Can Time-Varying Risk Premia and Household Heterogeneity Explain Credit Cycles? *

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Abstract

Using micro-level household mortgage data, I measure dispersion in the credit quality of borrowers in the housing market and show that it forecasts regional real economic activity. I provide empirical evidence that associates the predictive power of dispersion with heterogeneity in the exposure of households' labor income to economy-wide shocks. I explain these observations in a model featuring time-varying risk premia, incomplete markets, and household heterogeneity. Due to risk aversion, the consumption and investment responses of households have a convex association with their labor income exposure to aggregate risks. As a result, dispersion forecasts the aggregate output more strongly in more heterogeneous regions, consistent with the data.

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1 Introduction

The United States economy in the first decade of the twenty-first century experienced a cycle of boom and bust in both housing and credit markets that ended up in the 2008 financial crisis. The causal relationship between the expansion in credit markets before the crisis on the one hand, and the rise and fall of prices followed by a wave of defaults in the housing market on the other, has been a hot topic of economic research and policy debates. In the quest to answer this question, two main accounts have emerged in the literature as the roots of the crisis: the *subprime view* and the *expectations view*.[1]

In the subprime view of the financial crisis, it is the pre-crisis credit expansion that causes the increase in house prices and the subsequent recession. Deregulations and innovations in the financial sector resulted in an inefficient credit boom: less credit-worthy households were able to access mortgages. The hot housing market ensuing this increased demand for homeownership, resulted in widespread defaults and depressed economic conditions. However, in the expectations view, too optimistic expectations about the growth rate of house prices are the driver of the expansion in credit markets. The boom and bust in the housing market cause the credit boom and bust, and eventually the financial crisis. Both these explanations for the crisis, rely on severely misaligned incentives or irrational behavior in markets' participants.

In this paper, I explore an alternative explanation based on exogenous time-variation in risk premia and household heterogeneity. What appears to be a credit cycle, could originate from optimal consumption and investment decisions of households exposed to time-variation in the risk of economy-wide shocks. I start by presenting empirical evidence consistent with my proposed explanation and complement it with a formal analysis in a theoretical model.

[1] See Piazzesi and Schneider (2016), Guerrieri and Uhlig (2016) and Adelino, Schoar, and Severino (2018) for an in-depth review of this literature including a discussion of these two narratives.

In my empirical analysis, I use loan-level data from Fannie Mae and Freddie Mac to construct a new measure of regional credit risk. The data allows me to use detailed household balance sheet information at the origination of mortgages. Based on Merton (1974) credit risk model, I calculate expected default frequencies (EDF) of individual mortgages and aggregate them at different geographical levels. Moreover, I define a new credit risk measure called "credit dispersion." It measures the difference between the average EDF of households that borrow today and the average EDF of households that borrowed one year earlier. In other words, credit dispersion compares the current credit qualities of two sets of households: those who are increasing their leverage versus those who are decreasing their leverage. I call this new measure "credit dispersion." The definition of dispersion is motivated by Greenwood and Hanson (2013) and Gomes, Grotteria, and Wachter (2019), who examine the relationship between corporate credit risk and bond excess returns by studying the difference between EDFs of issuing and repaying corporations in the bond market.

I show that this new measure of regional credit risk forecasts regional economic activity both at the state and Metropolitan Statistical Area (MSA) levels. The observed association is both economically and statistically significant. A one standard deviation increase in the regional credit dispersion forecasts a one percent reduction in the growth rate of state-wide GDP per capita and a 0.5 percent reduction in employment growth over the following year.

These observations seem to confirm the above-stated views about the origins of the financial crisis. However, further empirical analysis reveals that they are more consistent with households' response to variation in risk premia. To be more specific, regional credit dispersion is based on the data of high-quality borrowers with sound credit conditions. My analysis reveals the data about credit scores of these borrowers does not support a story based on an inefficient credit boom or deterioration of borrowers' quality during the boom. This finding is consistent with recent evidence about the boom in mortgage originations and subsequent defaults among middle-income households during the financial crisis.[2]

More importantly, I show that the observed forecasting association is closely tied to regional heterogeneity in the exposure of households to the economy-wide shocks. I use publicly available data from the Quarterly Census of Employment and Wages, together with a simple statistical model to construct an index of heterogeneity in labor-income exposures to systematic shocks across different states through time. Using this index, I investigate the interaction between regional credit risk and heterogeneity of exposures. The results reveal that higher heterogeneity in a region is associated with more forecasting power for credit dispersion. There is no easy way to interpret this empirical finding using the two prominent narratives of the crisis. Neither the subprime view nor the expectations view provide a clear explanation of why the predictive association between credit risk and economic activity is stronger in more heterogeneous areas. In contrast, this pattern is consistent with risk-averse households deciding rationally about their consumption and investment in response to changes in the amount of aggregate economic risks.

I use these empirical observations to motivate a model in which households are differently exposed to the time-variation in the amount and price of risk in the economy. The time-varying aggregate risk in the economy is driven by the probability of rare economic disasters as in Wachter (2013). In the model, long-lived households earn labor income and are able to use that to invest in a government bond or a housing asset. Due to the incomplete markets assumption of the model, households are unable to insure against their labor income risk. Furthermore, their consumption and investment decisions are made rationally, maximizing their continuation utility. In the model, households' access to credit is only possible by using their houses as collateral, limited by debt-to-income and loan-to-value constraints. This generates a link between housing booms and expansions of credit in the economy.

[2]See for example Albanesi, De Giorgi, and Nosal (2017) and Foote, Loewenstein, and Willen (2016).

Next, I calibrate the model and show that under this simple setup, the dynamics of households' leverage reflects the time-variation in risk premia. Households invest less in the government bond and more in the housing asset when the amount of aggregate risk is low. An increase in the total investment of households in the housing asset is accompanied by an increase in the total amount of household debt in the economy. Hence, the amount and risk of household credit are also directly related to the aggregate risk. When the disaster probability increases, the price of the housing asset declines, and households increase their investment in the government bond for precautionary reasons. Unable to meet their financial obligations, some of the households default on their loans. Booms and busts in housing and credit markets are both driven by time-variation in the aggregate amount of risk; none of them is caused by the other as a result of misaligned incentives or behavioral biases.

The model implies that consumption and investment of households with more labor income exposure to rare disasters react more strongly in a non-linear fashion to changes in the systematic risk. Hence, even if average exposure to economic disasters is identical across different regions, comovements between credit risk and aggregate economic variables such as income or consumption are stronger for more heterogeneous regions. A simulation exercise reveals that the forecasting association between the credit risk and macroeconomic aggregates is stronger in regions where heterogeneity among households is larger, consistent with the empirical evidence.

The analysis in this paper does not rule out the possibility of an inefficient credit boom at the beginning of the century, as an outcome of deregulation and financial innovations, resulting in institutional and agency problems. Nor does it reject the possibility that behavioral biases and extrapolative expectations intensified the housing crisis. Rather, this paper fits as a complement to the two prominent narratives about the origins of the financial crisis. The empirical evidence and the theoretical model in the paper provide grounds for considering time-variation in risk premia and household heterogeneity as more significant contributors to the formation and amplification of the boom and bust in both housing and credit markets.

Related Literature

There is vast theoretical and empirical literature that studies the credit fluctuations and their contribution to the dynamics of asset prices. In a seminal theoretical study, Kiyotaki and Moore (1997) emphasized the role that durable assets such as housing play as collateral, in transmitting and exacerbating income and technology shocks.[3] After the Great Recession, many studies aimed to shed light on how changes in the household balance sheet before the financial crisis affected aggregate measures of economic activity during and after the crisis. In a series of influential papers, Mian and Sufi (2009, 2011, 2014) among others showed that an increase in home equity-based borrowing and household leverage prior to the Great Recession contributed to the amplification of the crisis in different regions of the country. The critical role of credit expansion in various regions during the boom period in the housing sector is the central theme in this literature. (See for example Di Maggio and Kermani, 2017; Justiniano, Primiceri, and Tambalotti, 2019).

Several papers in the literature challenge the subprime view by putting more weight on the role of expectations about house prices. Adelino, Schoar, and Severino (2016) exhibit that defaults and delinquencies among high-FICO borrowers increased during the financial crisis. Kaplan, Mitman, and Violante (2017) argue that changes in expectations were a more important contributor to the growth of house prices compared to the credit conditions. Rather than being driven by speculation, variation in tastes of the investors, or extrapolative

[3] Also see Bernanke, Gertler, and Gilchrist (1999), Iacoviello (2005), Mendoza (2010), and Eggertsson and Krugman (2012).

expectations[4], house price movements in my model are a product of changes in the amount of aggregate risk in the economy.

The role of household heterogeneity is another important area of research. Notably, Mian, Rao, and Sufi (2013) establish the importance of heterogeneity in the balance sheet of households as a determinant of consumption response across different regions. Guerrieri and Lorenzoni (2017) study the effect of tighter credit constraints on output and interest rate dynamics in a heterogeneous incomplete market model. More recently, Beraja, Fuster, Hurst, and Vavra (2019) show that the aggregate effects of the monetary policy on regional economies are related to the time-variation in the distribution of housing equity among households. In this study, I focus on the role of heterogeneity in the exposure of households' labor income to systematic shocks. The close tie between this measure and credit risk motivates modeling decisions of households as rational investment decisions under an incomplete market condition.

A different strand of empirical studies (For example see Gilchrist and Zakrajšek, 2012; Jermann and Quadrini, 2012; Greenwood and Hanson, 2013; Baron and Xiong, 2017) investigates how the quantity and riskiness of corporations' balance sheets are related to the aggregate economic activity and bond excess returns. Recently, Gomes, Grotteria, and Wachter (2019) studies the role of time-variation and heterogeneity in investment opportunities of firms for explaining these observed patterns in a complete markets model. In this paper, I focus on a similar rational explanation to understand the strong association between mortgages' risk of default and the regional economic activity.

The rest of the paper is organized as follows: In Section 2, I present data and empirical evidence, then discuss the role of time-varying risk premia and household heterogeneity in generating the observed patterns. Motivated by these results, Section 3 introduces a

[4]See Foote, Gerardi, and Willen (2012), Shiller (2014), and Glaeser and Nathanson (2017).

model that features the time-varying risk of rare disasters as the source of risk premia, and households with differential exposures to the realization of disasters. In Section 4, I calibrate the model and compare its implications with the empirical results. Section 5 concludes.

2 Empirical Analysis

In this section, I present and discuss the empirical findings of the paper. Section 2.1 discusses the data sources and the construction of different variables used in the empirical analysis. Next, in Section 2.2, I introduce the credit dispersion measure implied by mortgage data. In Section 2.3, I show that credit dispersion forecasts the state-level growth rate of GDP per capita and employment at various time horizons. Furthermore, I present evidence of the existence of this forecasting ability at the MSA level. Finally, Section 2.4 explores the role of heterogeneity in labor income exposures as a driving force for the observed patterns in the data.

2.1 Data

The primary sources of mortgage data in this paper are Fannie Mae and Freddie Mac Single-Family Loan-Level Datasets. The two organizations are furnishing these datasets for public use at the direction of the Federal Housing and Finance Agency (FHFA). The datasets contain origination data of the mortgages processed by Fannie Mae and Freddie Mac such as the amount and date of loan origination, the interest rate charged, length of the contracts, credit scores of the recipients, loan to value and debt to income ratios, credit insurance products purchased with the mortgage, etc. It also includes monthly loan performance data, actual loss data, legal costs, etc. which are not used in this study. The data is available from January 1999 to October 2018. The duration of these fixed-rate contracts is 15-35 years.

Thus, the dataset does not include adjustable rate mortgages, initial interest mortgages, or other contracts with step rates.

The geographical information in this dataset bears significant importance in my analysis. The data set provides information about the Metropolitan Statistical Area (MSA) of the house. The data also includes a column with the first three digits of the house zip code. I cannot use the information content of this column to assign mortgages to specific counties or MSAs; the 3-digit zip codes can only specify states uniquely. As a result, the most accurate geographical information in the data is the MSA location of the house.

I clean the data by dropping all the mortgages for which the geographical information is missing. Also, I drop the mortgages that are insured using credit insurance products allowing me to rely on mortgages that are only backed by the house value. This choice is also necessary as I rely on the Merton model for measuring the credit risk of the mortgages. What remains after combining the two sources is the data for near 50 million mortgages over the period 1990-2018. The number of observations is lower in the first few months and the last two years of the sample, most likely due to reporting issues.

I utilize Zillow county and MSA level house price data to follow the level and growth rate of house prices. In some cases, the MSA contains more than one county in which case I use a simple average of the growth rates across counties. This data is available from 1994 for most of the counties.

The Bureau of Economic Analysis furnishes the GDP data at various geographical levels. The quarterly state-level GDP data is available from 2005. I use Census population data to turn that into GDP per capita. Also, from December 2019, the BEA started publishing annual county-level GDP data going back to 2001.

For employment figures, I use the data from The Bureau of Labor Statistics. In this paper, I mainly rely on the Quarterly Census of Wages and Employment (QCWE) data that provides employment data at the county level. At each county, the monthly employment and total quarterly wages are classified by the industry using the North American Industry Classification System (NAICS) at 3-6 level digits precision.

2.2 Dispersion in Mortgage EDFs

Merton (1974) computed the value of a firm's equity by modeling it as a call option on the asset value with a strike price equal to the debt value. Under this simple modeling framework, the probability of default is calculated as a function of the expected average growth rate of the companies value, the volatility of the growth rate, and the leverage ratio. This probability is called the expected default frequency (EDF) of the company.

Borrowing this framework, I consider a similar approach to modeling the home-equity value of a household and its expected default. This means that the total value of a household's assets or at least the portion that matters for the default decision can be approximated by the house price. Moreover, the household equity is the levered claim on this asset.[5] EDF is calculated as:

$$\mathrm{EDF}_{it} = \mathcal{N}\left(\frac{-\log\frac{V_{it}}{B_{it}} - \left(\mu_{V_{it}} - \frac{1}{2}\sigma^2_{V_{it}}\right)}{\sigma_{V_{it}}}\right). \tag{1}$$

In the above V_{it} is the market value of the household i's house. B_{it} is the face value of the mortgage loan. Also, $\mu_{V_{it}}$ and $\sigma_{V_{it}}$ are mean and standard deviation of the growth rate of V_{it}. $\mathcal{N}$ indicates the standard normal cumulative density function.

As described in the previous section, the loan-level data from Fannie Mae and Freddie Mac provides the value of the house at the time of the origination of the mortgage. Also,

[5] For a majority of households, housing is the most important item in their wealth portfolio (For data about the US and other advanced economies see Jordà, Schularick, and Taylor, 2019). This assumption is also justified if the default decision is unrelated to the value of other household assets.

using the LTV ratio, I can find out B_{it}.

The values of $\mu_{V_{it}}$ and $\sigma_{V_{it}}$ for each house, are not available in the data. I assume that the values of all houses in a given geographical area are perfectly correlated. This assumption allows me to utilize the Zillow regional house price data to compute changes in V_{it}. I calculate $\mu_{V_{it}}$ as the growth rate over the last 12 months[6] and use a simple GARCH model to estimate $\sigma_{V_{it}}$. An alternative method is to compute the sum of squared returns over the last 12 months as a benchmark of $\sigma_{V_{it}}$. Both methods produce consistent outcomes.

Consider the pool of all the borrowers in region j at time t and call it $\mathbb{B}_{j,t}$. I define credit dispersion as the difference between the current average EDF of today's borrowers compared to the current average EDF of last year's borrowers:

$$Dispersion_{jt} = \frac{1}{n(\mathbb{B}_{j,t-1})} \sum_{i \in \mathbb{B}_{j,t-1}} EDF_{it} - \frac{1}{n(\mathbb{B}_{j,t})} \sum_{i \in \mathbb{B}_{j,t}} EDF_{it}, \tag{2}$$

where $n(.)$ denotes the number of households in the set.

The above definition is inspired by the definition of credit dispersion in the corporate bond market literature such as Greenwood and Hanson (2013) and Gomes, Grotteria, and Wachter (2019). Instead of comparing today's borrowers to last year borrowers, the main focus in the corporate bond market is on the average EDF of issuers compared to repayers. The variable captures how financing decisions of firms with different characteristics are related to the business cycle status or pricing of credit risk.

Due to the nature of housing debt, I cannot follow the same definition here. However, in the same spirit, the above definition allows me to compare households with regards to the timing of their decision to increase their leverage and invest in the housing market. Last

[6]In the corporate literature, it is conventional to use average returns over the past 12 months to calculate expected returns. Given that housing returns show stronger persistence in the data (with an annual AC coefficient of 0.7) compared to the equity returns, the use of this measure as a proxy for expected returns is more justified in the context of this paper.

year's borrowers are paying off their mortgage and hence decreasing their leverage, similar to repaying companies. In contrast, today's borrowers are increasing their leverage, analogous to those companies that are issuing debt in the bond market.

The major contrast between the set of "Last Year's Borrowers" in this paper and the set of "Repayers" in the bond credit risk literature is that the former does not include the entire pool of households that are paying off their debt. Instead, the focus is on the borrowers that are repaying their loan since last year, as they can be considered marginal entrants into the set of all households that are de-levering. Also, given that many households decide to refinance after a few years of mortgage origination, this choice makes sure that the set only contains households that are decreasing their leverage.

The first panel in Figure 1 shows the average values of EDF for today's borrowers versus last year's borrowers, aggregated by averaging across all the MSAs in the country. Panel B shows the $Dispersion$ at the national level. The average EDF of last year borrowers is much more volatile and is the dominant driver of $Dispersion$. This pattern resembles Gomes, Grotteria, and Wachter (2019) findings about dispersion in corporation' credit risk.

There is a clear countercyclical pattern apparent in the figures. Both variables in the first panel start increasing prior to the financial crisis and dampen afterward. Since the increase in the EDF of last year's borrowers is larger, $Dispersion$ also displays countercyclical dynamics.

Table 1 reports pairwise correlations between these three variables and measures of aggregate risk in the asset pricing literature. These measures include annual price-dividend ratio, CAY (Lettau and Ludvigson, 2001) , GZ credit spread (Gilchrist and Zakrajšek, 2012), and variance risk premium (Bollerslev, Tauchen, and Zhou, 2009). All variables are in monthly frequency except for CAY that is available at a quarterly frequency. I use a monthly version of CAY in this analysis by assuming it remains constant between quarterly updates. These results show that there is indeed a strong countercyclical pattern in all three variables.

How can we interpret these patterns? One first explanation is that in line with the "subprime view", these figures confirm the deterioration of borrowers' credit quality over the business cycle. However, this explanation is not consistent with the fact that the households in this paper are of relatively high quality. To be more precise, the data provides a direct measure of households' creditworthiness over time. The first panel in Figure 2 shows 5, 50, and 95 percentiles of FICO score distribution in the sample. Panel B provides the standard deviation of FICO scores. There is a small increase of around ∼30-40 points around 2009, partially reversed around 2014. Except for that, there is not much change in the average scores of these borrowers. Also, there is a reduction of ∼10 points in the standard deviation of scores. These are in contrast with bold patterns in Figure 1 that start well before the crisis.

As is clear from definitions in equations (1) and (2), the geographical EDF and $Dispersion$ measures are driven by changes in mean and variance of regional housing returns. Figure 2 is consistent with Adelino, Schoar, and Severino (2018) findings regarding the prevalence of defaults among middle income and high FICO borrowers. To summarize, at the national level $Dispersion$ seems to be closely related to measures of aggregate risk. Also, it does not seem to be driven by the quality of borrowers. Instead, by construction, it reflects changing growth expectations in the housing market.

2.3 Forecasting Macroeconomic Variables

In this section, I present evidence about the information content of the credit dispersion measure for economic activity. One possible weakness of this analysis is that the available time-series for our data is not very long. The 1999-2018 period contains only one major economic recession. Also, the quality of data at the beginning and end of the sample is relatively lower. On the plus side, the mortgage data provides regional variations that could be exploited to understand the forecasting power of credit dispersion. In order to do so, I aggregate the cross-section of available EDFs, up to specific geographical units (i.e. state level, MSA level), then use that to investigate the predictive power in panel regressions.

2.3.1 State Level Evidence

I aggregate loan-level data up to the state level and estimate regressions of the following type at different horizons:

$$\frac{1}{h}\Delta gdp_{i,t\to t+h} = \alpha_i + \alpha_t + \beta Dispersion_{i,t} + \xi\Delta gdp_{i,t-1\to t} + \epsilon_{i,t\to t+h}. \tag{3}$$

The regression is run with quarterly data and contains state and time fixed effects.

Table 2 reports the estimation results. Credit dispersion forecasts the growth rate of GDP per capita at different horizons. This finding is both economically and statistically significant. The coefficients suggest that a one standard deviation increase in the regional credit dispersion forecasts a one percent reduction in the growth rate of state-level GDP per capita. The statistical significance increases with the horizon. However, one should be careful about the possible role of persistence in the $Dispersion_{i,t}$ variable, and overlapping dependent variable. Adding time fixed effects reduces some of the observed predictive power. Nonetheless, the association remains highly significant; hinting to the fact that aggregate benchmarks of macroeconomic and financial risk fall short of explaining this strong forecasting relationship.

Table 3 outlines the results of similar predictive regressions at monthly frequency, where the dependent variable is employment growth:

$$\frac{1}{h}\Delta emp_{i,t\to t+h} = \alpha_i + \alpha_t + \beta Dispersion_{i,t} + \xi\Delta emp_{i,t-1\to t} + \epsilon_{i,t\to t+h}. \tag{4}$$

The findings are similar to the Table 2 results. Credit dispersion predicts employment growth at various horizons for up to a year. A one standard deviation increase in the dispersion predicts almost a 0.5% reduction in the growth rate of state-level employment in the following year. The predictive association remains significant even after adding time fixed effects. This finding suggests the cross-sectional association is not solely driven by macroeconomic trends.

2.3.2 MSA Level Evidence

The available data allow running similar predictive regressions at the MSA level. The dependent variables in Table 4 and 5 are GDP and employment growth respectively. Estimation results reaffirm the state-level evidence: credit dispersion strongly forecasts economic activity, this predictive power is not explained by aggregate measures of risk and increases with the horizon. [7]

2.4 Role of Heterogeneity

The evidence presented in the last section demonstrates the credit dispersion implied by mortgages as a state variable of the economy that comoves with benchmarks of aggregate risk. Also, credit dispersion predicts measures of macroeconomic activity such as GDP growth and changes in employment. Motivated by these findings, it is natural to ask what economic forces are behind these empirical patterns. In this section, I will explore a possible link between household heterogeneity and the observed predictive patterns in the data. First,

[7] It is worth mentioning that the results presented in this section and the previous one, contribute to the so-called "housing is the business cycle" view that identifies a strong relationship between investment in the housing sector and the business cycle. (For example see Leamer, 2007). As an example, these results are in contrast with the findings of Ghent and Owyang (2010). They report that among the MSAs of 51 US cities, house price declines are not followed by declines in the growth rate of employment. This section results show how the credit dispersion measure, links developments in the housing and mortgage markets to the employment growth at the MSA level.

I introduce a simple measure of heterogeneity in labor income exposures using the Quarterly Census of Employment and Wages data. Then, I revisit the predictive evidence of the last chapter, focusing on the role of heterogeneity in labor income exposures to economy-wide risks.

2.4.1 Measuring Heterogeneity in Labor Income Exposures

As explained in more detail in the data section, the Quarterly Census of Employment and Wages provides county-level employment data for different NAICS codes for each county. I assume that within a county, the labor income exposures of all the employees in a 6-digit NAICS industry are equal to each other. In order to gauge the exposure, I estimate the following regression for each industry-county:

$$\Delta emp_{i,t} = \alpha_i + \phi_i \Delta emp_{s,t} + \text{Seasonal Dummies}_i + \epsilon_{i,t}. \tag{5}$$

In the above regression, $\Delta emp_{s,t}$ measures the log change of employment in state s on month t. $\Delta emp_{i,t}$ identifies the same quantity for a give industry-county i. The regressions include month dummies that capture possible seasonalities in the employment data. The coefficient ϕ_i measures the exposure of employment in a certain industry-county, to the economy-wide employment shocks within a state.

If the data contains employment for all industry-counties in a state, then by definition, the average exposure of industry-counties in a state is one. However, since this is not the case, the average exposure can deviate from one. I compute the average exposure weighted by the (average) level of employment in each industry-county as follows:

$$\bar{\phi}_{s,t} = \sum_{i \in s} \frac{emp_{i,t}}{emp_{s,t}} \phi_i \quad , \quad \bar{\phi}_s = \sum_{i \in s} \frac{\overline{emp}_{i,t}}{\overline{emp}_{s,t}} \phi_i .$$

Next, I measure heterogeneity of labor income exposures for state s, using the standard deviation of exposure coefficients:

$$\sigma_{s,t}^{Expo} = \sqrt{\sum_{i \in s} \frac{emp_{i,t}}{emp_{s,t}} \left(\phi_i - \bar{\phi}_{s,t}\right)^2} \quad , \quad \sigma_s^{Expo} = \sqrt{\sum_{i \in s} \frac{\overline{emp}_{i,t}}{\overline{emp}_{s,t}} \left(\phi_i - \bar{\phi}_s\right)^2} . \tag{6}$$

Figure 3 depicts how heterogeneity of labor income varies among different states. A darker color is associated with a lower level of σ_s^{Expo} in the state. Also, in Figure 4 the time series variation in state-wide heterogeneity is presented.

There is a possibility of measurement errors in these calculations. First, the assumption that all the employees in a given industry-county have identical exposures might not always be realistic. The characteristics of different jobs in the same sector of the economy can be very diverse. Nevertheless, this is the most reasonable assumption given the limitations of the available data on the labor income or employment situation of individual households. Second, the employment data on numerous small industries is not available in all the years and months. This issue affects estimations in regression (5). To tackle this issue, I use only the data of industry-counties for which I have at least 15 years of data. While this helps reduce this measurement issue problem, it does not eliminate it. Finally, measuring variance or standard deviation is more sensitive to these issues compared to the average or median.

I use both the time-varying and time-invariant versions of this benchmark of heterogeneity of labor income exposures in predictive regressions. Although the existence of these measurement errors might introduce bias in the estimation results, it is natural to think that these problems attenuate the regression coefficients toward zero and hence works against finding a significant role for heterogeneity.

2.4.2 Credit Dispersion and Heterogeneity of Exposures

Table 6 presents the estimation results of the following regression:

$$\Delta gdp_{i,t\to t+k} = \alpha_i + \beta Dispersion_{i,t} + \gamma Dispersion_{i,t} \times \sigma_{i,t}^{Expo} + \delta\sigma_{i,t}^{Expo} + \xi\Delta gdp_{i,t-1\to t} + \epsilon_{i,t\to t+k}. \quad (7)$$

The setting allows me to investigate the forecasting association between credit dispersion and GDP growth in the presence of the time-varying measure of the heterogeneity of exposures $\sigma_{i,t}^{Expo}$. On the left panel, I shut down the interaction term. On the right panel, both the regression coefficient for exposure heterogeneity δ, and the interaction coefficient γ are estimated.

The left panel results show that credit dispersion retains its forecasting power in the presence of $\sigma_{i,t}^{Expo}$ at all horizons. However, on the right panel, the interaction term subsumes all the predicting power of credit dispersion. Interestingly the sign of δ is consistent with theoretical models that rely on time-varying heterogeneity to explain asset prices; an increase in heterogeneity forecasts lower economic growth in the future.

To further investigate the relationship, in Table 7, I consider the time-invariant measure of heterogeneity of exposures σ_i^{Expo}. Note that the δ coefficient in equation (7) is absorbed by the state fixed effects. Similar results are achieved, with the notable exception that the credit dispersion coefficient does not lose all of its statistical significance to the interaction term.

Tables 8 and 9 present the analogous regression results with employment growth as the dependent variable. The coefficient γ of the interaction term between credit dispersion and heterogeneity of exposures absorbs almost all of the negative forecasting association. This time the coefficient δ remains insignificant at all horizons.

The results brought up in this section indicate that the negative forecasting association between credit dispersion and measures of economic activity is more pronounced in states where there exists higher heterogeneity of labor income exposures. These results motivate recognizing a more significant role for heterogeneity of exposures in explaining the forecasting power of this measure of credit risk.

How do these results add to the existing evidence about the credit cycles and their relationship with the business cycles? There does not seem to be a straightforward explanation for these findings under the "subprime view" or "expectations view" of the financial crisis. Consider the first narrative. There is no intuitive way to connect increased lending to lower credit-worthy borrowers and the heterogeneity of exposures among households. Similarly, it is not easy to relate the notion of extrapolative expectations about house prices to higher heterogeneity. Why should households in more heterogeneous states rely more on extrapolation for their investment decisions?

In contrast, the most salient feature of rational decision-making is its emphasis on notions of covariation with or exposure to sources of systematic risk. When aggregate risk and its price change, investment and consumption decisions of households and firms change. Households and firms that are more exposed to systematic risk are expected to react more strongly to variation in the amount of aggregate risk. In the next section, I formalize how these patterns arise as a natural consequence of rational decisions of heterogeneous agents to invest in housing wealth in an incomplete market framework.

3 Model

3.1 Aggregate Economy and Stochastic Discount Factor

I assume that aggregate fluctuations are driven by a time-varying probability that the economy enters into a disaster. I assume that the disaster event is a Bernoulli random variable x_t that takes the value of 1 at time t with probability p_t. The probability of rare disasters follows a square-root process in discrete-time:

$$p_{t+1} \;=\; (1-\rho_p)\bar{p} + \rho_p p_t + \sigma_p \sqrt{p_t}\epsilon_{p,t+1}, \quad \text{where } \epsilon_{p,t+1} \overset{i.i.d.}{\sim} N(0,1). \tag{8}$$

In the above, $\bar{p}$ is the long-run mean of the disaster probability. The parameters ρ_p and σ_p determine the persistence and volatility of the process, respectively.

Furthermore, I assume that in the event of a rare disaster, aggregate consumption (or output) drops by the amount of ξ_{t+1}. This random variable is distributed according to an independent time-invariant distribution with moment generating function Φ_ξ.

Based on the definition of p_t and following the disaster risk literature, I specify the following stochastic discount factor:

$$\log M_{t+1} = -r_0 - r_p p_t + \sigma_{my}\epsilon_{y,t+1} + \sigma_{mp}\sqrt{\bar{p}}\epsilon_{p,t+1} + \xi_{m,t+1}x_{t+1}, \tag{9}$$

where $\epsilon_{y,t+1} \overset{i.i.d.}{\sim} N(0,1)$. All the real and financial assets in the economy are priced using the above stochastic discount factor.[8] The drift of $\log M_{t+1}$, is an affine function of p_t. Three innovations might impact the SDF through time. First, the SDF is affected by the normal

[8]Due to the incomplete market assumption of the model, it is not possible in our settings to derive the SDF from the Epstein-Zin preferences of a representative investor over total consumption or output. However, the adopted specification for the SDF is almost identical to the solution of the Epstein-Zin preferences for a representative agent. This is to make sure that the results of the model do not depend on discount rates being affected by heterogeneity and incomplete markets assumptions.

shock $\epsilon_{y,t+1}$ that represents the fluctuations in the aggregate consumption or output at time t. Second, the $\epsilon_{p,t+1}$ shock that relates the SDF to the probability of a disaster happening. Third, in the event of a disaster, the SDF jumps upward with the magnitude $\xi_{m,t+1}$. I assume that $\xi_{m,t+1} = -\gamma\xi_{t+1}$, where γ is the relative risk aversion. This assumption relates the magnitude of the jump in the discount rate with the magnitude of the macroeconomic disaster, consistent with CRRA or Epstein-Zin preferences for real consumption.

Based on the above assumptions, the risk-free rate is as follows:

$$\log R_t^f \equiv -\log\left(\mathbb{E}_t\left[M_{t+1}\right]\right) = r_0 + r_p p_t - \frac{1}{2}\sigma_{my}^2 - \frac{1}{2}\sigma_{mp}^2 p_t - \log\left(1 - p_t + \Phi_\xi(-\gamma)p_t\right). \quad (10)$$

Following Barro (2006) and Wachter (2013), I allow for the possibility of a partial default by the government on its debt. Conditional on a disaster happening, the government defaults partially on its debt with constant probability q and investors lose an amount equal to the size of the disaster. Denoting the event of government default by L we have:

$$\log R_{t+1}^b = \mu_t^b + L_{t+1}\xi_{t+1}x_{t+1}. \quad (11)$$

As a result of this assumption, as proven in the appendix, the face value of government debt is given by:

$$\mu_t^b = \log R_t^f - \log\left[1 - q + (\Phi_\xi(1-\gamma) - \Phi_\xi(\gamma))qp_t\right], \quad (12)$$

and the expected log-return on government debt is:

$$\mathbb{E}_t\left[\log R_{t+1}^b\right] = \mu_t^b + \Phi_\xi'(0)qp_t \quad (13)$$

3.2 Housing Sector

I assume that there is a housing asset available for investment that provides households with housing services (i.e. housing dividends or rents). The dynamics of housing dividends in region j is specified as:

$$\log s^j_{t+1} = \log s^j_t + \mu^j_s + \sigma^j_s \epsilon^j_{s,t+1} + \xi_{s,t+1} x_{t+1}. \tag{14}$$

In the above specification, the growth rate and volatility of these dividends are denoted by μ^j_s and σ^j_s respectively. In the event of a disaster, housing revenues encounter a decline equal to $\xi_{s,t+1}$. I assume that the size of the decline in revenues of the housing sector is related to the size of the disaster in the aggregate economy by the equation $\xi_{s,t+1} = \phi_s \xi_{t+1}$. Furthermore, the normal shock to the housing sector revenues is correlated with the shock to aggregate income or consumption, $\mathrm{corr}(\epsilon_{y,t+1}, \epsilon^j_{s,t+1}) = \rho^j_s$.

The price of a unit of housing asset in region j is determined by solving the Euler equation for the price-dividend ratio of the housing asset:

$$\mathbb{E}_t \left[M_{t+1} R^j_{h,t+1} \right] = 1. \tag{15}$$

I solve for $pd^j_{h,t}$ as a function of the model's state variable numerically.

3.3 Households

The regional economies are populated with long-lived households. Household i is endowed with labor income y^i_t which evolves as follows:

$$\log y^i_{t+1} = \log y^i_t + \mu^i_y + \sigma^i_y \epsilon^i_{y,t+1} + \xi^i_{y,t+1} x_{t+1}. \tag{16}$$

Household labor income grows with an average rate of μ_y^i and volatility σ_y^i. The normal shocks to household income are correlated with the aggregate shocks ($\text{corr}(\epsilon_{y,t+1}, \epsilon_{y,t+1}^i) = \rho_y^i$). The size of the shock to household labor income in the event of a disaster is $\xi_{y,t+1}^i = \phi_y^i \xi_{t+1}$. This parameter is the main source of heterogeneity in the model. Households are differently exposed to rare disasters as their ϕ_y^i can be different.

In order to simplify the calibration of these parameters throughout the paper, I add a few assumptions. First, instead of calibrating μ_y^i and σ_y^i for households separately, I assume that they are related to aggregate mean and volatility of income growth in the economy. More specifically, I assume that the average growth rate of income for individuals is determined as follows:

$$\mu_y^i = \mu_y + \log \mathbb{E}\Big[e^{\xi_{t+1} x_{t+1}}\Big] - \log \mathbb{E}\Big[e^{\phi_y^i \xi_{t+1} x_{t+1}}\Big]. \tag{17}$$

This assumption makes sure that the income share of highly exposed households does not shrink over the long-run. Hence the mean growth rate of income remains at μ_y.

Second, I assume that through each region and in the whole economy, the average ϕ_y^i adds up to 1 ($\int_i \phi_y^i = 1$). This makes sure that regions are not different when it comes to their average exposure to rare disasters. However, regions could still be different when it comes to cross-sectional variation in ϕ_y^i.

Third, I assume that $\sigma_y^i = \frac{1}{\rho_y^i} \sigma_y$ and that σ_y^i is equal for all the households in all the regions. While decreasing the number of free parameters, these assumptions make sure that the only source of heterogeneity in the model is the difference in labor income exposures of households to disastrous shocks.

Households can only invest in the government bond and the housing sector. When they decide to invest in the housing sector, the amount of debt that they can get compared to their labor income is restricted by the debt-to-income (DTI) ratio. If they decide to invest in the housing sector, there is a maximum level of leverage they can take which is determined by the LTV ratio. I assume that when investing, households use the maximum possible leverage and house price that is determined by these two ratios and their level of labor income.

To reduce the complexity of the model, I model household debt as a perpetuity contract similar to Beraja, Fuster, Hurst, and Vavra (2019). The required rate of return on household debt is determined by:

$$\log R_t^d = \log \mathbb{E}_t \left[\log R_{t+1}^b\right] + r_{debt} p_t \quad \text{where } r_{debt} > 0. \tag{18}$$

Based on the above equation, lenders demand a premium for the risk of defaults by households that is increasing in the probability of rare disasters.

Household derive utility from real consumption according to preferences specified as in Epstein and Zin (1989) and Weil (1990):

$$U_{i,t} = \left[(1-\delta)X_{i,t}^{\frac{1-\gamma}{\theta}} + \delta \mathbb{E}_t[U_{i,t+1}^{1-\gamma}]^{\frac{1}{\theta}}\right]^{\frac{\theta}{1-\gamma}}, \tag{19}$$

in which δ is the time discounting parameter, γ is the relative risk aversion, and $\theta = \frac{1-\gamma}{1-\frac{1}{\psi}}$ determines the preference of household toward the timing of uncertainty resolution and is calculated using γ and the IES parameter ψ. $X_{i,t}$ is a Cobb-Douglas function that aggregates the real consumption of household in housing ($s_{i,t}$) and non-housing ($c_{i,t}$) categories:

$$X_{i,t} = s_{i,t}^{\nu} c_{i,t}^{1-\nu}. \tag{20}$$

The parameter ν controls the optimal share of housing vs. non-housing consumptions. The specification of household preferences and consumption in this paper is identical to Chen, Michaux, and Roussanov (2020).

Households optimally decide about the level of their consumption and investment in a house or government bond in the presence of budget and debt constraints, trying to maximize their utility. Households are either in the set of homeowners, renters or defaulted households. Homeowners can decide to sell their house or continue owning it. If they cannot meet their financial obligation they default on their mortgage and forfeit all their wealth in government bonds.

The recourse laws about housing debt differ across different states. Many states consider mortgages a non-recourse debt. However, in this paper, I make a simplifying assumption and consider all mortgages recourse meaning that households savings in the government bond will be ceased upon default. Also, when households default, they are excluded from taking a mortgage and purchasing a house for a random period of time. After the default, a household will be eligible again to return to the housing market and become a homeowner with probability ω, independent of other shocks in the model. After being eligible again, households can decide to remain a renter or invest in the housing asset.

Household decisions are determined using Bellman's equation. Appendix B provides details of the model solution equations. Note that the model is solved under partial equilibrium. There is no equilibrium condition relating the sum of households' income or consumption to the stochastic discount factor.

4 Model Implications

I calibrate the model and use simulation exercises to study the behavior of different macroeconomic variables, their relationship with time-varying aggregate risk, and the role of heterogeneity. In the next subsection, I present a calibration of the model parameters. Next, I describe the simulation procedure and present some of the results that shed light on the effect of heterogeneity. Also, the impulse response functions of different model variables to changes in disaster risk are analyzed.

4.1 Calibration

Table 10 reports how model parameters are calibrated at the quarterly frequency. There are six categories of parameters that I need to calibrate in this model.

First, the calibration of preference parameters is relatively standard. Here, I use an annual rate of time preference of 1.2% as in Wachter (2013). This means that δ at quarterly frequency would be 0.997. The relative risk aversion parameter is set to be 4, in line with the equity premium puzzle literature. I set EIS to be 1.5, consistent with preferences for early resolution of uncertainty. The only remaining parameter in the specification of preferences is ν which is set to be 0.15, close to the estimated value of 0.134 in Chen, Michaux, and Roussanov (2020).

For the disaster risk parameters, I choose numbers in line with parameter values used in the literature. Disaster size distribution is according to Barro and Ursúa (2008) data. Their results suggest average rare disaster probabilities of 2.87% and 3.69% respectively for OECD and all countries in their sample. I set $\bar{p}$ to be 3.00% annually (0.75% quarterly). I set ρ_p and σ_p to be 0.98 and 1.75% in quarterly frequency. These numbers are consistent with an annual mean reversion and volatility parameter of 8% and 7% respectively, consistent with Wachter (2013). Finally, the parameter q, the probability of partial government default in the event of a rare disaster is 40%.

Next, I consider the SDF parameters. As explained in the model section, while the SDF in my model is not directly obtained from Epstein-Zin preferences of a representative investor, I try to be consistent with such an outcome while trying to match risk-free rate patterns in the data. I set r_0 and r_p to be 4% and 3 respectively. σ_{my} is calibrated to be

-0.02 consistent with aggregate consumption volatility of 0.5% and a relative risk aversion of 4 and σ_{mp} is calibrated to be 1.2.

Now, I turn to the calibration of housing dividends parameters. I use similar parameters across different regions to make sure that the simulation results are only driven by heterogeneity among investors. I assume a growth rate equal to aggregate consumption or income; 2% per year or 0.5% quarterly. I also set the volatility of the housing asset returns to 1% quarterly. I calibrate ϕ_s, the parameter governing the exposure to rare events, to be 3. This choice generates reasonable housing excess return and volatility with a price-dividend ratio consistent with the data from Zillow and long-run housing return data from Jordà, Schularick, and Taylor (2019).

I already explained how I set the average growth rate of labor income. I set σ_y^i to be 20% annually or 5% quarterly consistent with the numbers reported in Gorbachev (2011) about US household income volatility. To be consistent with the aggregate income volatility of 2% I set ρ_y^i of 10% for all households. I allow 3 different values for exposure of labor income to disaster risk: 0.5, 1, and 1.5.

Finally, the parameters associated with household debt are set according to the literature. The values of DTI, LTV and ω are determined to be 14, 0.8 and 0.15 in accordance with Chen, Michaux, and Roussanov (2020). I also use and r_{debt} of 1 to make sure of an average premium of 3% annually for mortgages compared to the government bond.

4.2 Simulation Results

4.2.1 Simulation Procedure

I simulate 20-year sample paths of the model after a sufficient burn-in period at a quarterly frequency for 10,000 times. The simulation outcome is then compared with the estimation results presented in Section 2. The choice of 20 years represents the length of the available

US data in the empirical analysis. Each simulation path contains an economy with three regions. There are 500 households in each region. The probability of rare disaster and house price dynamics are assumed to be similar across the three regions.

However, these three regions are different in terms of heterogeneity in exposures of their households to rare disasters. All the households in region 1, have the same exposure (ϕ_y^i) of 1. Hence, there is no heterogeneity in this region. In region 2, 25% of households have exposure parameter equal to 0.5, the parameter for 50% is equal to 1, and 25% have ϕ_y^i of 1.5. Lastly, in region 3, half of the households are exposed with a ϕ_y^i of 0.5, and the rest are exposed with the parameter equal to 1.5. Due to these simple assumptions, while regions are similar in terms of their average exposure to disaster risk, they are different when it comes to heterogeneity in the exposure of households to rare disasters. Standard deviations of ϕ_y^i, $\sigma(\phi_y^i)$ in these three regions are 0%, 35%, and 50% respectively.

Individuals make consumption and investment decision in the simulation path. I compute EDF for each mortgage following a similar procedure as in the data. Then I aggregate the data at the regional level to have a time-series of dispersion in each region. Also, I define GDP to be the sum of consumption and net investment of households in housing or government bond. Consequently, I can use the consumption and investment decisions of households to create regional macroeconomic time-series.

4.2.2 Impulse Response of Macroeconomic Variables to Disaster Risk

To investigate the role of time-varying risk premia in explaining the dynamics of different model variables, it is insightful to examine the response of variables to a change in the probability of rare disasters.

First, the model is simulated for a long enough (e.g. 100 years) burn-in period for 10,000 times. Then, at time 0 in each of the paths, I conduct two separate exercises. In the first exercise, I shut down all the shocks in the model after this point in time. In the second exercise, I set $\epsilon_{p,0} = 1$ and shut down all the shocks up until the end of the simulation. Hence, the second exercise represents a one standard deviation increase in p_t. The results from these two exercises are then compared by measuring the absolute and relative deviations in macroeconomic and credit variables. These changes are averaged across all the 10,000 sample paths to calculate the impulse response functions to a one standard deviation shift in the probability of disasters.

Figure 5 presents the results of this procedure. Panel A in the figure depicts the average absolute change in the quarterly probability of rare disaster in percentages. As a result of the one standard deviation positive shock, the probability of a disaster happening in the next quarter increases by almost 0.13% points ($\sim$ 0.5% annually). Given that all the future shocks are shut down, after time 0 the probability is decaying toward its long-run average. Note that as a result of high persistence in the dynamics of this state variable, even after eight quarters the probability remains elevated.

Panel B plots the absolute deviation in the *Dispersion* variable. The regional measure of credit risk increases for two quarters, then gradually decreases before reaching zero in the fourth quarter. These changes in regional *Dispersion* are driven by the increase in expected default frequencies and a decline in house prices as a consequence of increased aggregate risk in the economy. Given that all the shocks, including shocks to house prices, are zero after time 0, there remains no difference between the expected default frequencies of today's borrowers vs last year's borrowers at quarter 4. Hence, the absolute deviation in *Dispersion* dies out after four quarters. Being the result of subtracting two probabilities, *Dispersion* can take values in the range $[-1, 1]$. As a result of the one standard deviation shock to p_t, the value of *Dispersion* goes up almost 0.09 points. This is a relatively large increase given that *Dispersion* is positive but close to zero in most of the sample.

Panels C to F show a pattern of decline in aggregate macroeconomic and credit variables. In Panel C, the consumption per capita declines more than 2%. Panel D presents a similar response in GDP per capita. These declines are persistent as it takes time for the aggregate risk in the economy to return to its average long-run level. The investment in the risky asset (housing), faces a striking decline of close to 50% in the first two quarters after the shock, before returning to around -20% decline levels. This is driven by a decline in the value function of households and an increase in risk premia, as a result of increased aggregate risk in the economy. in Panel F we see a persistent decline in the amount of per capita household debt in the economy. Given the increased amount of risk, fewer households are willing to take new loans and invest in housing as observed in Panel E. Also, as time passes, some households de-lever or face default as their savings and wages turn out to be insufficient to cover their financial obligations.

How do these results change with various levels of household heterogeneity across different regions? Figure 6 answers this question. As discussed earlier, the standard deviation in labor income exposures of individual households is the lowest in region 1 and the highest in region 3. The figure shows that the GDP per capita declines more in response to a one standard deviation increase in p_t in the more heterogeneous region 3 compare to region 1. The consumption and investment responses of households to increases in p_t have a convex association with their exposure to rare disasters. As a result, if there is more heterogeneity among households, the average response is larger compared to a case where all households have similar exposure.

4.2.3 Predictive Regressions

This setting allows me to run panel regressions similar to what I have studied using the US state-level data in Sections 2.3 and 2.4. I estimate fixed-effect regressions of growth rate in GDP, consumption, and investment in the housing asset and investigate whether dispersion in mortgages has any predictive power for these macro-aggregates in future periods. Furthermore, I explore whether the association is stronger for regions with a higher income exposure heterogeneity.

Table 11 reports the results of this exercise in samples that did not experience a disaster over the 20-year period of simulations. The table reports the median value for the coefficient of a fixed-effect predictive regression at different horizons up to 4 quarters. Panel A reports the results for regression analysis similar to equation 3. Panel B reports the results for a regression that includes a term that interacts dispersion with our measure of household heterogeneity ($\sigma(\phi_y^i)$) for different regions.

Panel A results show a strong predictive power at different horizons for GDP growth. The coefficient β is very similar in the first quarter to what is observed in the data as reported in Table 2. One difference is that the predictive power declines with the horizon in our model while in the data it seems to be increasing. The median value for R^2 is also relatively close to my results from the data. Both the expected growth rates of consumption and housing investment decline as dispersion increases. The highest predictive power is reported for housing investment as expected. Households reduce their investment in risky assets following an increase

Panel B is helpful to understand the role of heterogeneity. As the estimated coefficient for interaction term (γ) shows, the predictive association between GDP growth and dispersion is stronger in a more heterogeneous region. This is in general consistent with the results reported in Tables 6 and 7. The magnitude of economic activity declines with higher dispersion and the decline is more pronounced wherever heterogeneity is higher. A difference between the model and data is that after adding measures of heterogeneity in exposure, the predictive power of dispersion disappears. In the model, dispersion's predictive power remains while it is stronger for more heterogeneous regions.

Another interesting finding is that the main channel for the strong association of dispersion with the growth rate of GDP is the investment channel. While consumption growth predictability dampens rapidly with the horizon and the role of dispersion disappears, the investment in housing remains closely associated with dispersion and heterogeneity even in longer horizons.

Table 12 presents a parallel analysis for all of our sample paths. There is not a significant difference between samples with or without disasters when it comes to the role of dispersion and heterogeneity.

5 Conclusion

The relationship between booms and busts in the housing market and the credit market has been a central question in the financial economics literature after the Great Recession. Leading hypotheses have emphasized the role of institutional issues, misaligned incentives, and behavioral biases of investors to explain the causal link between the two cycles. In this paper, I revisit this question by offering an explanation based on rational decision making by households that are exposed to time-variation in aggregate economic risks.

I construct a new measure of regional credit risk by employing loan-level mortgage data capturing the dispersion in the credit quality of borrowers in the housing market. The analysis in this paper shows that dispersion comoves with benchmarks of aggregate risk. While FICO scores of borrowers do not vary considerably in the data over time, this measure strongly forecasts both GDP per capita and employment growth at the regional level. Moreover, the predictive power of dispersion is closely related to regional heterogeneity in households' exposure to systematic risks.

These empirical patterns are consistent with optimal decision-making of households exposed to time-varying risk premia. I formally show this by introducing and solving a model featuring heterogeneous households under the incomplete-markets condition. The primary source of heterogeneity in the model is differential exposure of households' labor income to rare economic disasters. The model generates a predictive association between credit dispersion and regional economic activity that is stronger for more heterogeneous regions as in the data.

Appendix

A Euler Equation and Asset Prices

A.1 Return of the Government Bond

Given the dynamics of the stochastic discount factor and the definition of return on government bond in equations (9) and (11), the Euler equation implies that:

$$\mu_t^b = -\log \mathbb{E}_t \left[\exp\left(\log M_{t+1} + L_{t+1}\xi_{t+1}x_{t+1}\right)\right]. \tag{A.1}$$

Given that the realizations of government default L_{t+1} is independent of tghe rest of the shocks in the model we have:

$$\mu_t^b = -\log\left(\mathbb{E}_t\left[M_{t+1}\right]\left(1-q+q\frac{\mathbb{E}_t\left[\exp\left(\log M_{t+1}+\xi_{t+1}x_{t+1}\right)\right]}{\mathbb{E}_t\left[M_{t+1}\right]}\right)\right). \tag{A.2}$$

We use the definition of risk-free rate and its value under the model as in equation (10) to substitute the value of expectations in the above equation:

$$\mu_t^b = \log R_t^f - \log\left(1-q+q\frac{\exp\left(-r_0-r_pp_t+\frac{1}{2}\sigma_{my}^2+\frac{1}{2}\sigma_{mp}^2p_t\right)\times\left(1-p_t+\Phi_\xi(-\gamma)p_t\right)}{\exp\left(-r_0-r_pp_t+\frac{1}{2}\sigma_{my}^2+\frac{1}{2}\sigma_{mp}^2p_t\right)\times\left(1-p_t+\Phi_\xi(1-\gamma)p_t\right)}\right),$$

and achieve equation (12). It is straightforward to prove equation (13) given the definition of return to government bond and noting that $\mathbb{E}_t\left[\xi_{t+1}\right] = \Phi'_\xi(0)$.

A.2 Return of the Housing Asset

In this subsection I cover the derivation of price-dividend ratio and asset return dynamics for the housing asset. In the following, the region index j is dropped as the derivation is similar for all the regions. I rely on numerical methods as in Lettau, Ludvigson, and Wachter (2008) to solve for the price-dividend ratio. While achieving a closed-form solution is also possible by using Campbell-Shiller log-linearization, I use numerical methods to be more accurate.

The return to the housing asset can be expressed in terms of the log price-dividend ratio as $R_t^h = \frac{1+e^{pd_{t+1}^h}}{e^{pd_t^h}}.\frac{s_{t+1}}{s_t}$. As a result the Euler equation (15) implies:

$$\mathbb{E}_t\left[\exp\left(\log M_{t+1} + \log\left(1 + e^{pd_{t+1}^h}\right) - pd_t^h + \log s_{t+1} - \log s_t\right)\right] = 1. \tag{A.3}$$

Rearranging the above we can find pd_t^h in a recursive equation:

$$pd_t^h = \log \mathbb{E}_t\left[\exp\left(\log M_{t+1} + \log\left(1 + e^{pd_{t+1}^h}\right) + \log s_{t+1} - \log s_t\right)\right]. \tag{A.4}$$

According to equations (9) and (14) the above can be expressed in terms of our model parameters:

$$\begin{aligned} pd_t^h &= \mu_s - r_0 - r_p p_t + \frac{1}{2}\left(\sigma_{my} + \sigma_s\rho_s\right)^2 + \frac{1}{2}\sigma_s^2(1-\rho_s^2) + \frac{1}{2}\sigma_{mp}^2 p_t \\ &\quad + \log(1 - p_t + \Phi_\xi(\phi_s - \gamma)p_t) + \log \mathbb{E}_t\left[1 + e^{pd_{t+1}^h}\right]. \end{aligned} \tag{A.5}$$

We solve for the above recursively on a fine grid of p_t values.

B Household Problem

B.1 Homeowner Problem

In the model, homeowners need to choose their level of housing and non-housing consumptions (s_t, c_t). Also, they decide whether or not to sell the house and become a renter ($I_{t,Sell}$). These decisions are made conditional on the probability of entering a disaster p_t, level of labor income y_t, liquid wealth invested in the government bond w_t, outstanding amount of mortgage loan l_t, and the amount of debt services m_t. The Bellman equation for the homeowner is:

$$U_{i,t}^h(p_t, y_t, w_t, h_t, l_t, m_t) = \max_{c_t, s_t, I_{t,Sell}} \Big[(1-\delta)\left(s_t^{\nu} c_t^{1-\nu}\right)^{\frac{1-\gamma}{\theta}} \tag{B.1}$$
$$+\delta \mathbb{E}_t \left[\left((1-I_{t,Def})\left((1-I_{t,Sell})U_{i,t+1}^h + I_{t,Sell}U_{i,t+1}^r\right) + I_{t,Def}U_{i,t+1}^d\right)^{1-\gamma}\right]^{\frac{1}{\theta}}\Big]^{\frac{\theta}{1-\gamma}}$$

subject to

$$\begin{aligned}
I_{t,Def} &= \mathbb{1}_{y_t+w_t+h_t\left[1+\exp(-pd_t^h)\right]-(s_t+c_t+l_t+m_t)<0}, \\
w_{t+1} &= (1-I_{t,Def})\left[y_t + w_t + h_t\exp(-pd_t^h) - m_t + I_{t,Sell}(h_t - l_t)\right] R_{t+1}^b, \\
h_{t+1} &= (1-I_{t,Def})(1-I_{t,Sell})h_t R_{t+1}^{h,ex}, \\
l_{t+1} &= (1-I_{t,Def})(1-I_{t,Sell})l_t, \qquad m_{t+1} = (1-I_{t,Def})(1-I_{t,Sell})m_t, \\
& \text{and} \quad c_t, s_t \geq 0.
\end{aligned} \tag{B.2}$$

In the above, the value function of household i at time t owning a house, is denoted by $U_{i,t}^h$. Similarly, value to renter and defaulted households are denoted respectively by $U_{i,t}^r$ and $U_{i,t}^d$. As evident in the above equations, there is a possibility that a homeowner is unable to meet their financial obligations even at the minimum level of consumption ($s_t = c_t = 0$), even after selling the house. In that case the homeowner is in a state of default ($I_{t,Def}$). I assume that rents or dividends from owning a house are liquid such that the homeowner can decide to consume more or less of the housing consumption and use the rest for non-housing consumption and/or investment in government bond.

If the homeowner decides to sell the house, the proceeds are used to pay the outstanding balance of the mortgage and in the next period the balance $l_{i,t+1}$ and debt interest cost $m_{i,t+1}$ become zero.

Note that the parameter ν determines the optimal division of consumption between housing and non-housing goods at a given level of total consumption ($s_{i,t} + c_{i,t} = Cons.$), independent of other variables. To be more clear, in order to maximize $X_{i,t} = s_{i,t}^{\nu} c_{i,t}^{1-\nu}$, we have $\frac{c_{i,t}}{s_{i,t}} = \frac{1-\nu}{\nu}$.

B.2 Renter Problem

The problem for a renter household is to make consumption decisions in addition to the decision about increasing her leverage and investing in the housing asset $I_{t,Buy}$. The value for renter household is

$$U_{i,t}^{r}(p_t, y_t, w_t) = \max_{c_t, s_t, I_{t,Buy}} \left[(1-\delta) \left(s_t^{\nu} c_t^{1-\nu} \right)^{\frac{1-\gamma}{\theta}} + \delta \mathbb{E}_t \left[\left((1 - I_{t,Buy}) U_{i,t+1}^{r} + I_{t,Buy} U_{i,t+1}^{h} \right)^{1-\gamma} \right]^{\frac{1}{\theta}} \right]^{\frac{\theta}{1-\gamma}} \tag{B.3}$$

subject to

$$\begin{aligned} w_{t+1} &= \left[y_t + w_t - (s_t + c_t) + I_{t,Buy}(l_t - h_t) \right] R_{t+1}^{b}, \\ h_{t+1} &= I_{t,Buy} y_t \frac{DTI}{LTV} R_{t+1}^{h,ex}, \\ l_{t+1} &= I_{t,Buy} y_t DTI, \qquad m_{t+1} = I_{t,Buy} y_t DTI \left(R_{t+1}^{d} - 1 \right), \\ & \text{and} \quad c_t, s_t \geq 0. \end{aligned} \tag{B.4}$$

If the household decides to remain a renter, all her investment will be in the government bond and she does not have any other chance to increase her leverage. If she decides to invest, the value of the house and her available mortgage are constrained by the DTI and LTV ratios. To be more specific, the mortgage outstanding balance at origination is set to be equal to $y_t DTI$ and the house value is $y_t \frac{DTI}{LTV}$. As a result, the mortgage interest payment will be $y_t DTI \left(R_{t+1}^{d} - 1 \right)$.

B.3 Defaulted Household Problem

A defaulted household, is in essence a renter who is restricted from the mortgage market and as a result unable to invest in the housing asset. This restriction is a result of past default. The problem for a defaulted household is characterized by the following Bellman equation:

$$U_{i,t}^{d}(p_t, y_t, w_t) = \max_{c_t, s_t}\left[(1-\delta)\left(s_t^{\nu} c_t^{1-\nu}\right)^{\frac{1-\gamma}{\theta}} + \delta \mathbb{E}_t\left[\omega\left(U_{i,t+1}^{r}\right)^{1-\gamma} + (1-\omega)\left(U_{i,t+1}^{d}\right)^{1-\gamma}\right]^{\frac{1}{\theta}}\right]^{\frac{\theta}{1-\gamma}} \tag{B.5}$$

subject to

$$\begin{aligned} w_{t+1} &= \left[y_t + w_t - (s_t + c_t)\right] R_{t+1}^{b}, \\ &\text{and} \quad c_t, s_t \geq 0. \end{aligned} \tag{B.6}$$

With probability ω this household can become a(n unrestricted) renter and regain eligibility to receive a mortgage in order to invest in the housing market.

B.4 Numerical Procedures in Model Solution

As characterization of the household problem in previous subsections makes it clear, we can reduce the number of state variables by considering ratio of consumption and investment decisions with respect to labor income $y_{i,t}$ instead of considering their absolute values. This is helpful to reach stationarity in the state variables of the model too. Hence, I define

$$\tilde{s}_t = \frac{s_t}{y_t}, \quad \tilde{c}_t = \frac{c_t}{y_t}, \quad \tilde{w}_t = \frac{w_t}{y_t}, \quad \tilde{h}_t = \frac{h_t}{y_t}, \quad \tilde{l}_t = \frac{l_t}{y_t}, \quad \tilde{m}_t = \frac{m_t}{y_t}. \tag{B.7}$$

Gomes, Grotteria, and Wachter (2019) follow a similar scaling method to construct stationary state variables in their optimization problem.

I conjecture that we can use the scaled household value, $\tilde{U}_{i,t} = \frac{U_{i,t}}{y_{i,t}}$ in our numerical solution. Hence, the scaled household utility is represented as

$$\tilde{U}_{i,t} = \left[(1-\delta) \left(\tilde{s}_t^{\nu} \tilde{c}_t^{1-\nu} \right)^{\frac{1-\gamma}{\theta}} + \delta \mathbb{E}_t \left[\left(\frac{y_{t+1}}{y_t} \tilde{U}_{i,t+1} \right)^{1-\gamma} \right]^{\frac{1}{\theta}} \right]^{\frac{\theta}{1-\gamma}}, \tag{B.8}$$

in terms of scaled housing and non-housing consumption values and scaled utility in the next period.

I consider log-values for each of the scaled state and choice variables and discretize with 7-15 points in each dimension. The values inside this multi-dimensional grid are calculated using linear interpolation. For points outside the grid, I use the value at the nearest grid point.

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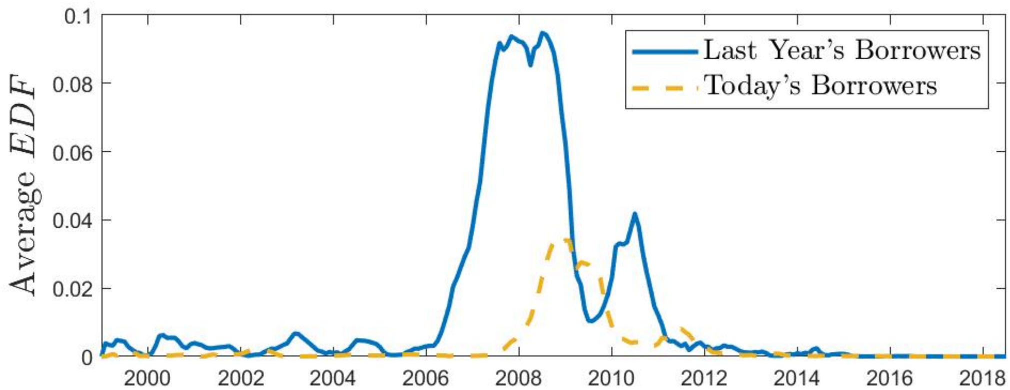
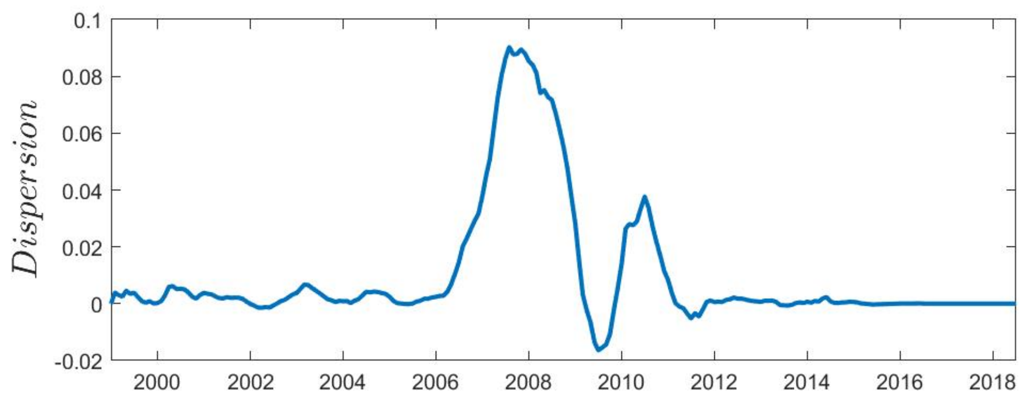
Figure 1: Nationwide Dispersion in Mortgage EDFs

Panel A: Average EDFs across all MSAs



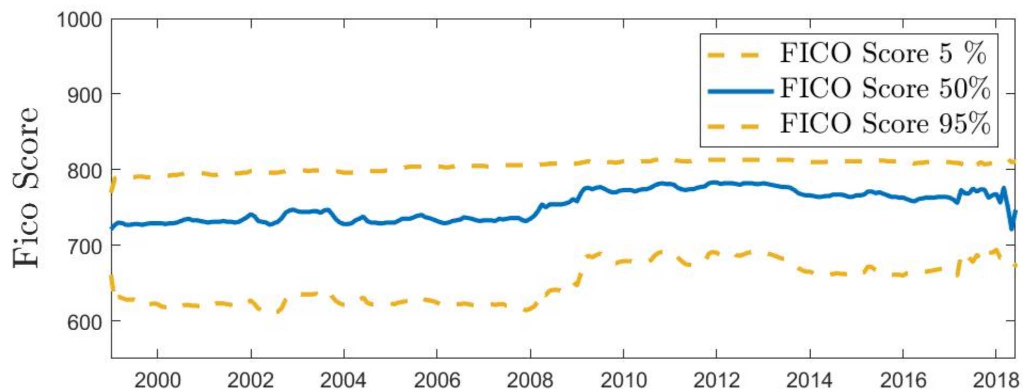
Panel B: Average Dispersion across all MSAs



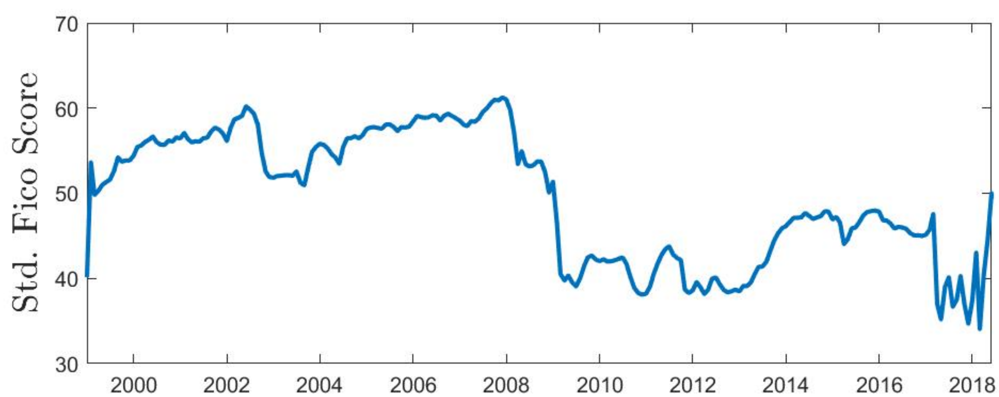
Notes: Panel A in this figure presents average EDF values for today and last year borrowers of mortgages, aggregated to the nation-wide level by averaging the associated EDF values for all the MSAs. Panel B shows dispersion in EDFs by subtracting EDF of borrowers from repayers. Most of the variation in dispersion is driven by changes in EDF of repayers.

Figure 2: Distribution of FICO Scores

Panel A: FICO scores

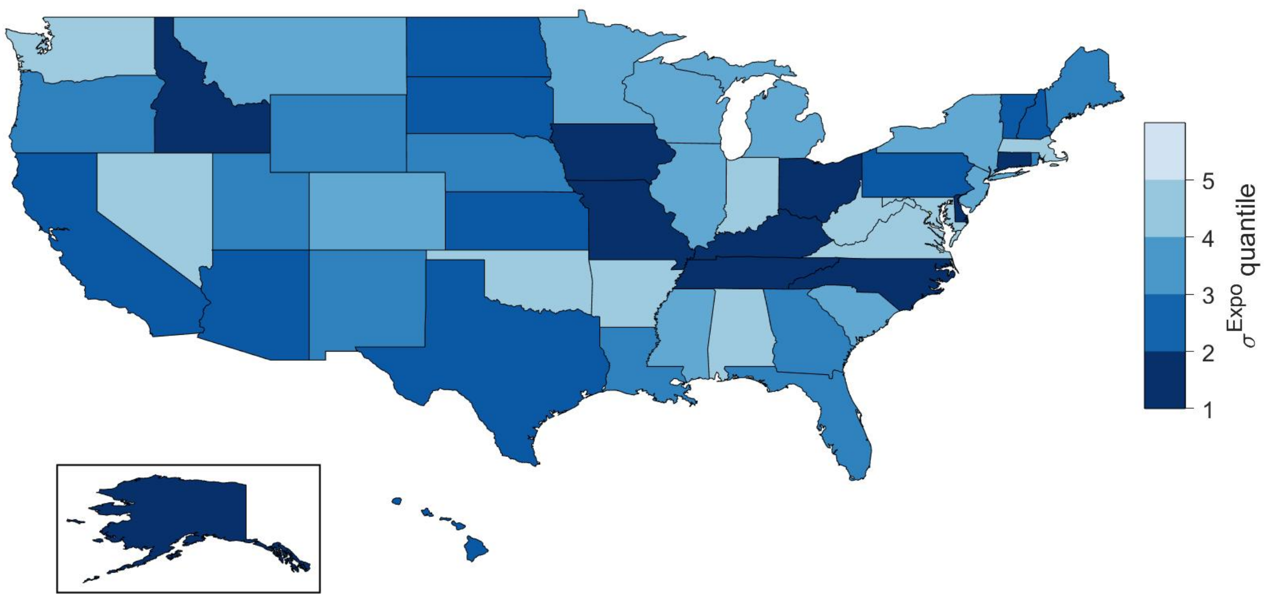


Panel B: Standard Deviation of FICO scores



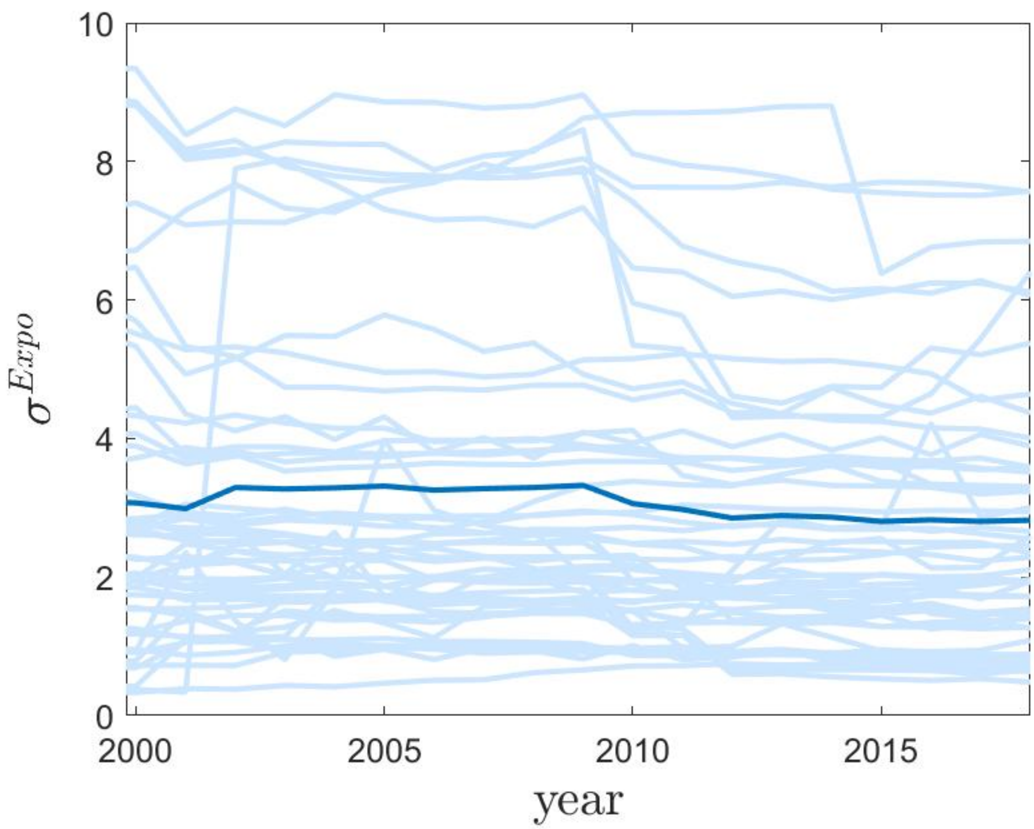
Notes: Panel A in this figure presents 5, 50 and 95 percentiles of FICO credit score distribution for all the borrowers in the data. Panel B depicts the standard deviation of FICO credit scores.

Figure 3: Heterogeneity in Labor Income Exposures Across States



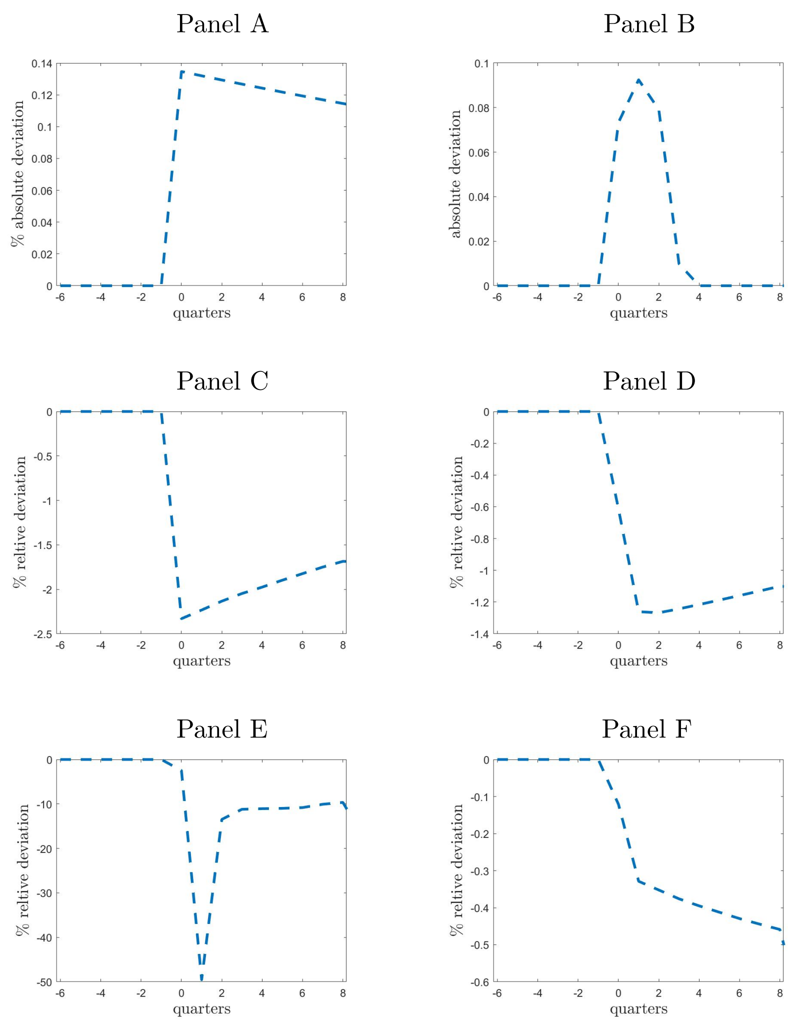
Notes: The figure depicts average heterogeneity in exposures, σ^{Expo}, across different states. Darker colors represent less heterogeneity in exposures.

Figure 4: Heterogeneity in Labor Income Exposures Across States in Time



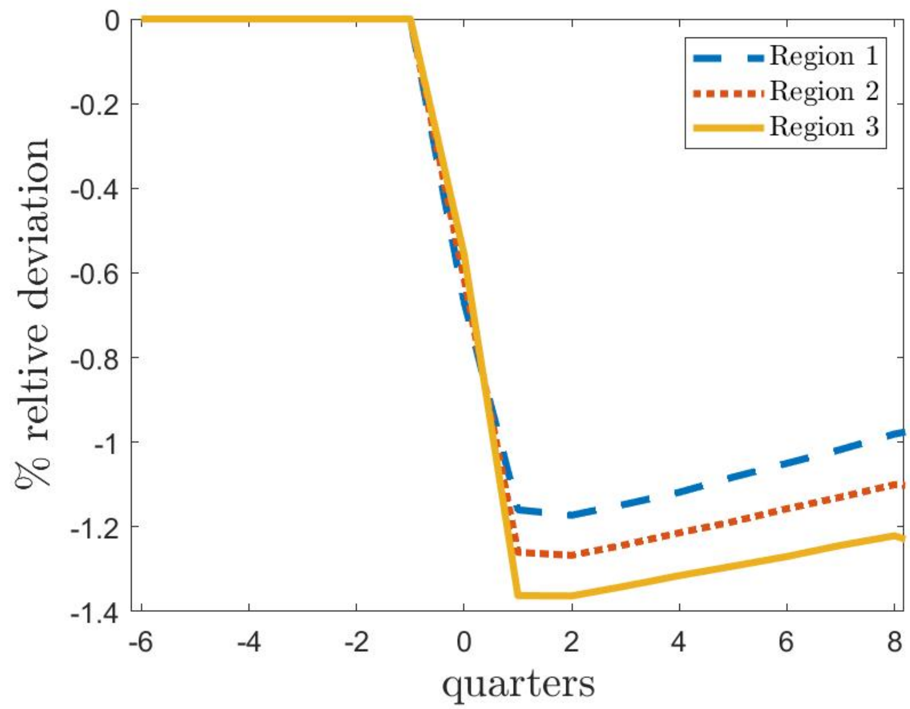
Notes: The figure depicts average heterogeneity in exposures, σ^{Expo}, across different states in time. The darker line represent average σ^{Expo} at each point in time.

Figure 5: Impulse Response Functions



Notes: This figure plots the impulse response function of model variables in the following 8 quarters, to a one standard deviation positive shock to probability of rare events. Panel A shows absolute change in probability of rare disaster in percentages. Panel B depicts the absolute change in $Dispersion$. Panels C, D, E, F show plot the relative change in consumption, GDP, housing investment and mortgage credit.

Figure 6: Heterogeneity and GDP Impulse Response Function



Notes: This figure plots the impulse response function of GDP per capita for the three regions in the simulations. The heterogeneity of labor income exposures increases from region 1 to region 3.

Table 1: Dispersion and Measures of Aggregate Risk

Variable							
Dispersion	1.00	0.26	0.96	-0.11	0.14	0.17	-0.16
Avergae EDF - today's borrowers	0.26	1.00	0.53	-0.54	0.09	0.74	-0.02
Avergae EDF - last year's borrowers	0.96	0.53	1.00	-0.25	0.15	0.37	-0.14
Price-dividend ratio	-0.11	-0.54	-0.25	1.00	0.48	-0.35	0.14
CAY (Lettau and Ludvigson, 2001)	0.14	0.09	0.15	0.48	1.00	0.32	0.15
GZ spread (Gilchrist and Zakrajšek, 2012)	0.17	0.74	0.37	-0.35	0.32	1.00	-0.02
VRP (Bollerslev, Tauchen, and Zhou, 2009)	-0.16	-0.02	-0.14	0.14	0.15	-0.02	1.00

Notes: this table reports pairwise correlations between *Dispersion*, average EDF of last year's borrowers, average EDF of today's borrowers, price-dividend ratio, CAY (Lettau and Ludvigson, 2001) , GZ credit spread (Gilchrist and Zakrajšek, 2012), and variance risk premium (Bollerslev, Tauchen, and Zhou, 2009). All variables are available in monthly frequency except for CAY which is reported in quarterly frequency. A monthly version of CAY is constructed by assuming it remains constant between quarterly updates.

Table 2: Forecasting GDP Growth

Horizon (Quarter)	1	2	3	4	1	2	3	4
β	-0.033	-0.036	-0.040	-0.041	-0.022	-0.023	-0.024	-0.024
	[-5.93]	[-7.35]	[-8.64]	[-9.78]	[-5.11]	[-6.08]	[-6.85]	[-7.58]
State FE	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	N	N	N	N	Y	Y	Y	Y
R^2	0.026	0.060	0.079	0.103	0.224	0.275	0.309	0.333

Notes: the table reports forecasting regression results for GDP growth at the state level using quarterly data. The fixed-effect regression is specified as follows:

$$\Delta gdp_{i,t\to t+k} = \alpha_i + \alpha_t + \beta Dispersion_{i,t} + \xi \Delta gdp_{i,t-1\to t} + \epsilon_{i,t\to t+k}.$$

Under the estimated coefficients, robust t-stats are reported in parenthesis.

Table 3: Forecasting Employment Growth

Horizon (Month)	1	3	6	9	12	1	3	6	9	12
β	-0.002	-0.003	-0.005	-0.006	-0.007	-0.001	-0.002	-0.002	-0.003	-0.003
	[-4.22]	[-5.00]	[-5.85]	[-6.72]	[-7.71]	[-2.58]	[-2.91]	[-3.38]	[-3.92]	[-4.56]
State FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	N	N	N	N	N	Y	Y	Y	Y	Y
R^2	0.691	0.614	0.481	0.406	0.345	0.734	0.725	0.676	0.648	0.628

Notes: the table reports forecasting regression results for employment growth at the state level using monthly data. The fixed-effect regression is specified as follows:

$$\Delta emp_{i,t \to t+k} = \alpha_i + \alpha_t + \beta Dispersion_{i,t} + \xi \Delta emp_{i,t-1 \to t} + \epsilon_{i,t \to t+k}$$

Under the estimated coefficients, robust t-stats are reported in parenthesis.

Table 4: Forecasting GDP Growth: MSA-Level

Horizon (Year)	1	2	1	2
β	-0.128	-0.110	-0.073	-0.064
	[-10.91]	[-12.55]	[-7.01]	[-7.96]
State FE	Y	Y	Y	Y
Time FE	N	N	Y	Y
R^2	0.0765	0.0763	0.204	0.225

Notes: the table reports forecasting regression results for GDP growth at the MSA level using annual data. The fixed-effect regression is specified as follows:

$$\Delta gdp_{i,t\to t+k} = \alpha_i + \alpha_t + \beta Dispersion_{i,t} + \xi \Delta gdp_{i,t-1\to t} + \epsilon_{i,t\to t+k}$$

Under the estimated coefficients, robust t-stats are reported in parenthesis.

Table 5: Forecasting Employment Growth: MSA-Level

Horizon (Month)	1	3	6	9	12	1	3	6	9	12
β	-0.008	-0.011	-0.014	-0.017	-0.022	-0.005	-0.009	-0.012	-0.013	-0.017
	[-4.22]	[-5.00]	[-5.85]	[-6.72]	[-7.71]	[-2.58]	[-2.91]	[-3.38]	[-3.92]	[-4.56]
MSA FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	N	N	N	N	N	Y	Y	Y	Y	Y
R^2	0.587	0.516	0.383	0.326	0.285	0.625	0.617	0.567	0.552	0.526

Notes: the table reports forecasting regression results for employment growth at the MSA level using monthly data. The fixed-effect regression is specified as follows:

$$\Delta emp_{i,t\rightarrow t+k} = \alpha_i + \alpha_t + \beta Dispersion_{i,t} + \xi \Delta emp_{i,t-1\rightarrow t} + \epsilon_{i,t\rightarrow t+k}$$

Under the estimated coefficients, robust t-stats are reported in parenthesis.

Table 6: Forecasting GDP: Role of Heterogeneity in Exposures

Horizon (Quarter)	1	2	3	4	1	2	3	4
β	-0.033	-0.036	-0.039	-0.040	0.005	0.000	-0.006	-0.010
	[-5.76]	[-7.22]	[-8.58]	[-9.81]	[0.62]	[0.02]	[-0.72]	[-1.46]
γ					-0.016	-0.016	-0.014	-0.013
					[-4.50]	[-4.08]	[-4.13]	[-4.23]
δ	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	[-2.67]	[-2.33]	[-2.21]	[-2.16]	[-2.53]	[-2.20]	[-2.09]	[-2.07]
State FE	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.028	0.067	0.090	0.117	0.032	0.074	0.099	0.127

Notes: the table reports forecasting regression results for GDP growth at the state level using quarterly data. The fixed-effect regression is specified as follows:

$$\Delta gdp_{i,t\to t+k} = \alpha_i + \beta Dispersion_{i,t} + \gamma Dispersion_{i,t} \times \sigma_{i,t}^{Expo} + \delta \sigma_{i,t}^{Expo} + \xi \Delta gdp_{i,t-1\to t} + \epsilon_{i,t\to t+k}$$

Under the estimated coefficients, robust t-stats are reported in parenthesis.

Table 7: Forecasting GDP: Role of Heterogeneity in Exposures

Horizon (Quarter)	1	2	3	4
β	0.002	-0.002	-0.009	-0.013
	[0.23]	[-0.26]	[-0.89]	[-1.51]
γ	-0.018	-0.017	-0.015	-0.013
	[-3.54]	[-3.30]	[-3.35]	[-3.42]
State FE	Y	Y	Y	Y
R^2	0.029	0.069	0.092	0.119

Notes: the table reports forecasting regression results for GDP growth at the state level using quarterly data. The fixed-effect regression is specified as follows:

$$\Delta gdp_{i,t\to t+k} = \alpha_i + \beta Dispersion_{i,t} + \gamma Dispersion_{i,t} \times \sigma_i^{Expo} + \xi \Delta gdp_{i,t-1\to t} + \epsilon_{i,t\to t+k}$$

Under the estimated coefficients, robust t-stats are reported in parenthesis.

Table 8: Forecasting Employment: Role of Heterogeneity in Exposures

Horizon (Month)	1	3	6	9	12	1	3	6	9	12
β	-0.002	-0.003	-0.005	-0.006	-0.007	-0.000	-0.000	-0.001	-0.001	-0.002
	[-4.20]	[-4.97]	[-5.81]	[-6.66]	[-7.61]	[-0.43]	[-0.58]	[-0.43]	[-0.57]	[-0.87]
γ						-0.001	-0.001	-0.002	-0.002	-0.002
						[-3.47]	[-3.36]	[-3.19]	[-2.97]	[-2.76]
δ	0.000	0.000	0.000	-0.000	-0.000	0.000	0.000	0.000	0.000	-0.000
	[0.40]	[0.24]	[0.10]	[-0.09]	[-0.31]	[0.49]	[0.34]	[0.23]	[0.06]	[-0.16]
State FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.689	0.612	0.479	0.405	0.345	0.689	0.613	0.481	0.409	0.351

Notes: the table reports forecasting regression results for employment growth at the state level using monthly data. The fixed-effect regression is specified as follows:

$$\begin{aligned}\Delta emp_{i,t\to t+k} &= \alpha_i + \beta Dispersion_{i,t} + \gamma Dispersion_{i,t} \times \sigma_{i,t}^{Expo} \\ &\quad + \delta \sigma_{i,t}^{Expo} + \xi \Delta emp_{i,t-1\to t} + \epsilon_{i,t\to t+k}\end{aligned}$$

Under the estimated coefficients, robust t-stats are reported in parenthesis.

Table 9: Forecasting Employment: Role of Heterogeneity in Exposures

Horizon (Month)	1	3	6	9	12
β	-0.000	-0.001	-0.001	-0.001	-0.001
	[-0.37]	[-0.61]	[-0.43]	[-0.52]	[-0.77]
γ	-0.001	-0.001	-0.002	-0.002	-0.003
	[-3.53]	[-3.31]	[-3.13]	[-2.91]	[-2.72]
State FE	Y	Y	Y	Y	Y
R^2	0.689	0.613	0.481	0.409	0.350

Notes: the table reports forecasting regression results for employment growth at the state level using monthly data. The fixed-effect regression is specified as follows:

$$\Delta emp_{i,t\to t+k} \quad = \quad \alpha_i + \beta Dispersion_{i,t} + \gamma Dispersion_{i,t} \times \sigma_i^{Expo} + \xi \Delta emp_{i,t-1\to t} + \epsilon_{i,t\to t+k}$$

Under the estimated coefficients, robust t-stats are reported in parenthesis.

Table 10: Calibration of Model Parameters

Preferences				
	δ	γ	ψ	ν
	0.997	4	1.5	0.15
Disaster risk				
	$\bar{p}$	ρ_p	σ_p	q
	0.0075	0.98	0.0175	0.4
SDF				
	r_0	r_p	σ_{my}	σ_{mp}
	0.01	3	-0.02	1.2
Housing sector				
	μ_s	σ_s	ρ_s	ϕ_s
	0.005	0.01	1	3
Household labor income	σ_y^i	ρ_y^i	ϕ_y^i	
	0.1	0.1	[0.5, 1, 1.5]	
Household debt				
	DTI	LTV	ω	r_{debt}
	14	0.8	0.0375	1

Notes: This table reports the parameters of the model, calibrated at quarterly frequency.

Table 11: Coefficients of Predictive Regressions: No Disaster Samples

Panel A					
	Horizon (Quarter)	1	2	3	4
GDP	β	-0.035	-0.024	-0.013	-0.008
	R^2	0.058	0.050	0.021	0.009
Consumption	β	-0.080	-0.032	-0.015	-0.008
	R^2	0.109	0.036	0.015	0.010
Investment in housing	β	-0.743	-0.506	-0.216	-0.161
	R^2	0.350	0.239	0.251	0.230

Panel B					
	Horizon (Quarter)	1	2	3	4
GDP	β	-0.032	-0.020	-0.010	-0.006
	γ	-0.012	-0.016	-0.010	-0.007
	R^2	0.056	0.049	0.020	0.009
Consumption	β	-0.077	-0.032	-0.016	-0.008
	γ	-0.019	0.000	0.003	0.004
	R^2	0.107	0.033	0.012	0.007
Investment in housing	β	-0.575	-0.499	-0.211	-0.158
	γ	-0.582	-0.068	-0.067	-0.022
	R^2	0.350	0.239	0.251	0.231

Notes: This table presents median coefficients and R^2s estimated in predictive fixed-effect regressions of the following form:

$$\Delta y_{i,t\to t+k} = \alpha_i + \beta Dispersion_{i,t} + \gamma Dispersion_{i,t} \times \sigma_i^{Expo} + \xi \Delta y_{i,t-1\to t} + \epsilon_{i,t\to t+k},$$

where y stands for growth rate of GDP, consumption, and investment in housing asset. The simulations include a total of 10,000 simulated economies simulated for 20 years, out of which 5,863 economies do not experience a disaster.

Table 12: Coefficients of Predictive Regressions: All Samples

Panel A					
	Horizon (Quarter)	1	2	3	4
GDP	β	-0.040	-0.027	-0.016	-0.010
	R^2	0.067	0.056	0.030	0.018
Consumption	β	-0.080	-0.034	-0.018	-0.010
	R^2	0.100	0.037	0.018	0.012
Investment in housing	β	-0.902	-0.586	-0.276	-0.203
	R^2	0.333	0.232	0.235	0.215

Panel B					
	Horizon (Quarter)	1	2	3	4
GDP	β	-0.038	-0.023	-0.013	-0.008
	γ	-0.008	-0.012	-0.007	-0.005
	R^2	0.066	0.055	0.029	0.017
Consumption	β	-0.082	-0.036	-0.019	-0.011
	γ	-0.001	0.006	0.006	0.006
	R^2	0.099	0.035	0.015	0.010
Investment in housing	β	-0.731	-0.587	-0.271	-0.202
	γ	-0.498	-0.006	-0.029	0.002
	R^2	0.333	0.232	0.235	0.215

Notes: This table presents median coefficients and R^2s estimated in predictive fixed-effect regressions of the following form:

$$\Delta y_{i,t\to t+k} = \alpha_i + \beta Dispersion_{i,t} + \gamma Dispersion_{i,t} \times \sigma_i^{Expo} + \xi \Delta y_{i,t-1\to t} + \epsilon_{i,t\to t+k},$$

where y stands for growth rate of GDP, consumption, and investment in housing asset. The simulations include a total of 10,000 simulated economies simulated for 20 years.