters a financial crisis in the model. Therefore, $p_t^k(\widehat{e}_t)$ gives the probability of the economy being in a crisis in k years *given* the current state. Note that this is distinct from the probability of a crisis happening at any time *between* now and year k.

I use two data sets based on data availability. First, I use monthly data on the log dividend yield, monthly stock volatility computed from daily S&P500 observations, and the BaaAaa default spread over the period 1927-2012. Thus $m_{t,data} = [\ln(d/p)_t, BaaAaa_t, \sigma_{R,t}]$. For the dividend yield I follow Lettau and Van Nieuwerburgh (2008) who use trend breaks in the dividend yield to account for low frequency shifts in the mean. As previously argued, since my calibrated investment grade bond behaves similarly to the BaaAaa spread (see results in Table 5), I will use this bond to proxy for the BaaAaa spread in the data.

I use my procedure to estimate the term structure of crisis probabilities month by month and then take a 3 month moving average of the resulting series. I also demean the dividend yield in the data and model since the model has a higher average dividend yield. I plot the estimated crisis probabilities for the next 1 quarter, 1 year, and 2 year horizons in Figure 17. The model identifies exactly three periods as financial crises: the Great Depression (both 1930-1933 and also 1937), the early 1980s, and the recent financial crisis. These are the three commonly identified banking crises in the literature, meaning the model does a good job picking out actual financial crises. Next, the results give a useful term-structure of recovery. When in each of these crises, the probability of remaining in the crisis in the next year is around 60%, whereas for two years it is around 20%. This gives a dynamic indication of recovery.

Next, I turn to higher frequency data on the term structure of risky assets, where I use daily observations of the VIX term structure and investment grade corporate bond term structure from 1997-2012. The advantage of this procedure is that it uses risky asset term structures which, by definition, should be highly informative about crisis probalities at various horizons. It also uses daily data which allows me to study how daily events affect probabilities of crises and recovery. Figure 16 gives the empirical results using 6 variables: the short (1 month) and long (12 month) VIX, the short (0-3 years) and long (7-10 years) corporate yield spreads, and the respective slope of each of these.

We can see that, as the model would predict, leading up to a crisis the long term crisis probability typically rises much earlier than the short term probability, yet also the data suggests the exact timing of a crisis is still fairly unpredictable. Looking to the 2008 financial crisis, the long term probability first starts moving up in February of 2007, at the same time Freddie Mac announces it will no longer buy the riskiest grade mortgages. As more negative news for the financial sector occurs over the next year, the probability of a crisis steadily increases. For almost the entirety of 2008, the one year probability of a crisis was around 20%, compared to only about 2% at the beginning of 2007, representing a large jump.[27] Therefore, the one year probability reflected the heightened probability of a financial crisis, but did not jump higher until Lehman collapsed in September, at which point it fairly quickly rose to 60%. This is consistent with the idea that while the probability of a financial crisis increased in 2008, the actual timing of the crisis was largely unpredictable. However, the probability of staying in a crisis in 2 years is still fairly low (17%) suggesting that the market expected the financial crisis to be over within 2 years. I also analyze the term structure

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[27]He and Krishnamurthy (2012b) also argue that the probability of a crisis was likely low around 2007.

of crisis probabilities for two additional days of interest: (1) October 14th, 2008 when the Treasury announces TARP and makes a \$250 billion capital injection available to the finance sector and (2) December 16th, 2008 when the Federal Reserve lower interest rates from 1% down to 0-0.25%. Both were policy attempts to alleviate the crisis. Both of these events reduced the market's expectation of the probability of remaining in a crisis in 1 year by around 20%. This highlights the usefulness of this procedure for analyzing how events and policies may have affected the recovery.

6   Conclusion

This paper argues that financial crises are important for understanding asset prices and risk premia. I first document this fact empirically by splitting disasters into wars and financial crises and showing that only the latter account for large spikes in risk premia. I then study a model that generates financial crises that quantitatively match those in the data. A key feature of the model and the data is that financial crises are events that temporarily have large impacts on risk premia and asset prices. Because of this, during a crisis the term structure of risky assets, such as corporate yield spreads, slopes sharply downwards as risk and risk premia are more concentrated in the near term. This fits new facts on the term structure of risk premia, which I help document. In turn, this makes the term structure informative about probabilities of financial crises at various horizons. Using this idea, I show how to back out probabilities of a crisis at different horizons using term structure variables. The probability of a crisis generates large fluctuations in asset prices as well a large unconditional equity premium and corporate bond yield spreads. Consistent with the model, I show that a measure of financial intermediary equity forecasts annual stock and corporate bond returns with a high degree of explanatory power of around 17-20%. My findings strongly support models of financial crises, such as He and Krishnamurthy (2012b) and Brunnermeier and Sannikov (2012), as being able to quantitavely explain macroeconomic and asset price data. This paper is the first to quantitatively tackle these issues, providing an explicit link between theories of financial intermediaries, risk premia, and stylized facts on financial crises.

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7   Appendix

7.1   Data Appendix:

Aaa, Baa, and long term government yield: Federal Reserve's FRED database series AAA and BAA represent Moody's corporate bond yields. LTGOVTBD, and GS20 represent long term government bond yields. LTGOVTBD is only available until from 1919-1999. I use the yield on the 20 year Treasury bond (GS20) afterwards.

CDS Data: From DataStream. Daily CDS mid quotes from January 2004 - September 2010. There are roughly 1 million firm, day pairs and roughly 6 million securities total (ie firm, day, maturity triplets). There are 843 firms covered that have the full spectrum of maturities (1, 3, 5, 7, 10 years) on at least one day.

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 crisis dates come from serveral sources: For 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)). When using Bordo and Haubrich (2012) and Gorton (1988) I date the financial crisis based on their banking crisis dates (see Gorton (1988) Tables 1 and 6, and Bordo and Haubrich (2012) Table 2). My main dates use Gorton (1988) when possible. For Bordo and Haubrich (2012) I drop 1975 as most authors do not consider this a crisis (i.e. Reinhart and Rogoff (2009), Jorda *et al.* (2010)). The results are robust to including additional dates used in other studies: for example, 1973-1975, 1988-1991 (Lopez-Salido and Nelson (2010)), 1984 (Reinhart and Rogoff (2009)).

For global and international crises, I use Reinhart and Rogoff (2009) which contains an extensive list. I also use dates from Barro (2006) for the Great Depression, and these are also characterized as financial / banking crises in the online dataset of Reinhart and Rogoff (2009).

The following Table summarizes dates for crises and war related disasters used in the paper. Superscripts P and G represent whether I have Price (dividend yield) data and / or

GDP data for each event to compute peak / trough calculations. For dividend yields where month is not specified I use end of year values. To the Reinhart and Rogoff (2009) original study, I also add Germany, France, Spain, Italy, Portugal, and Greece as having banking crises in 2008. These have been added to Reinhart and Rogoff's online database but were not part of the countries in the original study. I also drop Iceland due to lack of data. The inclusion or exclusion of these countries has little effect on main the results, but adds a larger panel.

Dates used for crises and wars:

Severe Crises: RR		Crises: Barro, RR		War Disasters: Barro		
Country	$Year$	France	$1929^{P,G}$	War Disasters	$Year\ 1$	$Year\ 2$
Spain	$1997^{P,G}$	Australia	$1928^{P,G}$	Austria	1913^{G}	$1944^{P,G}$
Japan	$1992^{P,G}$	Austria	$1929^{P,G}$	Belgium	1916^{G}	$1939^{P,G}$
Norway	$1987^{P,G}$	Canada	1929^{G}	Denmark	1914^{G}	1939^{G}
Philippines	$1997^{P,G}$	Germany	$1928^{P,G}$	Finland	1913^{G}	
Sweden	$1991^{P,G}$	Netherlands	1929^{G}	France	$1916^{P,G}$	$1939^{P,G}$
Columbia	$1998^{P,G}$	U.S.	$1929^{P,G}$			
Korea	$1997^{P,G}$	New Zealand	1929^{G}	Germany	$1913^{P,G}$	$1944^{P,G}$
Malaysia	$1997^{P,G}$	U.S. Crises:		Netherlands	1913^{G}	1939^{G}
Finland	$1991^{P,G}$	$Year$	$Month$	Sweden	1913^{G}	
Indonesia	$1997^{P,G}$	$1873^{P,G}$	9	Greece	1939^{G}	
Argentina	$2001^{P,G}$	$1884^{P,G}$	6	Spain	$1935^{P,G}$	
Hong Kong	1997^{P}	$1890^{P,G}$	11	U.K.	1918^{G}	$1943^{P,G}$
Hungary	2008^{P}	$1893^{P,G}$	5	U.S.	$1944^{P,G}$	
Ireland	2007^{P}	$1896^{P,G}$	10	Canada	1917^{G}	
Austria	2008^{P}	$1907^{P,G}$	10	Italy	1918^{G}	$1940^{P,G}$
U.K.	2007^{P}	$1914^{P,G}$	8	Japan	$1943^{P,G}$	
U.S.	2008^{P}	$1930^{P,G}$	10	Norway	1939^{G}	
Italy	2008^{P}	$1931^{P,G}$	3			
Portugal	2008^{P}	$1933^{P,G}$	1			
Spain	2008^{P}	$1982^{P,G}$	1			
Germany	2008^{P}	$2008^{P,G}$	9			
France	2008^{P}					
Greece	2008^{P}					

U.S. Recession Dates: NBER. For Figure 2 I use one year after the beginning of the recession as the event (this is when risk premia typically peak). For financial crises, I use dates above.

VIX term structure: Daily data from CBOE.

Corporate yield spreads and excess returns: Data are from Barclays. Maturity buckets are 0-3 years, 3-7 years, 7-10 years, 10+ years, and an average of the above. Payments

for each bond are matched to the appropriate Treasury curve and the appropriate risk free rate is subtracted off each. The yields are adjusted for optionality / callability. Excess returns are over a portfolio of Treasury returns of matched maturity. Data are from 1989-2012. I have each of these data separately for investment grade and high yield firms. Finally, for daily corporate yield spreads I use data downloaded from FRED (1996-2012). These are higher frequency but have a shorter sample. They behave similarly to the Barclays spreads over the 1996-2012 period. The BofA Merrill Lynch Option-Adjusted Spreads (OASs) are the calculated spreads between a computed OAS index of all investment grade bonds and a spot Treasury curve. An OAS index is constructed using each constituent bond's OAS, weighted by market capitalization. Series names (BAMLC1A0C13Y, BAMLC2A0C35Y, BAMLC3A0C57Y, BAMLC4A0C710Y, BAMLC7A0C1015Y, BAMLC8A0C15PY).

Moody's Analytics EDF Data: Data includes 1-5 year annualized EDF (expected default frequency) using average EDFs for panels of investment grade firms with between 330 and 570 firms per year. I also have analagous data for high yield firms. EDFs are computed following a two step process. First, Moody's constructs a default proxy using a structural option-based model of default by modeling equity as a call option. These are then improved upon by using the combined optimal forecast obtained statistically from using these default proxies and other explanatory variables to forecast realized defaults. Moody's KMV has the largest empirical default database available which allows them to construct EDF measures that are highly accurate. Moody's constructs longer maturity EDFs by setting the forward default rate equal to the forward default rate between years 4 and 5.

Historical Bond Data: Pulled from bond tables from the New York Times historical issues for each recession and financial crisis after 1929 for which I do not already have bond yield data. I use banking crisis dates (see above) and recession midpoint dates (i.e. the month halfway between the peak and trough). I use the last available day of each month and collect bond prices, coupon rates, and maturity dates, which I convert to yields. As much as possible I try to use firms with multiple maturity bonds outstanding. I drop any yields above 25% as these firms are close to default and will have a large influence on averages. I then use government bond yields from the same table to compute a risk-free curve where I just linearly fit points between maturities. When not enough government maturities are available, I supplement these government yields with data on 3-month Treasury bills from NBER Macro History (series M13029b) and data on long term government yields from FRED (series LTGOVTBD). I then sort corporate yields by maturity, compute equal weighted buckets by maturity (0-3 years, 5-7, 7-10, 10+) and subtract the closest possible government yield from each bucket. I ensure that there are at least 10 bond yields in each bucket for

each date.

Equity yields: Figure 15 is from van Binsbergen *et al.* (2012b).

GDP and Consumption Data: GDP data are from Robert Barro's webiste (see, e.g., Barro *et al.* (2011)). When computing GDP growth rates around financial crises and recessions, I subtract off the respective countries' long term economic growth rate, defined as the linear trend in log per capita GDP.

Dividends: Real dividends are from Robert Shiller's website. For the U.S. data, I use the annual sum of this real dividend series to compute price dividend ratios (real price divided by sum of previous year's real dividend) which controls for seasonality in dividends.

Country Level Price 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.

U.S. Market Excess Return: 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. I also pull the momentum, size and book-to-market portoflios from Kenneth French's website.

7.2 Solving the Term Structure of Risky Bonds, Equities, and Volatility

I show how to calculate prices and yields for risky bonds, equities, and volatility.

Throughout, I denote the SDF as

$$\frac{d\Lambda}{\Lambda} = -rdt - \lambda dB_t \tag{32}$$

Where r is the risk free rate and $\lambda = \frac{\mu-r}{\sigma}$ is the instantaneous Sharpe ratio or "price of risk." Given these objects in the model, we can price any asset including corporate bonds and dividend strips.

Asset prices are given by $P_t^{(N)} = E\left[\frac{\Lambda_{t+N}}{\Lambda_t} x_{t+N}\right]$ where x_{t+N} represents the cash flow the asset pays off at time $t+N$ and $P_t^{(N)}$ represents the price of this cash flow. I simulate $\frac{\Lambda_{t+N}}{\Lambda_t}$.using the formula $\frac{\Lambda_T}{\Lambda_0} = \exp\left(\int_0^T \left(\mu_\Lambda - \frac{1}{2}\sigma_\Lambda^2\right) dt + \int_0^T \sigma_\Lambda dB_t\right)$. I simulate the discount rate and cash flow processes forward, creating 3,000 realizations of $\frac{\Lambda_{t+N}}{\Lambda_t}$ and x_{t+N} and then take an average to find the price $P_t^{(N)}$.

Pricing formulas for various assets: Given the discount factor, pricing various assets simply amounts to specifying their cash flow process. I will generally use lower case letters to denote logs.

Risk free bonds: $x_{t+N} = 1$. $P_t^{(N)} = E\left[\frac{\Lambda_{t+N}}{\Lambda_t}\right]$ where N is years to maturity. I will define risk free bond yields as $y_t^{(N)} = -\frac{1}{N}p_t^{(N)} = -\frac{1}{N}\ln\left(P_t^{(N)}\right)$. In the model, the risk free term structure is flat since the interest rate is constant.

Dividend Strips: $x_{t+N} = \frac{D_{t+N}}{D_t}$. Define $\frac{S_t^{(N)}}{D_t^{(N)}} = E\left[\frac{\Lambda_{t+N}}{\Lambda_t}\frac{D_{t+N}}{D_t}\right]$ as the price of the aggregate dividend paying off in period N. I divide by current dividend for scale. Let $sd_t^{(N)} = \ln\left(\frac{S_t^{(N)}}{D_t}\right)$. The process for $\frac{D_{t+N}}{D_t}$ is straightforward to simulate since it is given direcly in the model by $\frac{dY}{Y}$.

Thus

$$\ln\left(\frac{S_t^{(N)}}{D_t^{(N)}}\right) = \ln\left(E\left[\exp\left(\int_t^{t+N}\left(\mu_{Y,t} - r - \frac{1}{2}\left(\sigma^2 + \lambda_t^2\right)\right)dt + \int_t^{t+N}\left(\sigma - \lambda_t\right)dB_t\right)\right]\right)$$

It is useful to decompose dividend strips into a growth component, a risk free component, and a risk premium component. Define the following:

$$sd_t^{(N)} = N\left(g_t^{(N)} - y_t^{(N)} - rp_t^{(N)}\right)$$
$$\text{Where} \quad g_t^{(N)} = \frac{1}{N}E_t\left[\ln\left(\frac{D_{t+N}}{D_t}\right)\right]$$
$$\text{Define} \quad ys_t^{(N)} = -\frac{1}{N}sd_t^{(N)}$$
$$\text{Then} \quad ys_t^{(N)} = -g_t^{(N)} + rp_t^{(N)} + y_t^{(N)}$$
$$ef_t^{(N)} \equiv rp_t^{(N)} - g_t^{(N)}$$

The object $ef_t^{(N)}$ (the "forward equity yield") is useful since it is related to either risk premia or growth expectations (see van Binsbergen *et al.* (2012b) who define and study this object empirically).

VIX: $x_{t+N} = \int_t^{t+N}\sigma_{R,u}^2 du$. VIX is the square root of the expected variance under the risk neutral measure Q (where $E^Q\left(x_{t+N}\right) = \frac{1}{E\left[\frac{\Lambda_{t+N}}{\Lambda_t}\right]}E\left[\frac{\Lambda_{t+N}}{\Lambda_t}x_{t+N}\right]$). We can therefore simply think of this as an asset paying the integrated variance as its cash flow. I specify the VIX term structure for maturity N as

$$VIX_{t,N}^2 = \frac{1}{N}E\left[\frac{\Lambda_{t+N}}{\Lambda_t}x_{t+N}\right] = \frac{\exp\left(-rN\right)}{N}E^Q\left(\int_t^{t+N}\sigma_{R,u}^2 du\right)$$

Of course, as with equity yields, we can represent VIX as an expected variance component and a variance risk premium. There are multiple ways to define the risk premium. In this paper, I will use: $rpv_t^N = VIX_{t,N} - \sqrt{\frac{1}{N}E\left(\int_t^{t+N}\sigma_{R,u}^2 du\right)}$. Some papers instead define the

risk premium as $rpv_t^N = VIX_{t,N}^2 - \frac{1}{N}E\left(\int_t^{t+N} \sigma_{R,u}^2 du\right)$. There is not a substantial difference between these methods in terms of my results. The main advantage of my approach is that the numbers are more easily interpretable since they will be in the same units as the VIX.

Defaultable bonds (credit spreads): I set $x_{t+N} = (1 - \Phi_{t,t+N}LGD)$ where $\Phi_{t,t+N} = 1$ if the bond defaults between t and $t+N$ and $\Phi_{t,t+N} = 0$ otherwise. $(1 - LGD)$ is the payoff if the bond defaults, and therefore LGD is the Loss Given Default. The bond price can be computed as

$$PB_t^N = E_t\left[\frac{\Lambda_{t+N}}{\Lambda_t}(1 - \Phi_{t,t+N}LGD)\right]$$

And we can define yields and yield spreads accordingly.

For the decomposition into a default and a risk premium component, it is useful to define the (negative) log expected cash flow as $def_t^N = -\frac{1}{N}\ln E_t(x_{t+N}) = -\frac{1}{N}\ln(1 - E_t(\Phi_{t,t+N}LGD)) \approx \frac{1}{N}p_{def}^N LGD$, where p_{def}^N is the probability of default between now and time N. This approximation is especially close here because I focus on investment grade bonds with very low probability of default. Then we can define the risk premium rpc_t^N to satisfy

$$PB_t^N = \exp\left(-N\left(rpc_t^N + def_t^N + y_t^N\right)\right)$$

where y_t^N is the yield on a risk less bond maturing at time N. It is straightforward that the corporate yield spread can be written as

$$yb_t^N - y_t^N = def_t^N + rpc_t^N$$
$$yb_t^N - y_t^N \approx \frac{1}{N}p_{def}^N LGD + rpc_t^N$$

The definition of rpc_t^N as a risk premium is justified because of the following relationship

$$E_t\left[\frac{R_{t+N}^{corp}}{R_{f,t+N}}\right] = E_t\left[\frac{(1 - \Phi_{t,t+N}LGD)}{PB_t^N}P_t^N\right]$$
$$= \exp(N\left(rpc_t^N\right))$$
$$rpc_t^N = \frac{1}{N}\ln\left(E_t\left[\frac{R_{t+N}^{corp}}{R_{f,t+N}}\right]\right)$$

Therefore the risk premium is equal to the annualized log expected return ratio. If there were no risk premium for default risk, then the expected return on risky vs. risk free bonds would be the same and we would indeed see $rpc_t^N = 0$. We can also approximate rpc_t^N as a difference in expected log returns, provided the term $E_t\ln((1 - \Phi_{t,t+N}LGD)) - \ln(E_t(1 - \Phi_{t,t+N}LGD))$ is small, which is true when LGD and default probabilities are relatively small. I avoid using log returns because of the potential case where $LGD = 1$ (or close to 1) so that realized returns can be zero.

7.3 Details of Model Solution

The ODE to solve is

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

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 condtions. 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 $\mu_e = e\left(\sigma^2 - \psi - g\right) < 0$. 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.
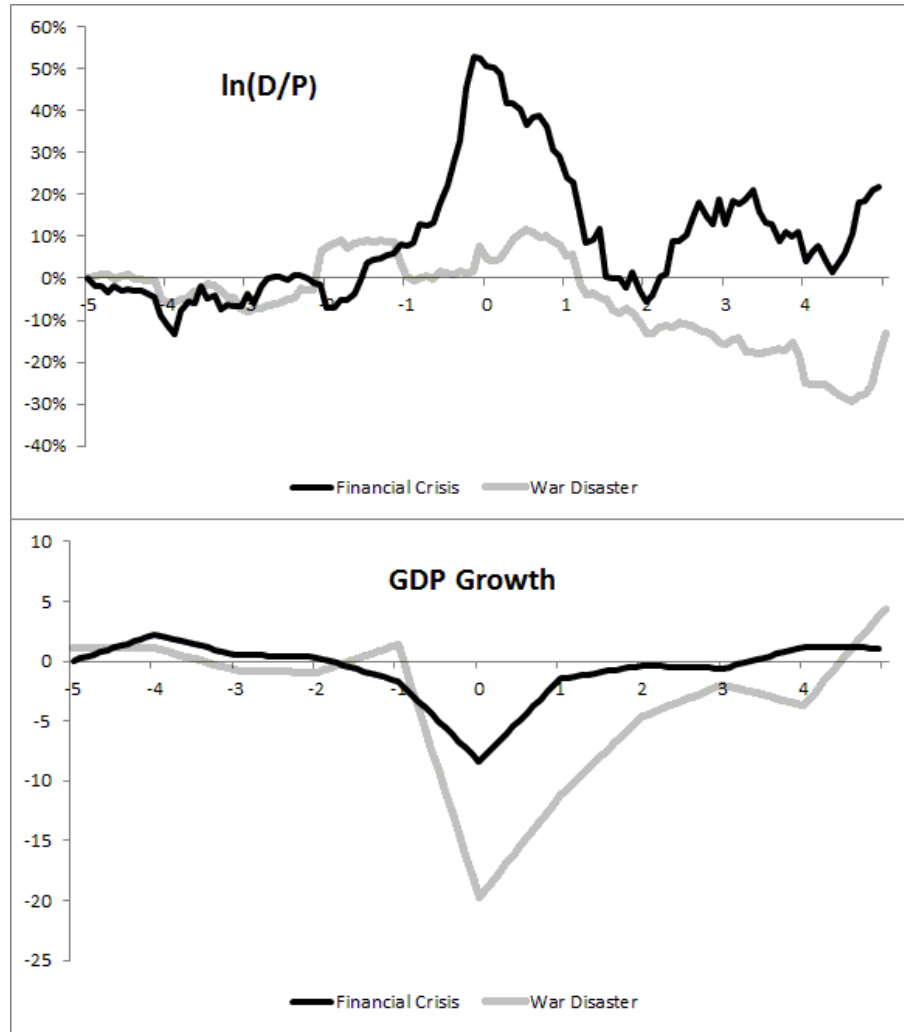
8 Figures/Tables

Figure 1: This figure plots the average log dividend yield (top panel) and GDP growth (bottom panel) in 10 year windows around financial crises vs war related disasters. Disaster dates taken from Barro (2006), crisis dates from Reinhart and Rogoff (2009) and Barro (2006). The dates are reproduced in the appendix. The log dividend yield is a common measure of risk premia and the initial dividend yield is normalized to zero. In both the model and data, I subtract off the economies' long term average growth rate when plotting GDP growth.
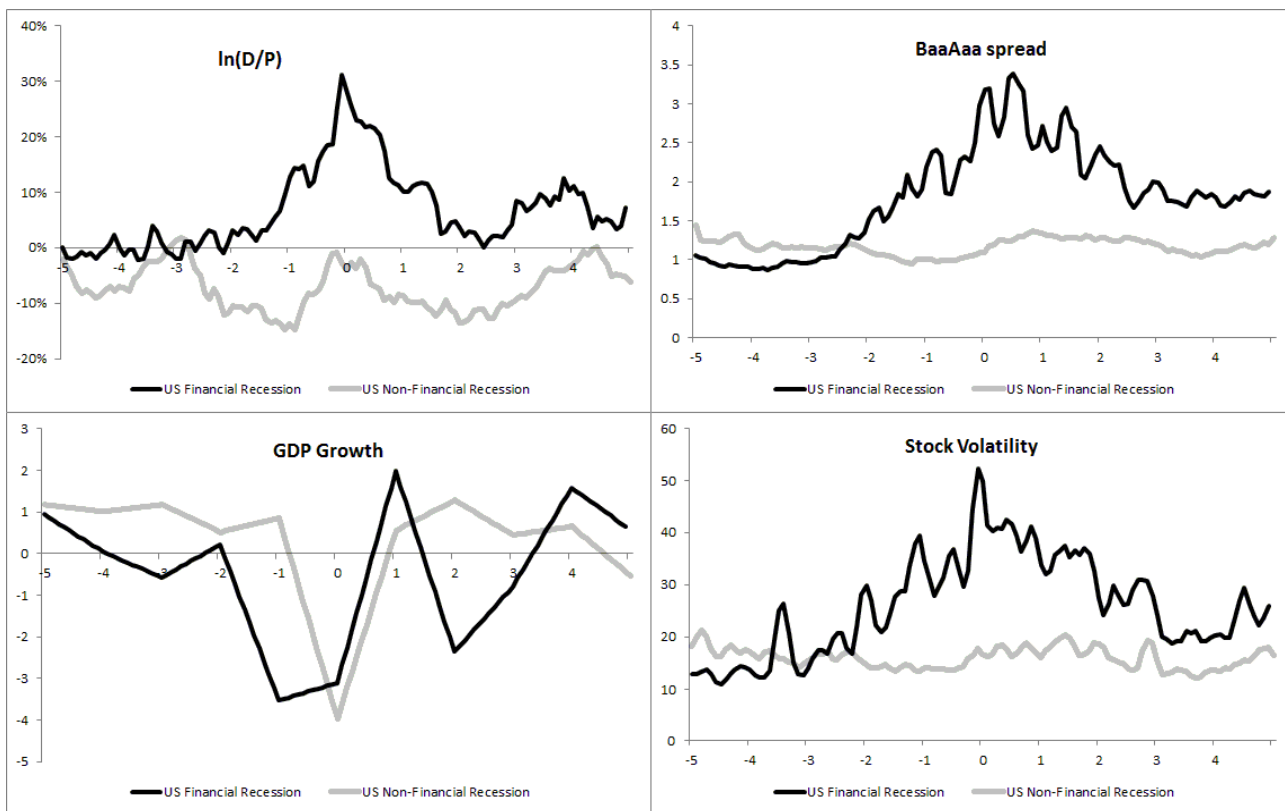
Figure 2: I split US recessions into those involving a financial crisis (black lines) and those not involving a financial crisis (gray lines). For non-financial recessions I use one year after the beginning of recession dates marked as zero, as this is the typical peak for risk premia. For financial recessions I use crisis dates from the appendix. I compare the two events in terms of risk premia as measured by the log dividend yield (upper left panel), the BaaAaa default spread (upper right panel), GDP growth (lower left panel), and stock market volatility (lower right panel). I use a 10 year window centered around the event. Recession dates from NBER. See appendix for dates and data sources.
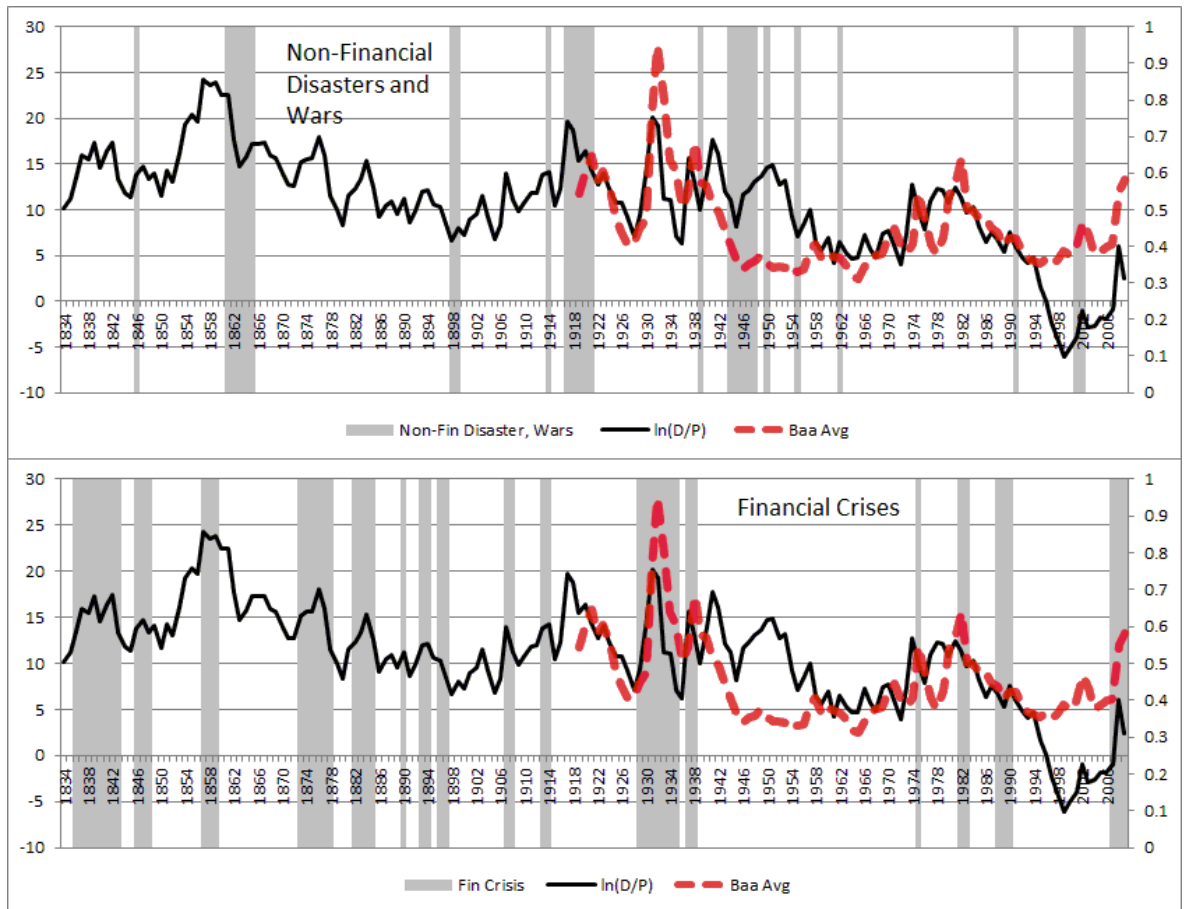
Figure 3: I provide a historical perspective of proxies for risk premia in the US from 1834-2012. Both panels plot the log dividend yield and BaaAaa spread from 1834-1919 as measures of risk premia. In the top panel, shaded areas represent war related disasters or the beginning of wars. In the bottom panel, shaded areas indicate financial crises or periods of high financial distress. For the period 1834-1871, I use the consumption to price ratio instead of the dividend to price ratio since the dividend series does not extend back this far. I normalize the consumption price ratio to have the same mean and standard deviation as the dividend price ratio. In the later sample, these two series are very highly correlated.
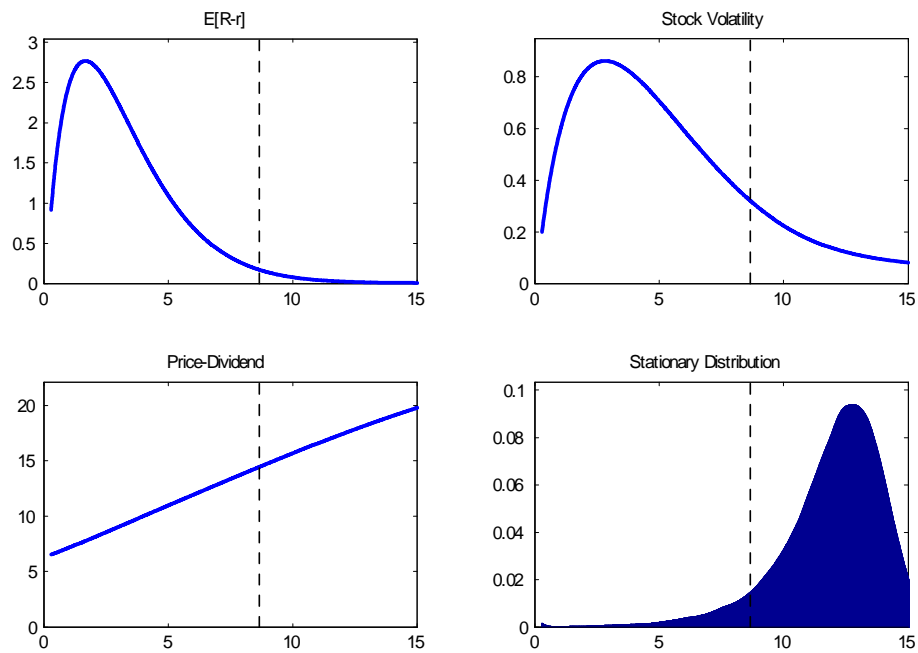
Figure 4: I plot the model solution as a function of the state variable e defined as intermediary equity divided by output. The key feature of the model solution is the spike in volatility and risk premia when e is low. The upper left panel gives the equity premium, the upper right gives equity volatility, 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.
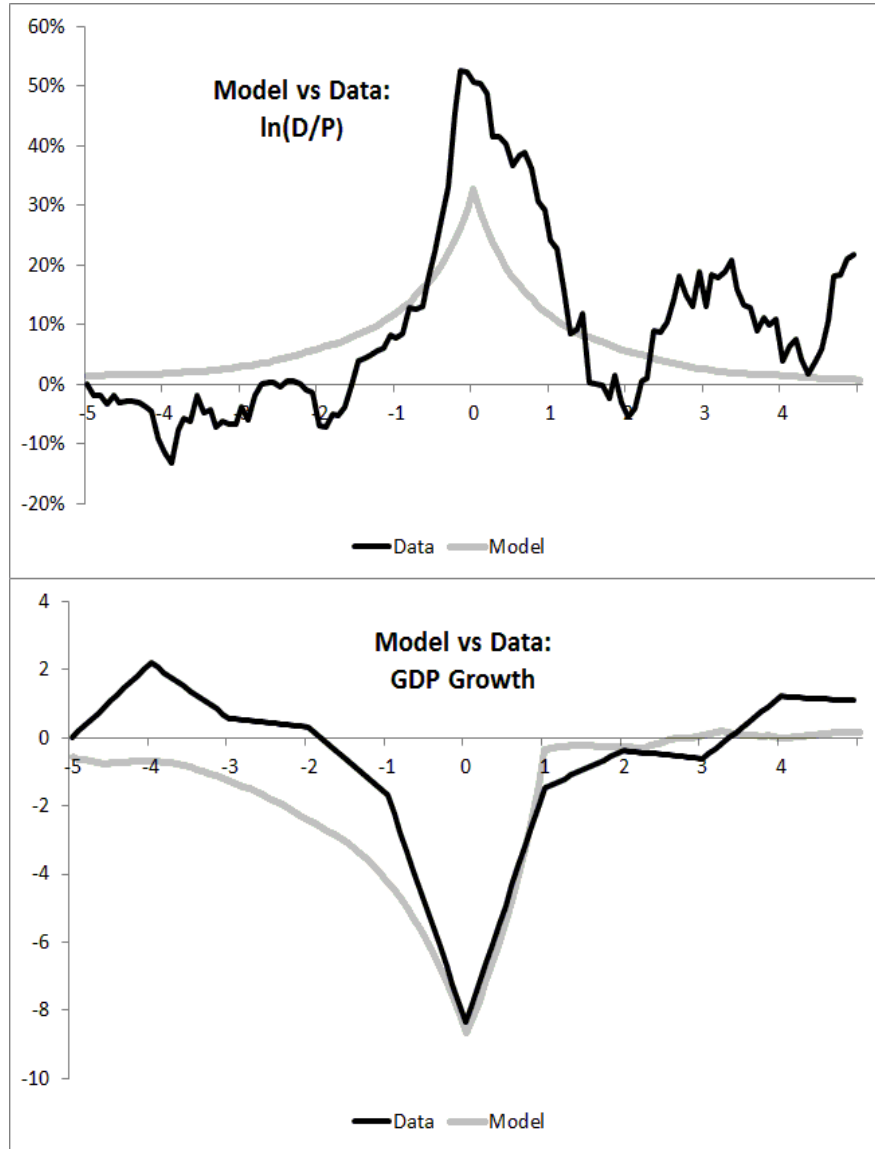
Figure 5: This figure plots the average log dividend yield (top panel) and GDP growth (bottom panel) in a 10 year window around a financial crises. The model is indicated in gray while the data is in black. In both the model and data, I subtract off the economies long term average growth rate.
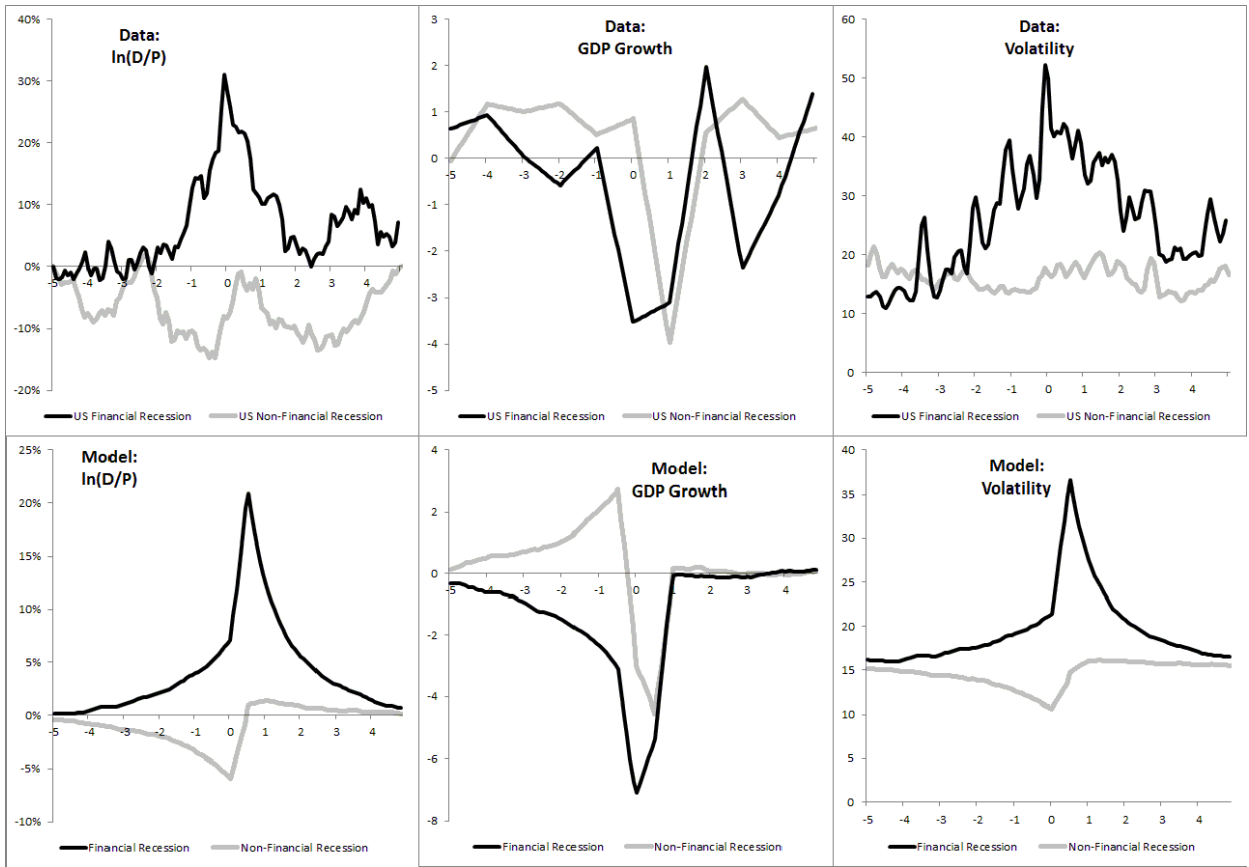
Figure 6: I compare financial recessions (a recession for which a financial crisis occurs) in black lines to non-financial recessions (those without a financial crisis) in gray lines. The top panel plots the data (U.S.), while the bottom panel plots the analagous objects in the model. I use recession dates from NBER. For non-financial recessions I use one-year after the recession begins as year zero, as this is the typical peak for risk premia. For financial recessions I use dates as close as possible to the crisis.
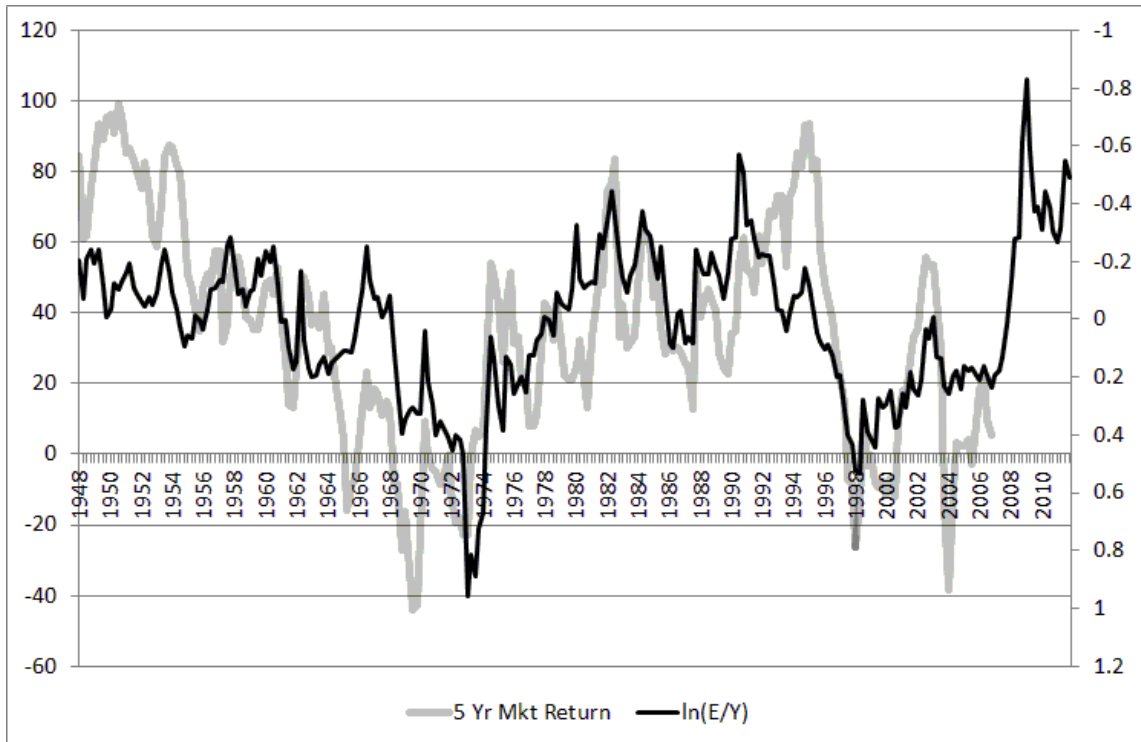
Figure 7: I plot the log of the ratio of intermediary equity to GDP (black line, right axis, decreasing scale) which is the state variable in the model, along with the subsequent 5 year excess return on the market (gray line, left axis). Intermediary equity is defined as the total market capitalization 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.
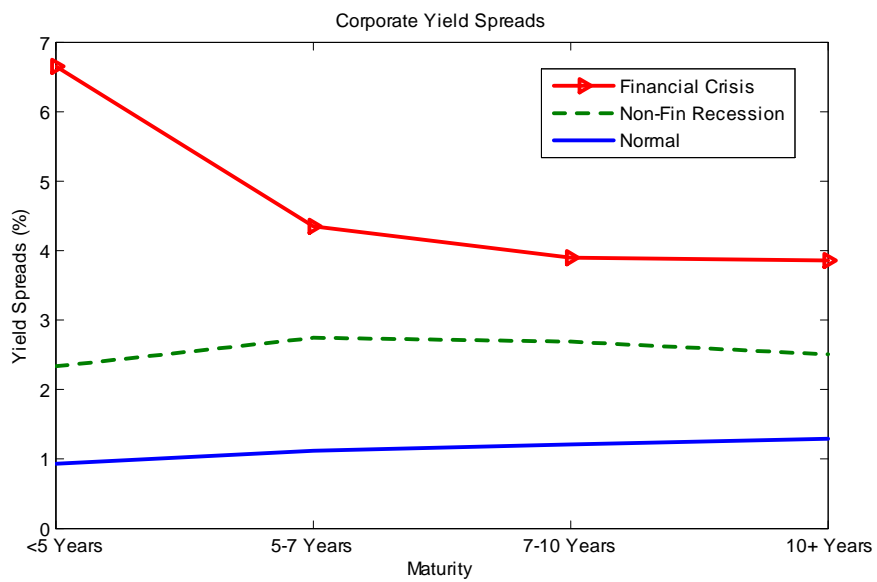
Figure 8: I plot the term structure of corporate bond yields over Treasuries in financial crises (arrows) vs. typical recessions (dashed line) in the data. I also plot the unconditional term structure for reference (solid line). Data prior to 1980s are hand collected from the New York Times and use end of month values from NBER recession midpoints. The appendix contains the crisis dates. The term structure is typically upward sloping but is downward sloping in financial crises.
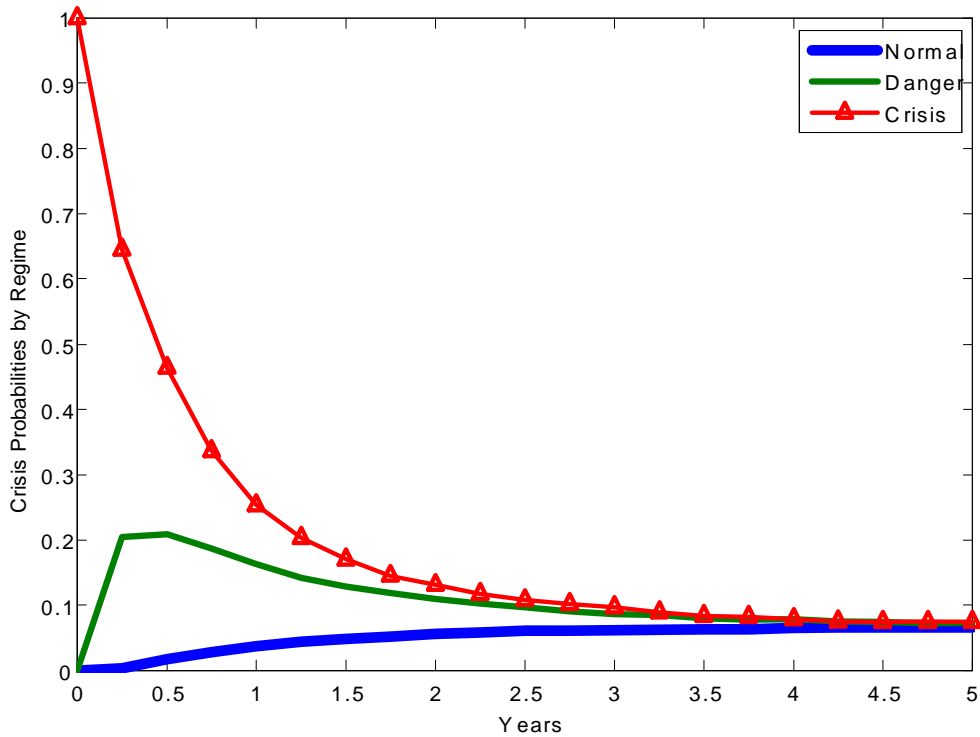
Figure 9: I plot the term structure of crisis probabilities implied by the model, conditonal on the state of the economy. Each maturity corresponds to the probability of being in a crisis state at that point in time. Normal, danger, and crisis correspond to the current value of intermediary equity to output, e, where normal is the 20th percentile and above, danger is between the 7th and 20th percentile, and crisis is the bottom 7th percentile. In normal times the term structure slopes up since a crisis in the immediate future is highly unlikely, while in the long term it is higher. In contrast, when in a crisis, recovery next month is low, but is more likely in several years. This feature of the model helps me match key features of the term structure of risky assets in the data.
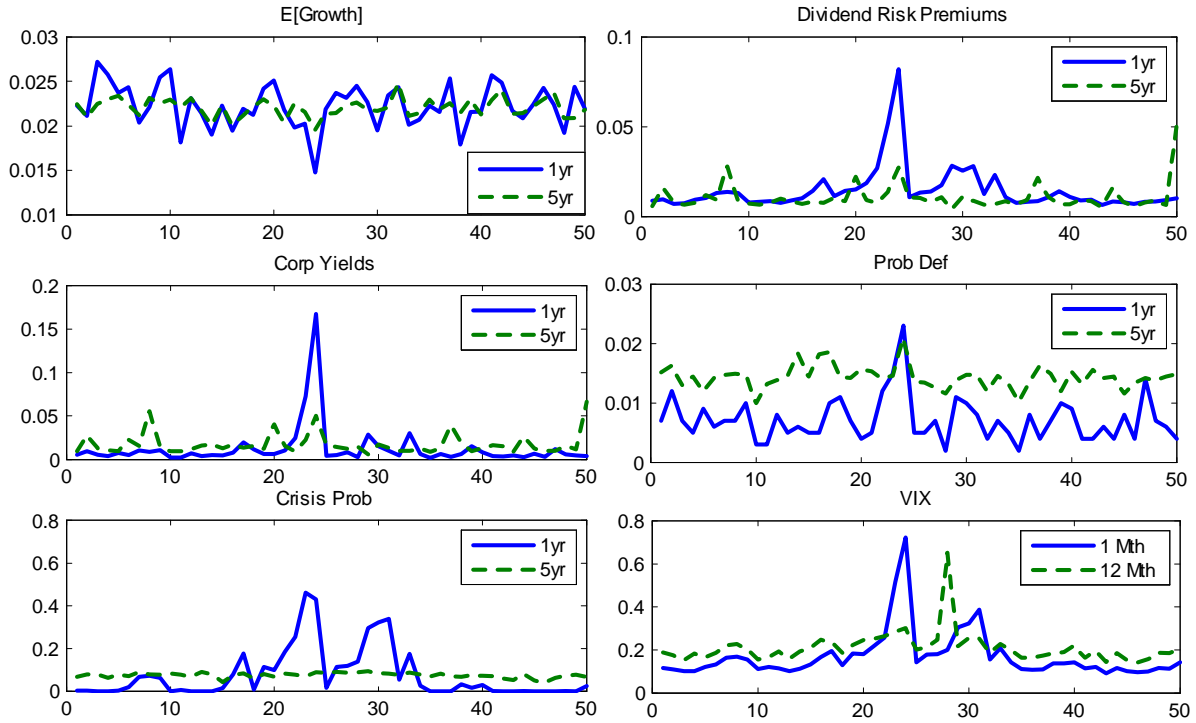
Figure 10: This figure plots simulated data from the model for several term structures using two maturities: 1 year (solid line) and 5 years (dashed). The upper left panel gives expected economic growth in a given year. Upper right gives dividend risk premia by maturities (or term structure of equity premia). Middle left gives corporate yield spreads by maturity, middle right give corresponding default rates. Lower left gives probabilities of a crisis, and lower right gives the term structure of VIX (quoted instead in months to match typical VIX data). In the simulated data there is a mild financial crisis in year 24. Normally, these term structures are upward sloping but each inverts during the crisis.
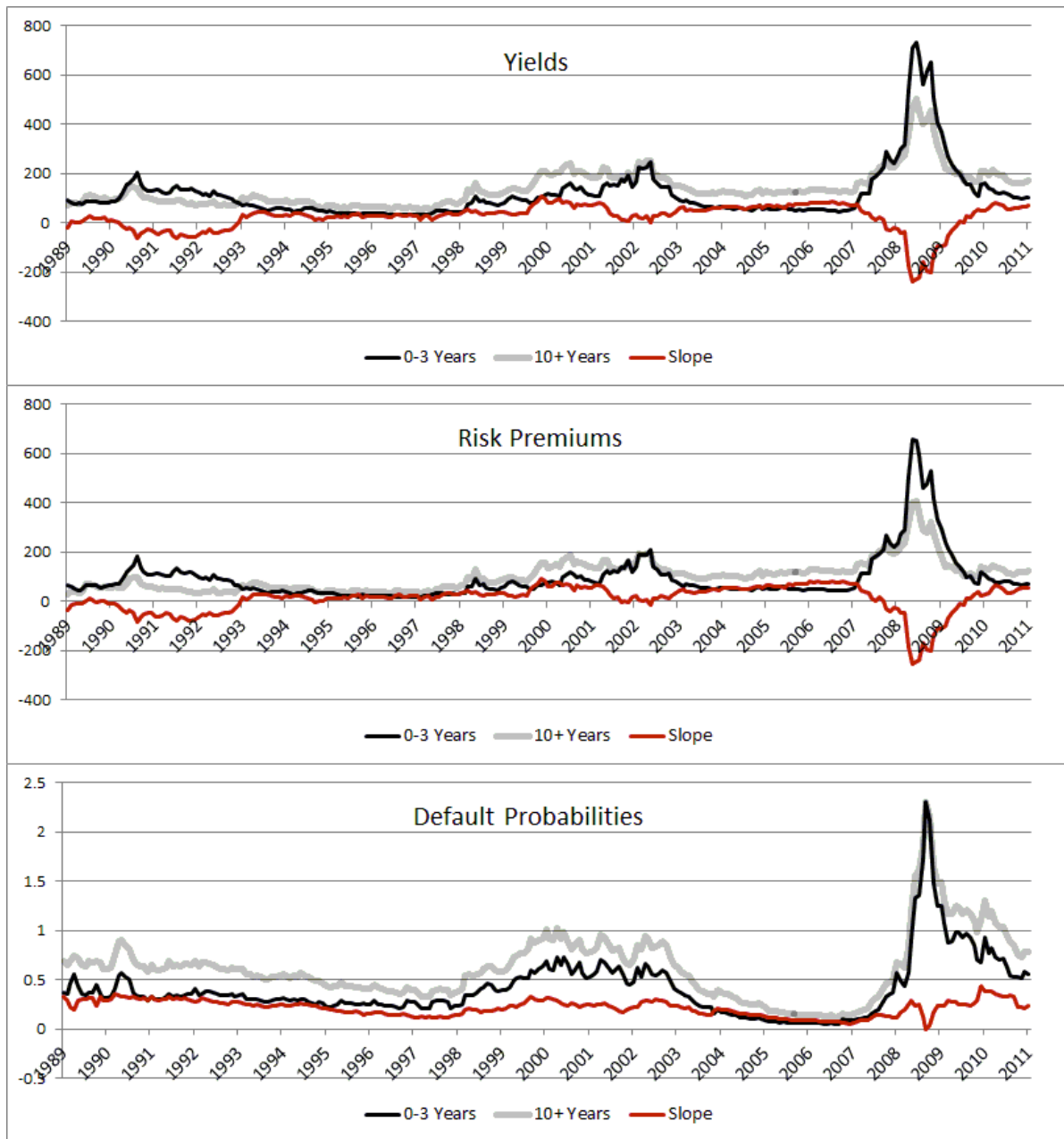
Figure 11: I plot investment grade US corporate yield spreads of varying maturities. I use maturities between 0-3 years (black line) and above 10 years (gray line), but all resutls hold including intermediate maturities as well. The top panel plots the yield spreads in basis points, the middle panel plots the risk premium component of yields in basis points, and the bottom panel plots the annualized probability of default based on Moody's EDF data. In each panel, the lower thin line plots the slope of the term structure considered (long maturity minus short maturity). The plot suggests an inversion in yields during crisis times that is mainly due to risk premia. See appendix for details on the data.
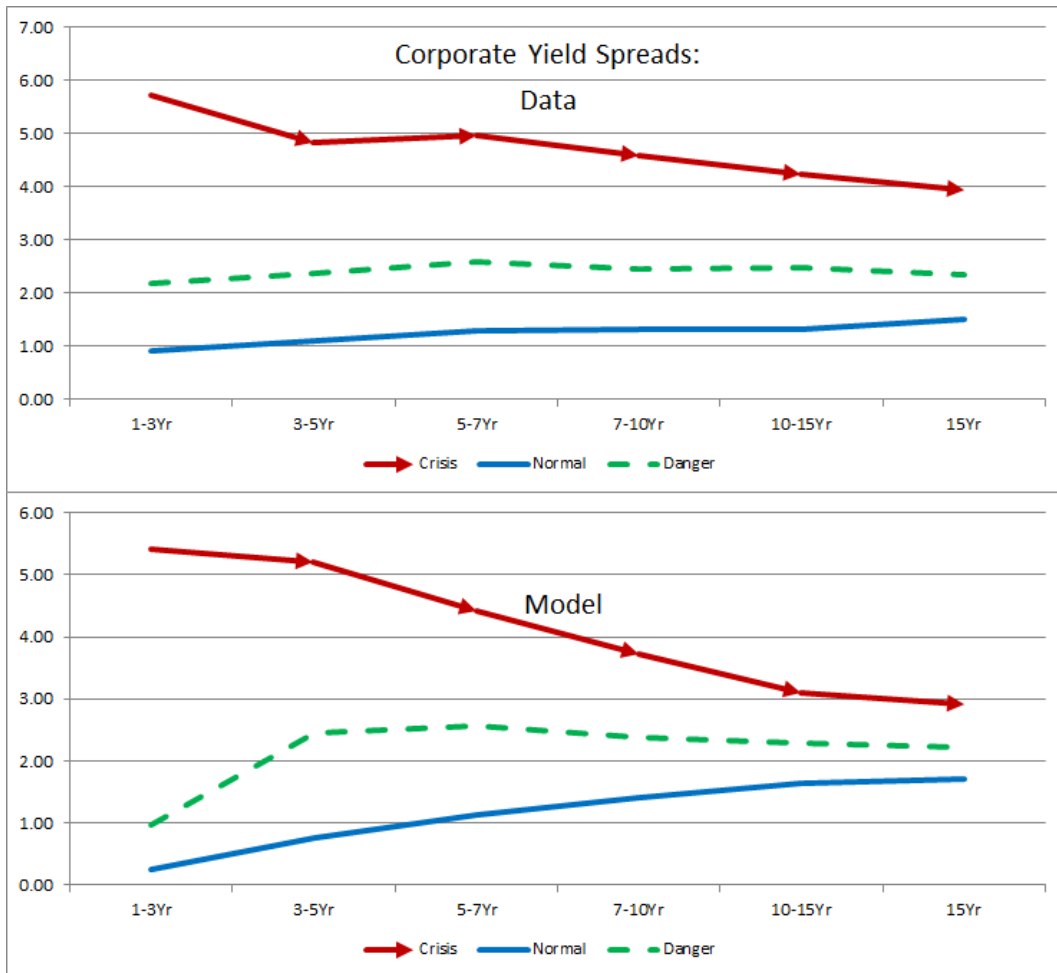
Figure 12: I plot the term structure of corporate yield spreads in 3 regimes based on the level of yields. Normal represents the corporate term structure in normal times when a crisis is unlikely, defined as the lowest 80% of the level of yields. Danger represents realizations between the 80th and 93th percentile, when the economy is at risk of falling into a crisis. Crisis represents the highest 7% of realizations where the economy is in crisis. The top panel is the data, the bottom is computed using simulated data from the model.
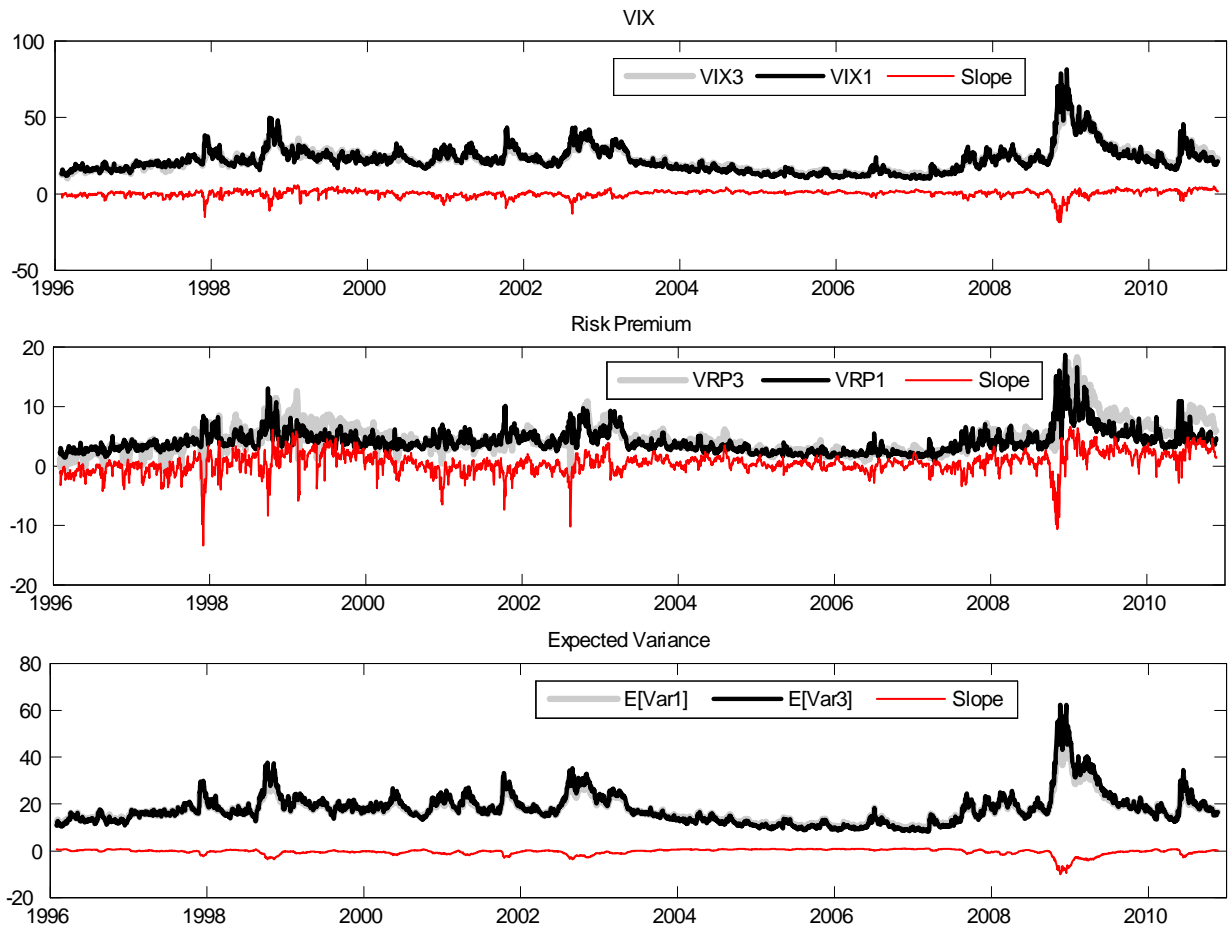
Figure 13: The top panel plots the daily VIX term structure in the data for maturities 1 month (thick gray line) and 3 months (black line), along with the slope of the term structure (thin lower line). The middle and lower panels decompose the VIX into a risk premium component (middle panel) and an expected variance component (lower panel). The expected variance is the square root of the expected integrated variance so that its units are consistent with the VIX. I plot the term structure and slope for each of these. See paper for details on estimation.
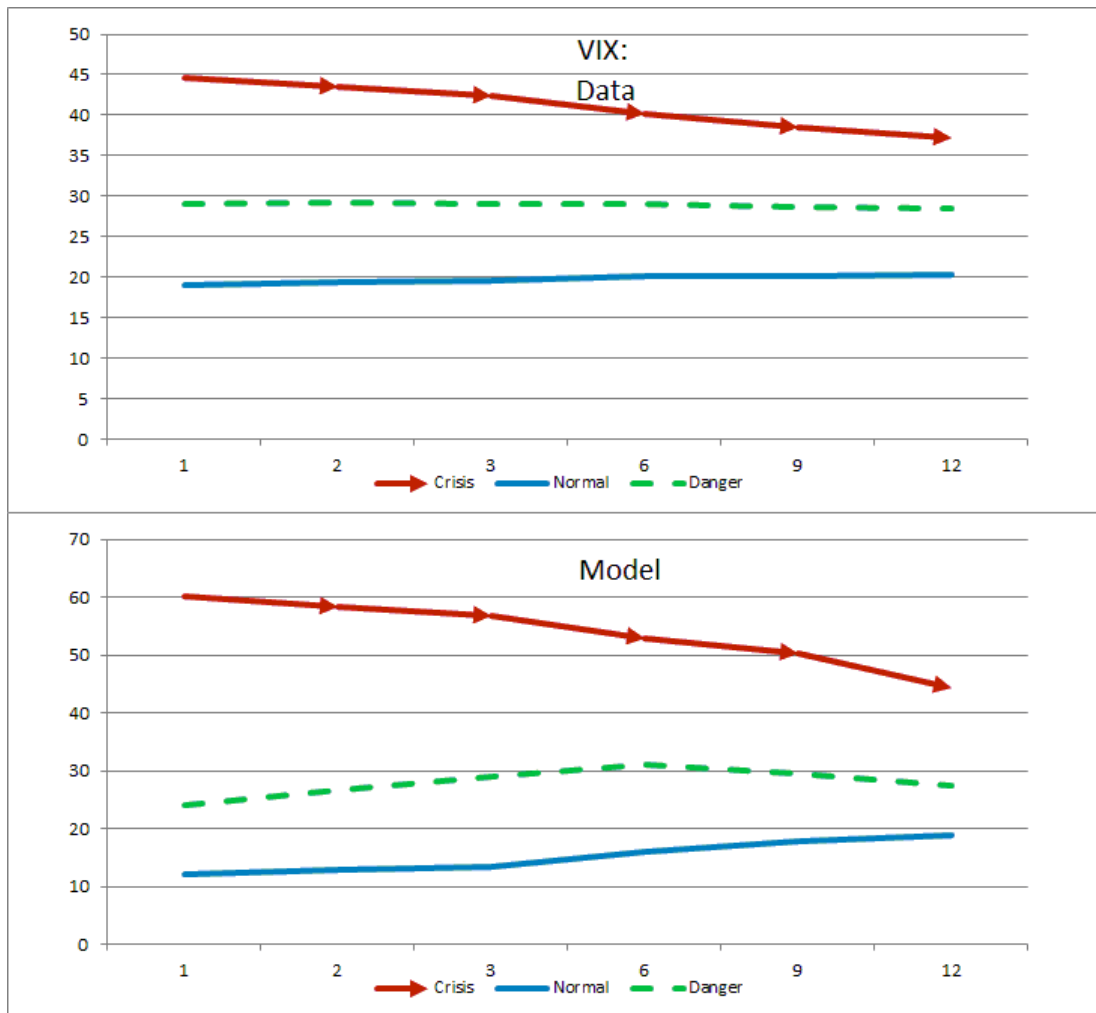
Figure 14: I plot the VIX term structure in both the data and the model in 3 regimes. The x-axis is in months. Normal represents the VIX term structure in normal times when a crisis is unlikely, defined as the lowest 80% of VIX realizations. Danger represents realizations between the 80th and 93th percentile, when the economy is at risk of falling into a crisis. Crisis represents the highest 7% of realizations where the economy is in a crisis. The top panel is the data, the bottom is computed using simulated data from the model.
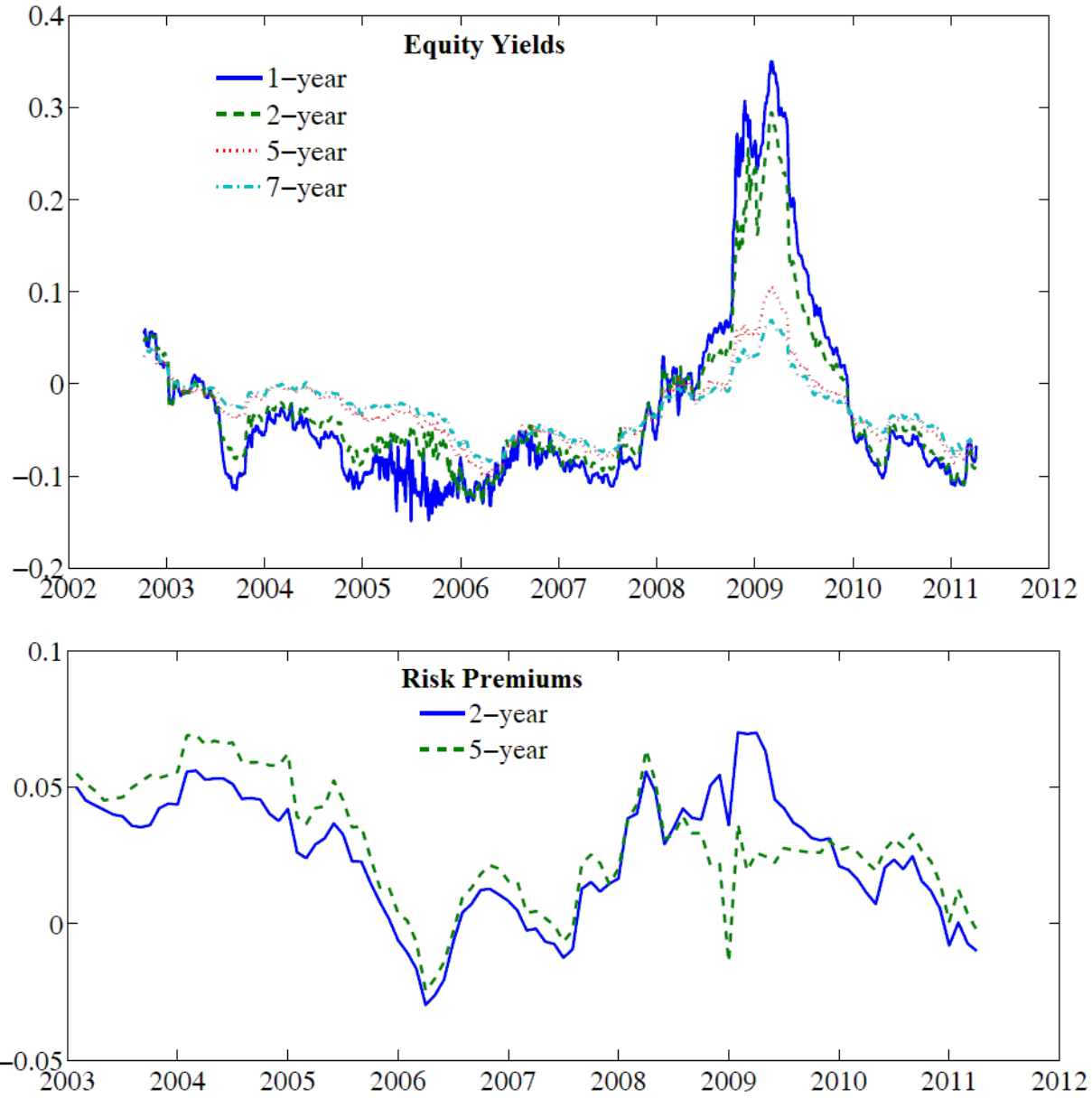
Figure 15: The top panel corresponds to Figure 1 in van Binsbergen *et al.* (2012b). The figure plots equity yields of various maturities on the S&P 500. Equity yields are the forward yields of a claim to the dividend growth rate on the S&P 500 over n years, where n corresponds to the maturity. The bottom panel plots equity yield risk premia, as estimated by van Binsbergen *et al.* (2012b), Figure 6. Both panels suggest that the equity yield curve and equity risk premium curve is typically upward sloping but slopes downward in the recent financial crisis.
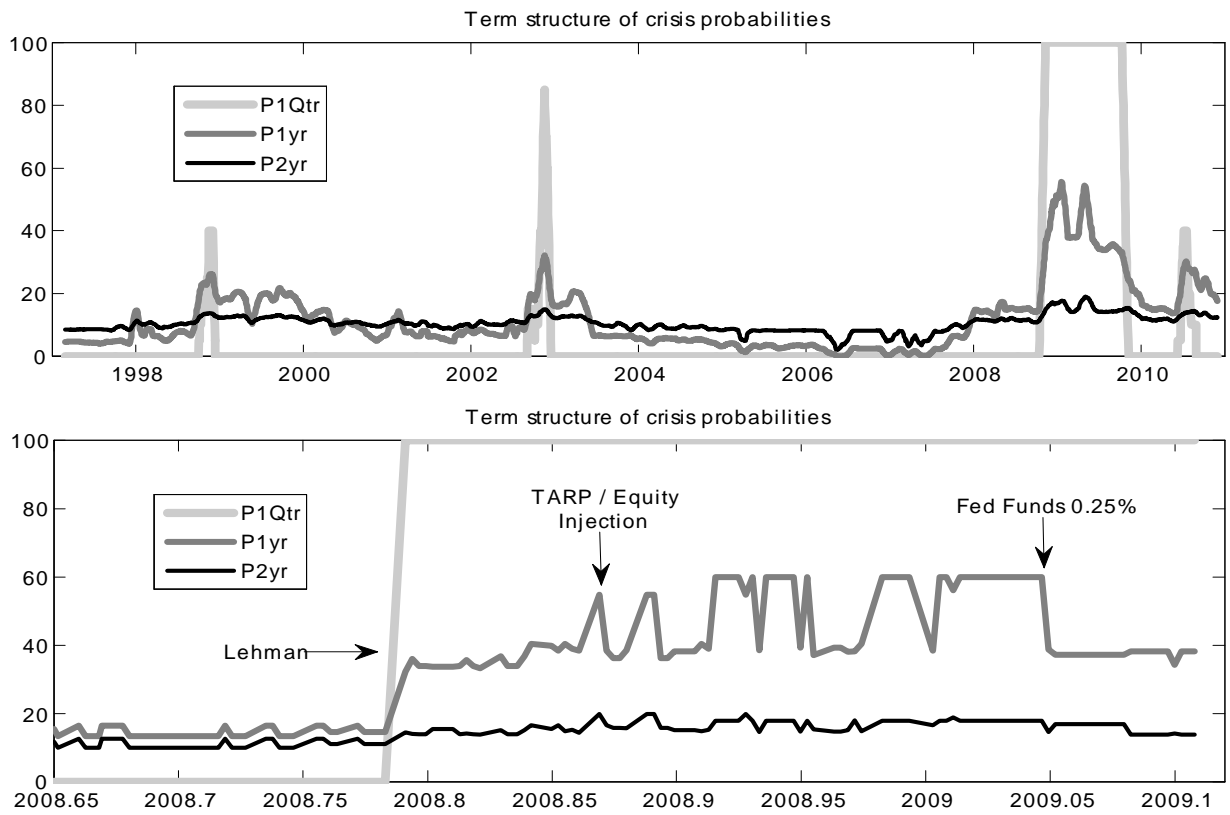
Figure 16: I plot the term structure of crisis probabilities implied by the model from 1997-2011 estimated daily using the VIX and corporate yield spread term structures. The maturities shown are 1 quarter, 1 year, and 2 years. The top panel plots a 20 day moving average. The bottom panel plots the term structure on each trading day during the 2008-09 financial crisis. I label several important events, including the collapse of Lehman, the announcement of TARP and equity injection into banks, and the Fed lowering the interest rate to zero. See paper for details.
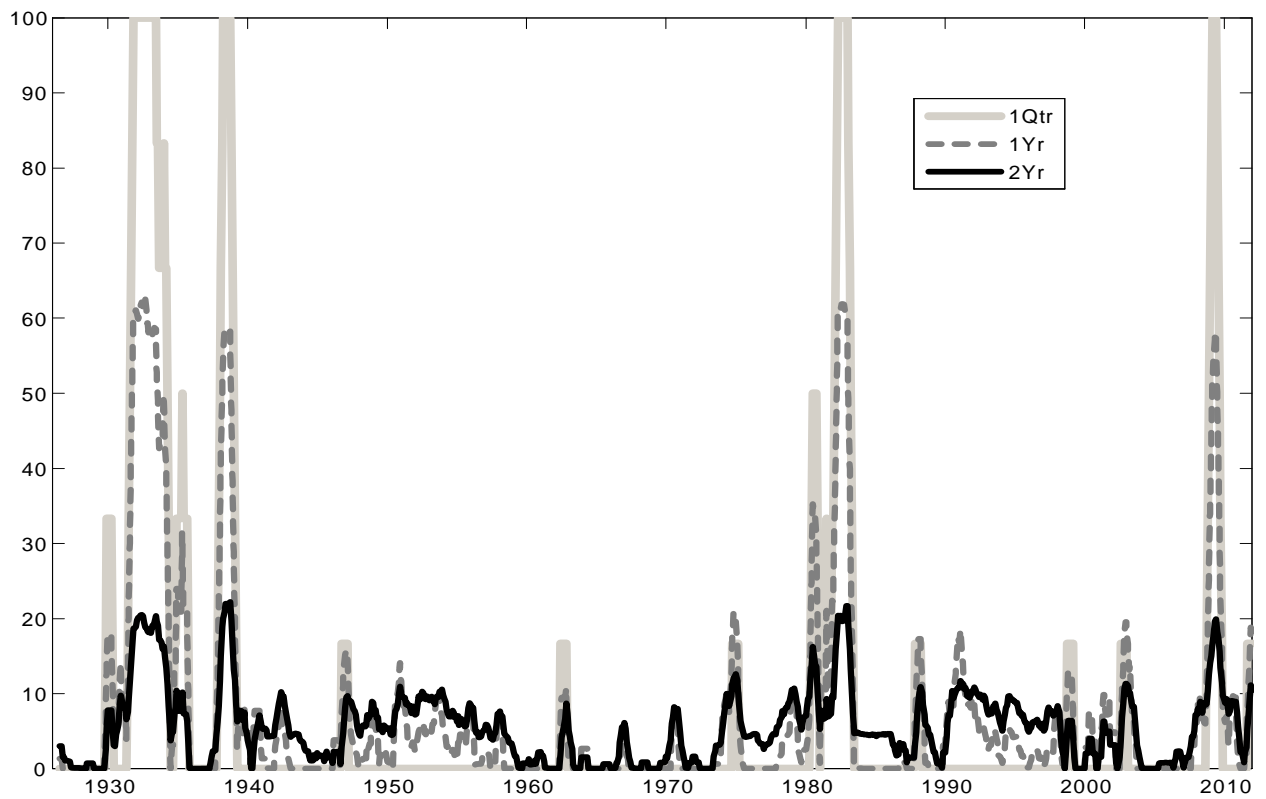
Figure 17: I plot the historical term structure of crisis probabilities for 1 quarter, 1 year, and 2 years implied by the model. As data, I use the dividend yield, the BaaAaa default spread, and the monthly volatility of the S&P500. I estimate the term structure each month and plot the 6 month moving average.

Table 1: This table compares changes in risk premia, GDP, and consumption, around wars, financial crises, and recessions. I compute the log change in dividiend yield from X years before the event to their event peak (top panel) and X years before the event to the start of the event (bottom panel). I provide the average log change in dividend yield along with the 10th and 90th percentiles from the empirical distribution below in brackets. See appendix for financial crisis dates and war related disaster dates. For recessions, I use 1 year after the onset of the recession as the event date, since this is typically when risk premia are highest. The event peak is calculated as the highest realization of the dividend yield in a 3 year window around the event to allow for flexible dating of the event. Panel C computes peak to trough declines in GDP and consumption around each of these events and again includes the10th and 90th percentiles from the empirical distribution below in brackets.

| Panel A: Log-change in dividend yield from X years before event to event peak					
Years before event	Financial Crisis	War related disaster	All US Recessions	Financial US Recessions	Non-Financial US Recessions
5 years	0.80	0.23	0.17	0.29	0.11
	[0.2,1.3]	[0.0,0.6]	[-0.2,0.5]	[0.1,1.0]	[-0.3,0.6]
2 years	0.87	0.21	0.22	0.32	0.16
	[0.2,1.3]	[0.0,0.4]	[-0.3,0.9]	[0.1,1.1]	[-0.1,0.7]
1 year	0.72	0.15	0.30	0.38	0.26
	[0.3,1.4]	[0.0,0.4]	[0.0,0.8]	[0.1,0.8]	[0.0,0.8]

Panel B: Log-change from X years before event to event					
Years before event	Financial Crisis	War related disaster	All US Recessions	Financial US Recessions	Non-Financial US Recessions
5 years	0.52	0.06	0.05	0.25	-0.07
	[-0.1,1.2]	[-0.1,0.3]	[-0.5,0.5]	[-0.1,0.6]	[-0.5,0.4]
2 years	0.59	0.04	0.11	0.29	-0.02
	[0.0,1.0]	[-0.3,0.4]	[-0.2,0.5]	[0.1,0.6]	[-0.3,0.3]
1 year	0.45	-0.01	0.19	0.33	0.05
	[0.1,0.8]	[-0.4,0.3]	[-0.2,0.4]	[0.0,0.5]	[-0.3,0.3]

Panel C: Peak to trough percentage decline in GDP and Consumption					
	Financial Crisis	War related disaster	All US Recessions	Financial US Recessions	Non-Financial US Recessions
GDP	11.4%	46.7%	6.5%	8.2%	5.5%
	[1.3,23.4]	[16.4,74.4]	[0.2,14.6]	[2.7,13.5]	[0.0,14.2]
Consumption	13.3%	45.4%	4.8%	7.0%	3.6%
	[0.2,26.7]	[10.7,79.4]	[0.0,15.6]	[0.3,15.5]	[0.0,11.5]

Table 2: This table provides calibrated parameters in the model. All values are annualized.

Parameter		Description	Targeted Moment
σ	5%	Volatility of output	Vol output
ρ	3%	Time discount	Time discount, risk free, price dividend
a	0.2%	Growth sensitivity	Crisis GDP Dynamics
μ	2.5%	Long run growth	Average growth
ψ	8%	Intermediary death rate	Well behaved dynamics
δ	13%	Depreciation for HH	Lowest p, entry
$p(0)$	6.25	Liquidiation value	*Defined* as $\frac{1}{\rho+\delta}$
		Boundary condition	

Table 3: This table provides moments on quantities and asset prices implied by the model vs the US 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 growth in the model. Sources: GDP data from Barro and Ursua (2012) uses US real GDP from 1900-present, stock return data from Ken French 1926-2012, p/d statistics taken from Bansal and Yaron (2004). For more details on series, see data appendix.

Basic Moments (% per year):		Model		
	Data	Mean	95%	5%
$E\left[dY/Y\right]$	2.14	2.23	3.08	1.44
$\sigma\left[dY/Y\right]$	5.17	5.00	5.17	4.84
$P\left[crisis\right]$	7.2	7.0	8.3	5.8
$E\left[r_f\right]$	0.60	3.00	—	—
$E\left[R-r_f\right]$	7.36	6.94	10.24	3.67
$\sigma\left[R-r_f\right]$	18.95	19.98	22.03	18.16
$\frac{E\left[R-r_f\right]}{\sigma\left[R-r_f\right]}$	0.39	0.35	0.50	0.19
$E\left[\sigma_{R,t}\right]$	17.98	16.39	16.82	15.83
$\sigma\left[\sigma_{R,t}\right]$	9.20	10.30	11.40	9.40
$E\left[\ln\left(p/d\right)\right]$	3.28	2.84	2.85	2.83
$\sigma\left[\ln\left(p/d\right)\right]$	0.29	0.12	0.13	0.11
$AC1\left[\ln\left(p/d\right)\right]$	0.81	0.50	0.55	0.44

Table 4: This table provides moments on the depth, duration, and distribution on outcomes surrounding financial crises. I create an artificial sample of crises in the model with the same number of crises as the data. I then calculate corresponding statistics over 10,000 of these samples. Panel C runs panel regressions to test for increases in annual dividend yields during crises, controlling for lagged annual dividend yields. Data on GDP are from GDP data from Barro and Ursua (2012), data on real equities uses dates from Reinhardt and Rogoff (2009), data on dividend yields from Global Financial Data and Shiller (monthly, US).

Panel A: Crisis Severity (Peak to Trough Decline):				
	Data		Model	
	Loss	*Duration*	*Loss*	*Duration*
Equities	-55.9%	3.4 yrs	-40.2%	3.3 yrs
GDP	-11.4%	3.0 yrs	-16.5%	4.5 yrs

Panel B: Distribution of GDP (Peak to Trough):				
	Data		Model	
	Loss	*Duration*	*Loss*	*Duration*
10%	-1.3%	1.0 yr	-9.5%	1.6 yrs
90%	-23.4%	5.0 yrs	-24.9%	9.1 yrs
Max	-49.9%	15.0 yrs	-40.9%	15.9 yrs

Panel C: Increase in Risk Premia				
$\ln{(d/p)}_{i,t} = \alpha_i + \beta 1_{crisis,t} + \rho_i \ln{(d/p)}_{i,t-k} + \varepsilon_{i,t}$				
	Data		Model	
	β	*s.e.*	β	*s.e.*
RR Crises	0.41	(0.08)	0.32	(0.00)
US Crises	0.24	(0.07)		

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Table 5: This Table calibrates default in the model using Moody's EDF (expected default frequency) data for investment grade bonds. I compare resulting yield spreads and risk premia in the data and model, both unconditionally and in crises. I also give the average yield spread for the BaaAaa spread in the data. Sources: Default probabilities given by Moody's EDF, yield spreads are from Barclays, BaaAaa spread from FRED, loss given default (LGD) level and variation from Chen (2008).

Panel A: Calibration for Investment Grade (I.G.) Bonds				
	Unconditional		Crisis (7%)	
	Data	Model	Data	Model
Probability of Default (PD)	0.48%	0.53%	1.17%	1.49%
Loss Given Default (LGD)	52%	50%	65%	50%
(PD)*(LGD)	0.24%	0.26%	0.76%	0.74%
$E\left[YieldSpread\right]$	1.33%	1.02%	4.12%	3.62%
Implied Risk Premium	1.09%	0.72%	3.36%	2.88%
$\sigma\left[PD\right]$	0.27%	0.31%		
$\sigma\left[YieldSpread\right]$	0.91%	0.87%		
Avg IG Default Slope	0.28%	0.67%	0.20%	0.53%
Panel B: Baa-Aaa Spread				
Baa-Aaa Yield Spread	1.14%		3.12%	
$\sigma\left[BaaAaa\right]$	0.73%			

Table 6: I provide log changes in dividend yields during recessions in the model. I measure peak dividend yield during the recession and subtract the dividend yield from X years before. Recessions in the model are defined as 2 quarters of negative GDP growth. Non-financial recessions are those not involving a financial crisis. Financial crisis are recessions in which a crisis occurs. The main text uses the lowest 7% of realizations as the crisis cutoff, and I show robustness to alternate cutoffs as well in the last two columns.

	Model: Log-change in dividend yield from X years before event to event peak				
X Years	All Recessions	Non-Fin Recessions	Financial Crisis (7%)	Financial Crisis (10%)	Financial Crisis (2%)
5 years	0.09	0.03	0.32	0.22	0.43
2 years	0.09	0.04	0.27	0.18	0.39
1 year	0.09	0.05	0.21	0.13	0.30

Table 7: 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: $\ln(P/D)$		
Return	β	$t(\beta)$	R^2	β	$t(\beta)$	R^2	β	$t(\beta)$	R^2
$R^e mkt_{t+1}$	-0.42	(-13.2)	3%	-0.26	(-2.9)	2%	-0.10	(-2.3)	1%
$R^e mkt_{t+3}$	-0.39	(-14.4)	7%	-0.27	(-3.4)	5%	-0.11	(-2.5)	2%
$R^e mkt_{t+12}$	-0.28	(-15.0)	21%	-0.28	(-4.6)	17%	-0.11	(-2.5)	8%
$R^e mkt_{t+60}$	-0.10	(-14.9)	32%	-0.27	(-6.8)	44%	-0.13	(-3.9)	29%
$R^e fin_{t+12}$	-0.92	(-20.6)	51%	-0.30	(-4.8)	20%	-0.12	(-1.8)	7%
$R^e corp_{t+12}$	-0.16	(-13.4)	32%	-0.09	(-3.8)	17%	-0.03	(-1.9)	10%

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)		

Table 8: This table provides both unconditional moments and moments conditional on crises episodes implied by the model vs the US data. I focus on moments that reflect the dynamics of risk premia, in particular that show that risk premia "spike" in crises but are temporary, as evidenced by lower autocorrelation of risk premia proxies and negative slope of the term structure of risk premia during crises. Corp represents corportae yield spreads. Panel B computes the persistence of dividend yields with a dummy for whether the economy is in a financial recession (ie a recession in which there is a financial crisis). I use two measures of dividend yields: (1) raw log dividend yields, and (2) dividend yields with two breaks in 1954, and 1994, following Lettau and van Niewerburgh (2008). T-stats are in parenthesis. The data appendix describes the various dates and sources of different series.

Panel A: Dynamics of Risk Premia (Annualized Numbers)				
	Model		Data	
	Unconditional	Crisis	Unconditional	Crisis
$E\left[\ln\left(p/d\right)\right]$	2.80	2.21	3.20	2.30
$E\left[Corp\right]$	1.02	3.62	1.33	4.12
$E\left[CorpSlope\right]$	1.48	-2.50	0.24	-1.49
$E\left[VIX\right]$	17.75	53.76	22.43	40.98
$E\left[VIXSlope\right]$	2.31	-15.83	0.35	-6.21

Panel B: Persistence of dividend yields in financial crisis

$$\ln(d/p)_{t+12} = a + \rho \ln(d/p)_t + 1_{fin}\rho_{fin} \ln(d/p)_t + \varepsilon_{t+1}$$

			Data	
	Model		Two-Break	No-Break
ρ	0.57	(39.5)	0.67 (9.3)	0.89 (18.5)
ρ_{fin}	-0.03	(-16.0)	-0.31 (-2.0)	-0.19 (-1.4)
$\rho + \rho_{fin}$	0.53		0.36	0.70

Table 9: I run predictive regressions of returns and dividend growth on lagged dividend yields. I include indicators for recessions (NBER dummies) which I split into recessions containing a financial crisis and ones that do not. I use two measures of dividend yields: (1) raw log dividend yields, and (2) dividend yields with two breaks in 1954, and 1994, following Lettau and van Niewerburgh (2008). Standard errors computed using Newey-West with 12 lags. The dividend yield is defined as the sum of the last 12 monthly real dividends divided by real price. Dividend growth is defined as the log change in the sum of the 12 monthly real dividiends. Data are from 1927-2012.

Panel A: Return predictability in crises and recessions

$R_{t+1} - r_{f,t} = a + b\ln(d/p)_t + c1_{fin}\ln(d/p)_t + d1_{non,fin}\ln(d/p)_t + \varepsilon_{t+1}$

	a	b	c	d	Adj R^2
Raw dp	0.18	0.12			6.9%
(t-stat)	(3.90)	(2.69)			
Raw dp	0.18	0.11	0.27	-0.04	12.0%
(t-stat)	(4.21)	(2.71)	(1.77)	-(0.74)	
Two Break dp	0.07	0.30			14.6%
(t-stat)	(4.17)	(4.55)			
Two Break dp	0.07	0.21	0.29	0.26	17.2%
(t-stat)	(3.72)	(3.27)	(2.09)	(1.85)	

Panel A: Dividend growth predictability in crises and recessions

$\ln\left(\frac{d_{t+1}}{d_t}\right) = a + b\ln(d/p)_t + c1_{fin}\ln(d/p)_t + d1_{non,fin}\ln(d/p)_t + \varepsilon_{t+1}$

	a	b	c	d	Adj R^2
Raw dp	-0.01	-0.03			2.0%
(t-stat)	(-0.51)	(-1.24)			
Raw dp	-0.01	-0.03	0.12	0.02	8.6%
(t-stat)	(-0.37)	(-1.37)	(2.52)	(0.93)	
Two Break dp	0.01	-0.09			6.6%
(t-stat)	(1.22)	(-2.80)			
Two Break dp	0.01	-0.06	-0.13	0.06	9.4%
(t-stat)	(1.61)	(-1.86)	(-1.93)	(0.71)	