The Option Value of Consumer Bankruptcy. Can uninsured idiosyncratic risk explain bankruptcy patterns?*

Ethan Cohen-Cole†
University of Maryland - College Park
Robert H Smith School of Business

Initial Draft: 5 January 2009
This Draft 5 June 2009

Abstract

This paper contributes to the literature on the causes of consumer bankruptcy. It presents the bankruptcy decision as an irreversible choice with an embedded real option. The principal empirical finding is that cross-sectional variances of economic factors, such as unemployment, are strong predictors of bankruptcy rates and consistent with the real options model. This supports evidence that individuals face increased uncertainty and indicates that uninsurable economic shocks are poorly characterized by local information. Finally, the paper concludes that policy discussions may be disproportionately focused on credit variables such as utilization rates and supply of credit rather than exposure to risk.

JEL Classification Codes: D14, I30, K45

Keywords: Bankruptcy, Idiosyncratic Risk, Real Options

*Nicholas Kraninger and Jonathan Morse provided excellent research assistance. Some portion of this work was completed while Cohen-Cole was in residence at University of California - Berkeley. The author benefitted from discussions with Matt Brown, Dean Corbae, Mary Daly, Erik Hurst, Todd Prono and Rob Valleta. The views expressed in this paper are solely those of the authors and do not reflect official positions of the Federal Reserve Bank of Boston or the Federal Reserve System.

†Ethan Cohen-Cole: University of Maryland – College Park, Robert H Smith School of Business, Van Munching Hall College Park MD 20742 617.229.5027. ecohencole@gmail.com

1 Introduction

This paper aims to contribute to the growing empirical literature on the causes of consumer bankruptcy in two ways. First, it finds that cross-sectional variances of economic factors are strong predictors of bankruptcy rates. This suggests both that the economic shocks faced by households may be poorly characterized by local information and that the impact of income risk may be larger than previously thought. Second, it suggests that policy regarding changes in the bankruptcy rate may be disproportionately focused on credit variables such as utilization rates and supply of credit rather than exposure to risk.

The stylized fact that personal bankruptcy filings have risen dramatically over the past 30 years has proven very hard to explain with purely empirical methods. While Fay *et al.* (2002) find that the 'benefit' to bankruptcy is the most important factor amongst the range that they analyze, it nonetheless explains a relatively small portion of the variation in bankruptcy rates. Indeed, Cohen-Cole and Duygan-Bump (2008), among others, find that the gamut of risk factors is relevant to the bankruptcy decision, but of very small magnitude.

Similarly, the hypotheses in Fay *et al.* (2002) and Gross and Souleles (2002) hold that while social factors are important to the bankruptcy decision (see also Cohen-Cole and Duygan-Bump, 2008), they are insufficient to explain the time series or cross-sectional patterns in the data. Indeed, a great deal of variation in bankruptcy rates remains unexplained. Why?

The hypothesis, and empirical investigation, in this paper is that available data, as currently analyzed, does not proxy well for the exposure to financial risk that individuals currently face. That is, over the past generation, individuals in the United States have faced increased volatility of current income, decreased access to long-term income guarantees such as private pensions, an increased risk that the social security system will be inadequate at the time of retirement, increased cost and access to health insurance, etc. Each of these can lead to bankruptcy either directly or indirectly. For example, health shocks can lead directly to increased expenditures. Less directly, the lack of long-term income insurance can lead to increased short term risk taking.

A problem, of course, is that we, as researchers, cannot easily observe the distribution of risk faced by individuals. In many economic studies, including the existing work on bankruptcy, these risks are proxied by information on various demographic or local economic variables. The data are often collected at individual or local levels and will include such information as age, gender, community income or education levels, unemployment, etc. The individual level variables are single observations and are, as a consequence, potentially unable to characterize distributional differences in exposure to risk. Similarly, community level variables are typically included as mean measures at some geographic level. As a result, though these measures can capture location specific risks of some types, they pose two problems. One, they are similarly limited as individual data in their ability to characterize local risk distributions. The average educational level does not necessarily characterize the risks faced by the more or less well educated community members. Two, they cannot provide information on exposure to other risks that individuals face. That is, if highly educated individuals face shocks due to change at the level of their occupation, on a national rather than local scale, then local averages provide little salient information.

To help characterize individual behavior related to bankruptcy, the paper looks to two sources. First, it uses the standard model of permanent income as intellectual motivation and as the basis for some exploratory data analysis. Second, the paper provides a highly stylized model of the bankruptcy decision that is motivated by the permanent income model. The goal of each here is broadly to explain patterns of rising bankruptcies in the US. The permanent income model holds that income can be decomposed into a permanent and transitory factor. Moreover, a number of papers have included a permanent component that is described by a random growth process (see Gottschalk and Moffitt, 2008). This is useful in the discussion of the bankruptcy, because such a decision can be described and analyzed using the tools of the real options literature.

That is, one can interpret the bankruptcy declaration as a 'real' option, in the tradition of McDonald and Siegel (1986) and Dixit and Pindyck (1994). Indeed, this framework has been used to explain corporate liquidation (Mason, 2005) and security valuation (Brockman and Turtle, 2003). Declaring bankruptcy is tantamount to changing one's current financing structure and taking on a new set of risks. On the revenue side, an individual obtains a new revenue stream, one that does not include debt service payments. On the cost side, the individual incurs some non-zero cost associated with a change in individual credit standing. This type of model is well known in the corporate finance literature and its well known implications are explored below. The paper will discuss the model as a tool to understand drivers of behavior and illustrate that its conclusions are largely consistent with the data.

Once this mapping is complete, the paper turns to a two-part empirical analysis of the bankruptcy decision. Beginning with the time series dimension, the paper uses income volatility information provided by Jacob Hacker[1] and a methodology from Gottschalk and Moffitt (1994, 2002, 2008), to show that permanent income variation can explain more than 90% of the change in bankruptcy rates over time. As would be expected, variation in transitory income has little or no impact on bankruptcy rates.

To confirm this result, the paper conducts an analysis in the cross-section using a dataset of more than 27 million individual credit reports. Using information from June 2006 and December 2007, the paper evaluates the bankruptcy choice by expanding the empirical work in Fay *et al.* (2002) and Gross and Souleles (2002) to include proxies for exposure to other forms of risk. The empirical results confirm the intuition of the permanent income and the simplified real options model. Proxies for volatility of permanent income are strong predictors of bankruptcy. While a doubling of the local unemployment rate increases the bankruptcy rate by only 0.08, a ten percent increase in the cross-sectional variance leads to a three-fold increase in the bankruptcy rate.

Crucially for policy purposes, these measures of risk appear to be of much greater empirical importance than existing credit or socio-demographic factors.

The paper continues in Section 2 with some background on the literature on bankruptcy and measurement of income variation. Section 3 discusses the prototypical model of income. Sections 4 and 5 discuss the simple outlines and implications of a real options model that builds on the intuition in Section 3. Section 6 discusses the credit bureau data used in the empirical component

[1] http://pantheon.yale.edu/~jhacker/PSID_Data_NYT.htm

of the paper and Section 7 presents baseline results. Section 8 concludes.

2 Background

2.1 Bankruptcy

The three decades to the present have seen an incredible rise in consumer bankruptcy (see Figure 2). Accompanying this rise has been an active policy debate and a large research agenda to explain this pattern and household bankruptcy decisions in general. The literature to date can be placed into two categories, according to the approaches used: i) quantitative macroeconomic models that calibrate stylized economic models to match related moments of the data, such as the increase in household debt and / or the bankruptcy rate itself and ii) applied analyses that use micro data to understand, from an empirical perspective, the factors that drive households' bankruptcy decisions. Unfortunately, due to a general lack of data, the number of studies in this second group is quite small. This paper draws on prior work by the author (Cohen-Cole and Duygan-Bump, 2008) as well as a much more comprehensive review in White (2007).

Quantitative macroeconomic models include Livshits *et al.* (2007a) and Chatterjee *et al.* (2007), which outline dynamic equilibrium models where interest rates vary with borrowers' characteristics. These models can match levels of U.S. bankruptcy filings and debt-income ratios with reasonable parameter values. Indeed the latter paper (Chatterjee *et al.* 2007) is stylistically similar in form to ours in that it characterizes distinct earnings paths for individuals in order to infer default and allows agents to choose when to default. This setup allows them to characterize the behavior of different types of agents, and thus to predict which types file for bankruptcy. Since our paper is empirically based, we look to infer the risk faced by individuals across a wide range of population subsets. Overlain is the *real option* to default; that is, agents understand that the filing choice is an irreversible choice that can be exercised once.

Athreya (2002) analyzes the welfare implications of different bankruptcy laws while Li and Sarte (2006) analyze consumers' choice of Chapter 7 versus Chapter 13 using dynamic equilibrium models of bankruptcy.

In an intellectual antecedent to this paper, Livshits *et al.* (2007b) use these models to evaluate possible alternative explanations for the rise in bankruptcies. They consider two sets of explanations. The first is the possibility that there has been an increase in idiosyncratic uncertainty at the household level due to increased labor earnings volatility or an increase in the number of households without medical insurance coverage (Barron *et al.*, 2000 and Warren and Warren Tyagi, 2003). This category also captures the demographic scenario that argues that the passing of the baby-boomers through the prime bankruptcy ages and changing family structure have increased the number of risky households (Sullivan *et al.* 2000).

The second category they analyze is the role of the changes in the credit market environment that have made bankruptcy more attractive or expanded credit to a broader set of households, including higher-risk ones. This second set of explanations includes the story that credit market innovations (such as the development and spread of credit scoring) facilitated the increase in credit granted to households by reducing the transaction costs of lending (Athreya 2004). But it also includes the possibility that the personal costs incurred by defaulters have fallen substantially, either as a result of improved bankruptcy filing procedures, the learning by households from each other as to how to navigate the bankruptcy process, or a decrease in social stigma associated with default. The results from their quantitative exercise show that the rise in filings mainly reflects the changes in the credit market environment. They find that credit market innovations can largely account for the rise in consumer bankruptcy.

The empirical results below will find that increases in uncertainty are considerably more important in explaining bankruptcy rates than the credit factors that Livshits *et al.* (2007b) find important. There is no immediate explanation to link the difference between the theoretical and empirical findings.

Athreya (2004), on the other hand, argues that the increases in bankruptcy due to a decrease in stigma should generate a supply-side response whereby borrowing on the unsecured credit market grows more expensive. In other words, lenders should respond by increasing interest rates if borrowers become more willing to default, which would in turn lead to smaller debt holdings across households: an observation that contradicts the stylized facts for the period under study. In particular, he uses an equilibrium model of personal bankruptcy (similar to Athreya 2002) to show that decreasing the non-pecuniary cost of bankruptcy, as a fall in stigma implicitly does, indeed increases bankruptcy rates but yields counterfactual implications for the time path of debt held by households. Consequently, he concludes that the facts can be better explained by changes in the credit market environment and the associated decrease in transaction costs, but that social stigma is still relevant to a small degree. Although these results do not speak directly to the stigmatization question or to the question on the decomposition of the social effect, they do lend support to a declining cost story, a phenomenon correlated with increased information exchanges.

These findings are in general consistent with those reported in the two seminal papers in the applied analysis category based on micro data. Fay *et al.* (2002) estimate a model of the household bankruptcy decision using the Panel Study of Income Dynamics (PSID), and show that households are more likely to file for bankruptcy when their financial benefit from filing—the value of debt discharged in bankruptcy minus the value of nonexempt assets—rises. Similar to the findings of Livshits *et al.* (2007b), they find little support for the alternate hypothesis that households file for bankruptcy when adverse events occur. They also find that, even after controlling for state and time fixed effects, households are more likely to file for bankruptcy if they live in districts which have higher aggregate bankruptcy filing rates. Their interpretation of this finding is that local trends in bankruptcy filings are an important determinant of whether households file. They conjecture that this result "could reflect local differences in the level of bankruptcy stigma or local differences in the administration of bankruptcy law that make the district differ from the state, or could reflect the influence of information cascades."[2]

Gross and Souleles (2002) use administrative credit-card account data to analyze credit card delinquency and personal bankruptcy. They estimate duration models for default to disentangle

[2] Fay *et al.* (2002), p. 710.

the two explanations of default: a deterioration of the risk-composition of borrowers and declining default costs that lead to an increase in borrowers' willingness to default. To capture the changes in associated costs of default, they use time dummies to capture the changes in the hazard function over time, as well as the lagged bankruptcy filing rate in the state as in Fay *et al.* (2002). Their results rule out the risk effect and conclude that households did appear to be more willing to default in the late 1990's than in earlier periods, all else equal. The authors do acknowledge that these results do not directly identify what underlies the estimated demand effect, even though the finding that default rises with the bankruptcy filing rate in the state is "suggestive" of a decline in stigma or information costs.

To understand the relative importance of social factors, Cohen-Cole and Duygan-Bump (2008) use data from a US credit bureau to disentangle the relative contributions of social stigma and information sharing. Their results show that information sharing is more likely than stigma to be a cause of the changes in bankruptcy rates. However, they conclude that much remaining variation is left to explain.

Perhaps the largest remaining disconnect between the empirical and the quantitative macro papers is that the latter's apparent ability to explain patterns of bankruptcy is belied both by some disagreement and by the inability of empirical work to explain the full variation in bankruptcy rates either over time or in the cross section. To be clear, the few available empirical studies have been crucial to understanding bankruptcy patterns and in motivating future work, but many questions remain open.

2.2 Income stability

Gottschalk and Moffitt's seminal 1994 paper documented the fact that the rise in earnings inequality was in part due to the rise in volatility of earnings. The importance of this finding was to establish that both changes in trend earnings due to factors such as skill-biased technological change *and* idiosyncratic volatility can generate the phenomenon of rising inequality. Gottschalk and Moffitt (1994) used data from the PSID to decompose the permanent and idiosyncratic components of the individual income process using a method attributed to Carroll (1992).[3]

This paper has generated a wide range of studies, in which there is very little agreement on the results of this decomposition. Haider (2001), for example, used PSID data for 1967-1991 to conclude that temporal earnings instability increased throughout. Cameron and Tracy (1998) use CPS data from 1967-1996 to replicate most of Haider's conclusions. Dahl *et al.* (2008) used Social Security earnings histories for 1980-2003 to find similar trends. They further find indications of a rise in men's earnings volatility in the early 2000s. Others, including Moffitt and Gottschalk (2002) and Hacker (2006) find that transitory variance rose in the 1980s, then fell in the 1990s. Daly and Valleta (2008) find relatively small increases in permanent and transitory components in

[3] Specifically, Carroll (1992) noted that the identification of the canonical income model with permanent and transitory components can be obtained with information from covariances in the income process at points in time sufficiently far apart such that transitory shocks have vanished.

the 1980s and 1990s but conclude that both appear important across a literature that has come to little agreement.

Regardless of the consensus in this literature, for the purposes of this paper, the question is the potential impact of income volatility on bankruptcy. Bankruptcy decisions are without a doubt related to exposure to economic shocks. A common explanation is that individuals are more likely to file for bankruptcy after facing some type of income shock, for example, related to unemployment, health, divorce, etc. The permanent component of these shocks will be a critical factor in the bankruptcy choice. Indeed, from an understanding of the nature of these shocks, we should have an improved understanding of the resulting bankruptcy. As a result, one can potentially infer changes in bankruptcy rates from the nature of the income process itself. We turn to this in the next section.

3 Modeling Income

In each time period, one can look at the covariance of the earnings in that time period with prior earnings. One can use a model of permanent vs. transitory income to separate the permanent and temporary variances as follows:

$$y_{it} = \mu_i + \nu_{it},$$

where y_{it} denotes income at time t, μ_i is the permanent component and ν_{it} the transitory. Variances of μ_i and ν_{it} are σ_μ^2 and σ_ν^2 respectively. If one makes the assumption that the two are uncorrelated; the variance of log income is the sum of the two: $\sigma_y^2 = \sigma_\mu^2 + \sigma_\nu^2$. Thus, one can also state that σ_μ^2 is equal to the covariance of log earnings between two time periods sufficiently distant that transitory errors are uncorrelated. That is, $cov\left(y_{it}, y_{it'}\right) = \sigma_\mu^2$ if $cov\left(\nu_{it}, \nu_{it'}\right) = 0$. With this, one can simply look for a case where this is true and use the estimated σ_μ^2 and the measured total σ_y^2 to calculate period-specific σ_ν^2 as $\sigma_\nu^2 = \sigma_y^2 - \sigma_\mu^2$.

This simple model is expanded in various ways. For the purposes here, the model is expanded to include a further decomposition of the permanent component of income. For example, one can write that the permanent component evolves according to random growth process such as:

$$d\mu_i = \alpha_i \mu dt + \tilde{\sigma}_i \mu d\zeta, \tag{1}$$

where time, t, is continuous and ζ is a Weiner process. This describes the permanent component of income as following a geometric Brownian motion (GBM) with a drift. It implies that the distribution of shocks to income changes over time. Moreover, the subscript, i, notes that the changes in the income process are individual specific. The shock process faced by John K. may be growing while Jim D.'s is shrinking.

The dispersion in μ_i can now be thought of as being generated by changes in the trend income and some variation around it. The first broadly corresponds to phenomena such as skill-biased technological change. High skilled individuals that have seen regular increases in earnings are largely associated with positive α, while the portion of low skilled individuals that have seen real wage declines have a negative α. The latter term, denoted with $\tilde{\sigma}_i$, broadly corresponds to the fact that there is a great deal of variation in the nature of shocks at the individual level. Figure 3 illustrates this point. It shows three realizations of the process described in (1). The three lines are identical up to the specification of the α term. When the paper turns to estimation, it will use proxies for these two components of the permanent variance.

4 A Model

This section will provide the outlines of a real options model of the bankruptcy decision. Individuals are viewed as having the choice (option) to enter bankruptcy. As is well understood, this option has some associated value. The innovation here is to incorporate the intuition of the income volatility literature to allow this option to have stochastic properties. In doing so, it is possible to relate the implications of the model to observed phenomenon.

Conceptual Set-Up

The model appropriates a standard stochastic dynamic optimization model by translating the McDonald and Siegel (1986) firm into an individual facing a bankruptcy decision. The starting point for the translation to an individual is that the classic problem views a firm as having zero cash flow and 'waking up' one day with an investment opportunity. This opportunity will pay a constant return once initiated; however, prior to the investment, the future return fluctuates stochastically according to some process. A similar pattern exists on the cost side. Again, no costs prior to investment, followed by a constant cost determined by the time of initiation.

In this model, we can think of an individual facing two stochastic processes as well. These will jointly constitute the permanent component of the bankruptcy decision. The first process, the 'return,' can be thought of as the payoff to declaring bankruptcy. This payoff, once taken, is a constant future benefit; however, in advance, one can think of the potential benefit to declaring to have a stochastic component. This process is determined by a combination of idiosyncratic and macroeconomic factors that impact an individual's ability to pay his debts. The model takes the presence of previously incurred debts as exogenous.

Costs of declaring bankruptcy are also stochastic. These costs have been widely discussed in the literature and may include social stigma and / or some degree of exclusion from credit markets. While both of these may have stochastic components post- as well as pre-bankruptcy, this paper incorporates the full variation into the advance decision; that is, individuals can 'lock-in' their costs by choosing the right time to go bankrupt such that stigma is relative low and there is relatively easy access to credit ex-post.

Of course, prevailing conditions may also provide some trend component to both individual payoffs and costs.

Some Details

Expected returns and costs to bankruptcy follow geometric Brownian processes (GBM). Such processes are standard in the capital budgeting literature, and are used here both for convenience and because they have been proposed within the income variation research agenda as being potential components of the permanent income process. Since the goal is to talk about bankruptcy, and thus removal of debt obligations, this translates nicely to consideration that all payoffs are debt funded. Of course, the 'funding' is associated with removing rather than adding debt, but the math will remain the same. The cost process is allowed to be correlated with investment returns to allow for the fact that changes in the availability of credit overall may change both the benefits of expunging debt as well as the difficulty of obtaining new debt.

Individuals have a single choice to make: whether to declare bankruptcy. The return and cost processes can be modeled as:

$$dB = \phi B dt + \omega B dz \quad (2)$$

$$dC = \beta C dt + \eta C dy, \quad (3)$$

where B is the GBM for the benefit 'process' and C is the GBM for the cost process. The parameters ϕ, β and ω, η are constants. The model includes two standard Weiner processes labeled z and y. The paper also allows time, t, to be continuous and individuals to operate with an infinite horizon. Note that B and C have possibly correlated fundamental innovations. The correlation between the two is assigned a correlation coefficient ρ. To add some traction and reality to the model, one can introduce fixed costs of filing for bankruptcy. These are labeled κ.

Of course, this model has a well known solution. In an unconstrained market, individuals choose when to declare bankruptcy. To obtain a solution, one calculates first the individual value function. Let W be the value of declaring bankruptcy, inclusive of costs and benefits. Note that given the structure of the underlying processes, one can rewrite this decision problem in terms of a single process:

$$\mu = \frac{B}{C},$$

given this, the problem reduces to a well known one that has been studied extensively.

The solution follows standard methods. Then the Hamilton-Jacobi-Bellman equation can be written as follows:

$$rW = \alpha \mu W_\mu + \frac{1}{2}\sigma^2 \mu^2 W,$$

where W_μ and $W_{\mu\mu}$ are the first and second partial, respectively of W with respect to μ, r is the current interest rate paid on an individual's own debt, and α and σ are the appropriate trend and variance terms for μ. In these models, r is the risk-free rate. Investors are able to choose between the risk free investment that pays r and a risky investment opportunity that pays an uncertain amount. In the bankruptcy case, the risk-free option is akin to renegotiating current debt obligations at a long-term fixed rate outside of a bankruptcy proceedings. Thus, r is the relevant cost of funds for the individual. As is standard, this is a no-arbitrage condition. The right-hand side is the combination of the expected returns, net of costs, to bankruptcy, $\phi \mu W_\mu$, and the real option value, $\frac{1}{2}\omega^2 \mu^2 W_{\mu\mu}$.

There are two remaining equations needed to close the model. First, a value-matching condition that sets the first derivatives of the Bellman equation equal at the time of bankruptcy:

$$W^* = \mu^* - \kappa.$$

The value-matching condition is effectively a guarantee of continuity at the optimal exercise point. Also note that W^* and μ^* indicate the values at the optimal point. Second, a smooth-pasting condition, sets the second derivatives of the Bellman with respect to μ equal:

$$W_\mu = 1.$$

This ensures that the decision made is not only correct up continuity, but also that there is no 'kink' in the value function at the optimal point. Smooth-pasting ensures that the derivative of the value function is continuous at the optimal point. Another way to view this is to see that the bankruptcy choice is a trade-off between the size of the net benefit today and the effect of discounting by waiting, where the appropriate discount rate is the individual's own cost of debt.

Finally, the model includes a zero barrier condition that ensures that the Brownian process for μ does not go below zero. This ensures that no agents are faced with bankruptcy process that are net costly. Once the bankruptcy laws were revised in 1973 to make bankruptcy fully elective, there is little reason to believe that individuals would declare bankruptcy if the net payoff were negative:

$$W(0) = 0.$$

Model Solution

After a bit of math, it's possible to show that W is indeed the solution to

$$rW = \alpha\mu W_\mu + \frac{1}{2}\sigma^2\mu^2 W_{\mu\mu}, \tag{4}$$

where $\alpha = \phi - \beta$, $\sigma^2 = \omega^2 + \eta^2 - \omega$, and the functional form guess from the literature is $W = \delta\mu^\theta$. After plugging into (4), the solution is

$$r\delta\mu^\theta = \delta\tilde{\alpha}\theta\mu^{\theta-1}\mu + \frac{\sigma_i^2}{2}\theta(\theta-1)\mu^{\theta-2}\mu^2,$$

where $\tilde{\alpha} = \phi - \beta - \frac{1}{2}\eta^2 - \frac{1}{2}\eta\omega\rho$. This solution follows if θ satisfies:

$$r = \alpha\theta + \frac{\sigma^2}{2}\theta(\theta-1).$$

Looking only at the positive root, it is optimal to declare when the process $\mu = \mu^*$. The value of μ at μ^* can be expressed as

$$\mu = \frac{\theta}{\theta-1}\kappa,$$

and θ can be written as

$$\theta = \frac{1}{2} - \frac{\alpha}{\sigma^2} + \sqrt{\left(\frac{\alpha}{\sigma^2} - \frac{1}{2}\right)^2 + \frac{2(r-\beta)}{\sigma^2}}.$$

5 Simulation and Intuition from Model

In this section, the paper provides the output of the real options model developed in Section 4 above. To start, one can make a few adjustments to the baseline model in order to capture additional features of the data. As indicated in equations (2) and (3), bankruptcy can be viewed as the interaction of two stochastic processes representing the benefits and costs of filing:

$$\begin{aligned} dB &= \phi B dt + \omega B dz && (5) \\ dC &= \beta C dt + \eta C dy, && (6) \end{aligned}$$

Of course, as have been noted for some time (Fay *et al.* 2002), the benefit to filing varies widely by individual. Indeed, they find that it also is a key factor in the decision to file. As such, one needs to allow the B process to vary across individuals in some fashion. In keeping with the income variation literature, this paper posits that both the trend and variation of the process are likely to differ across individuals. At a high level, one can think of the benefit to filing as being a proxy for both accumulated debt and an individual's income process. Trend increases in debt will impact α, variation in this number will impact σ. As well, all else equal, trend income will impact the level of this debt and windfall shocks to income or expenses will impact σ.

To justify the use of differentiated α, σ parameters, one needs look no further than the observed heterogeneity in each of the factors. Table 5 provides a number of informative cross-tabs to make this assumption clear. Each row is a distinct socioeconomic group. The first column shows income trends, the second variation of income for this socioeconomic group across locations. Finally, the fourth column shows the variance of credit limits, again across locations. As should be clear, there is sufficient apparent heterogeneity.

Similarly, there is reason to believe that the costs to filing differ by individual. A recent paper by Cohen-Cole *et al.* (2009), finds that the 'penalty' for bankruptcy varies systematically according to ex-ante credit quality, as well as the demographic characteristics of the location in which the bankrupt files.

As such, one assume that one can re-write (5) and (6) as

$$\begin{aligned} dB_i &= \phi_i B dt + \omega_i B dz && (7) \\ dC_i &= \beta_i C dt + \eta_i C dy, && (8) \end{aligned}$$

or the joint process as

$$d\mu_i = \alpha_i \mu dt + \sigma_i \mu d\zeta,$$

which is identical in form to equation (1), above.

5.0.1 Impact of σ

Recall first that σ^2 is the joint variance of ω and η and can be written as $\sigma^2 = \omega^2 + \eta^2 - 2\rho\omega\eta$. As is well known, this type of model generates the phenomenon that increased σ leads to longer wait-times prior to action. In this case, it would mean that higher variance in benefit to bankruptcy leads to individuals waiting longer to declare bankruptcy until an optimal time. Some evidence of this is apparent in the rush to file prior to the 2005 bankruptcy law change. Prior to this change, individuals that had a positive μ, that is a potential benefit from filing, may not have filed in order to wait to maximize their payoff when doing so. Removing the option to wait lowered the option value and led individuals to act more quickly.[4] Analytically, one can think of the problem as imposing a new set of processes B' and C' where $\mu' = \frac{B'}{C'}$ and the solution to this problem $W'^{*} < W^{*}$.

However, this dimension does not help to explain the increase in bankruptcy rates over time, only the rush to file in a short time period. Indeed, it would suggest that variances of income shocks and debt exposures have been falling over time, a pattern that is largely rejected by the data.

5.0.2 Impact of cross-sectional variance in α_i

One can look as well at the impact of cross-sectional variance in α. Recall that α is the net trend, $\alpha = \phi - \beta$. That is, each individual in the model faces some Brownian process that in part determines the decision to file for bankruptcy. The paper simulates two cases to illustrate the point that changes in cross-sectional variation have a different impact than changes in α itself. Case 1 shows the distribution of bankruptcy rates for 100 simulations of the model economy over 5 year periods. Case 2 repeats the exercise by imposing a mean-preserving spread on α and generating bankruptcy rates over 5 year periods again. Figure 1a shows these. The assumption of the model is that individuals face some degree of uncertainty around the payoff to declaring bankruptcy related to the cost of debt, social perceptions and other factors. For simplicity, the model assumes these follows a geometric Brownian process. These processes have the property that the best guess of tomorrow's value is equal to the value today.

This implies that individuals with no benefit of declaring bankruptcy today have no reason to expect that things may change tomorrow. However, once we add a 'trend' to this process, the expectations indeed can change. The cross-sectional variation in α implies individuals face changes in the probability of bankruptcy over time. Some face increasing probability and some decreasing. Figure 3 illustrates. Thus, a mean-preserving spread in α can lead to increased bankruptcies with no change in σ.

5.0.3 Impact of cross-sectional variance in σ_i

Well known results from the real options framework above include that increases in σ lead to increased value of the investment option. In the bankruptcy context, this value is derived from the uncertainty over the post-bankruptcy situation. Volatility in social norms, regulations, credit availability and other factors allow agents to choose a strategic filing time. As a result, once the model imposes increased cross-sectional variance of σ_i, the individuals with higher σ will have a higher valued option and the individuals with a lower σ_i a lower value.

[4] See the seminal paper, Geske and Johnson (1984), for a solution to the value of a put option as a function of time to expiry.

In figure 1b, the paper shows the impact of a mean-preserving spread of σ_i. As in panel A, case 1 shows the distribution of bankruptcy rates for 100 simulations of the model economy over 5 year periods. Case 2 repeats the exercise by imposing a mean-preserving spread on σ. Two results can be observed. The average bankruptcy rate is largely unchanged, consistent with the notion that half the population will file more quickly on average and the other half will file more slowly. However, these averages mask a large asymmetry. Individuals with lower σ file more quickly on average. Individuals with higher σ file more slowly on average, however, as the size of the σ change increases, the associated volatility leads to a wide dispersion in this difference. The impact on the bankruptcy decision is explored empirically below.

6 Data

6.1 Choosing Proxies

As the model illustrated, as researchers we may be able to draw inference from the cross-sectional variation in risk. While such variation does not alter each individual's decisions directly, if one is unable to observe the distribution of exposures faced by each individual, the cross-section can provide a proxy for this object. To capture this feature, one can include a number of additional variables. In particular, this paper will include variables intended to proxy for the trend and variance terms on the bankruptcy process above.

To match the income variance literature, one would like to use the variance of individual income over time. This would be a direct proxy for μ itself. This is done in a limited time series with national data below.

Finding proxies for the cross-section poses more difficulties. Effectively, one needs variables for the bankruptcy processes specified above that have reasonable intellectual mappings to the trend (α) and innovation (σ) terms. For the trend terms this can include trends in income or trends in availability of credit. Steady decreases in real income make the benefit to bankruptcy greater; existing debt will become increasingly hard to service over time. Increased availability of credit (to non-bankrupt individuals) also decreases the benefit to bankruptcy, while increased availability post-bankruptcy (see recent work by Cohen-Cole *et al.*, 2009) increases the benefit.

The variance term should reflect a measure of the outcome of idiosyncratic risk to individuals. Ideally, one would measure the risk itself as the variance of the increments of the change in bankruptcy payoffs or the variance of the innovations of the permanent component of the income process. The problem with direct measures of income in this type of analysis is that variations in income include both the permanent and transitory component. Because bankruptcy is very unlikely to be a function of a transitory shock, estimates of the relevance of income measures on bankruptcy may be either imprecise or biased as a result.

Since a direct measure is unavailable and income measures may be imprecise, it's possible to use a variety of variables such as changes in interest rates, unemployment rates, health shocks, etc. If rates are fixed, interest rates change the value of debt that an individual holds and thus matters for bankruptcy decisions; unfortunately for this model, most consumer unsecured debt that is a candidate for forgiveness under bankruptcy rules carries floating interest rates. One may also wish to capture health shocks, but this is particularly difficult information to collect.

As a result, we turn to employment figures. Unemployment rates are an aggregate measure of the realization of shocks. Unemployed individuals can be viewed as having experienced a realization of the bankruptcy process that leads to bankruptcy being much more beneficial. For the unemployed individual, the net monthly income minus debt can be negative while the relative benefit of access to credit may be diminished. That is, the incentive to finance a new car is much lower.

To analyze the relevance of unemployment from an empirical perspective, this paper distinguishes between the realization of unemployment in an area and the cross-sectional distribution of unemployment. That is, when unemployment is viewed on a local basis alone, the data point may provide insufficient information to infer a trend as a single data point may be reflective of individual realizations of the process. However, by looking across locations with similar populations, with the assumption of exchangeability, one can observe the full distribution of shocks. Higher variance implies more dispersion in the trend. Higher dispersion implies that a greater fraction of the population is subject to a relatively low or high trend. Thus, we can interpret high cross-section variances as informative of the probability of bankruptcy for an individual.[5] In practice, we can use the cross sectional variance of unemployment across locations as a proxy for α. As the model illustrations above showed, a high dispersion in α implies a higher bankruptcy rate.

Continuing, the variance of the cross-sectional variance, can be used as a measure of the σ_i term in the Brownian process. As has been shown in Figure 3, the variance around each trend is a measure of the uncertainty in the innovations of the bankruptcy process. In the aggregate, the variance of the variance of α_i can be used as a measure of σ_i. Of course, since this is not measureable, one can use two types of measures. The first is a measure of uncertainty around the variation of the α coefficient and the second is the kurtosis in the distribution of α. In the first case (uncertainty), the model provides clear intuition on the implied coefficient. Increased σ leads to longer expected stop times and thus lower bankruptcy rates. In the second case, a fat-tailed distribution of α implies that there is a portion of the population with particularly large variance of unemployment that does not have an extremely high bankruptcy rate. Both suggest a nonlinearity in the relationship between the variance of unemployment and the bankruptcy rate. The relative importance of these two will be shown in the empirical work below.

To make the exchangeability assumption above such that the cross-sectional distribution of shocks is reflective of shocks faced by individuals, one needs to define the underlying groups accurately such that the claim of similar shocks is reasonable. The question is how to divide the population into groups of similar type. Because of the strong emphasis in the income literature on educational attainment, the starting point, used in the baseline example below is to use the intersection of income and education.

Most results below subdivide the population into the intersection of five quintiles of education

[5]The point is that the higher dispersion also leads to the conclusion of higher probability of no bankruptcy. Of course, this doesn't appear in the data. Thus, high variance with a symmetric distribution of α can be used to justify using the variance of unemployment as a proxy for increased trend risk.

and five of income. These twenty five groups are included in most specifications below.

6.2 Credit Bureau Data

This paper draws primarily on a very large proprietary data set provided under contract by Transunion, one of the three large US credit agencies. The data are drawn from a geographically stratified random samples of individuals, and include information from personal credit reports. In particular, the file includes individual month of birth, a variety of account and credit quality information such as the number of open accounts, defaulted accounts, current and past delinquencies, size of missed payments, credit lines, credit balances, etc. The information spans all credit lines, from mortgages, bank cards, installment loans to department store accounts. Transunion also provides a summary measure of default risk (an internal credit score). As is customary, account files have been purged of names, social security numbers, and addresses to ensure individual confidentiality. However, they do provide geo-coding information that allows matching these personal credit history files with information from the US Census.

The data were drawn from credit reports from the middle of 2006 and the end of December 2007. It is comprised of a very large repeated cross-section with about 27 million individuals, as well as a smaller short panel of about 2.2 million individuals. The very large size of the dataset is useful in particular in helping to understanding the heterogeneity present in the data while maintaining explanatory power. Twenty seven million individuals amount to an approximate 1 in 9 draw of all individuals with a credit history.

One of the benefits of the credit database used here is that it includes a measure of credit risk. For each individual, Transunion includes a proprietary credit score. Credit scores in general are inverse ordinal rankings of risk. That is, an individual with a credit score of 200 is viewed to have higher risk of default than an individual of score 201. However, while most credit scoring systems in use are based on a logarithmic scale, the difference in risk between 200 and 201 may or may not be equal to the change from 201 to 202. As in Gross and Souleles (2002) and Cohen-Cole and Duygan-Bump (2008), this paper uses the score as a control for changes in the risk composition of borrowers, together with account information on credit lines, balances, and utilization rates.

The data set includes information on individual public bankruptcy filings. Transunion keeps the bankruptcy on file for at least 7 years after the filing, so the data encompass bankruptcies as early as June 1999. All historical bankruptcies are included in the analysis. Given the availability of geo-coding information for the individuals, one can compute *local* bankruptcy rates.[6] To understand the impact of macroeconomic risk, this location information will allow calculations of precise proxies of risk.

These data also have a number of advantages that mirror other studies using individual level credit card data (e.g. Gross and Souleles, 2002). First, these data allow us to look at various

[6] The bankruptcy variable itself is an indicator of whether an individual has filed bankruptcy in the past seven years. This has the advantage of capturing the impact of an unemployment shock over a period of time. Since the unemployment data is from the 2000 census (1999 information), the data capture seven years of the shock. The disadvantage is that the lag may encompass other relevant unemployment shocks.

features of borrowing behavior without concern for measurement error, which is quite common in survey data. Second, there are many individuals who have filed for bankruptcy—a low probability event that is hard to capture in samples like the PSID. The key disadvantage is that, unlike survey data, there is no direct information on household income or employment status.

Table 4 provides some detailed cross-sectional information on bankruptcy rates. Each panel shows bankruptcy rates by education and income quintiles for 2006 and 2007.

6.3 Census Data and Other Information

Together with the credit information, the paper uses an individual's geo-coded census block address from the Transunion data and links a wide variety of information on location characteristics. In particular, because there is no individual-level data on variables such as income and education, the paper relies on the following variables to control for local economic and demographic conditions. For demographic controls (education, race, and marital status), the paper uses data from the US 2000 Census national summary files and merges information at the neighborhood level (defined as a 1 mile radius). This paper uses data on median household incomes and poverty rates from the US 2000 Census and the 2005 and 2006 American Community Surveys at the county level. One can also match information from the Current Population Survey and Local Area Unemployment Statistics of the BLS on health insurance coverage (at the state level) and unemployment rates (at the county level), respectively, for the corresponding years. The key advantage here is that one can link information at a more granular level (in most cases) than the state-level information as used in the Gross and Souleles (2002) framework. By using this degree of granularity, one can control for the wide heterogeneity in economic shocks faced in the US economy.

When all this information has been merged a certain number of individuals get dropped due to missing data, for example on credit scores. Once these and other similar missing observations are removed, the paper has about 12 million observations for 2006 and a similar number of observations for 2007.[7] Table 1 provides detailed description of all the variables used in the analysis as well as their respective sources and Table 2 presents some summary statistics.

The descriptive statistics for cross-sectional variances used in the baseline case are shown in Table 2 as well. They are calculated by taking the variance, across census blocks, of the census information (or credit data) for each variable in question. Variance and Kurtosis for each cross-sectional group is shown in Table 6.

Trimming

Individuals living in particularly well educated and high income areas, as well as those in particularly poorly educated and low income areas, exhibit less variance in the rate of unemployment.

[7] Missing credit information comes from gaps in the original data. Missing information from the demographic files is due to discrepancies between the geo-codes from the credit bureau and the census. When a geo-code from the credit bureau lay more than a mile from the closest census block group centroid from the census, the data point is excluded. One can also match these remaining points by associating the individual with the closest centroid and run the risk of connecting the individual with an incorrect neighborhood. Nonetheless, the key coefficients on a regression using this methodology are substantively unchanged from the baselines below.

For these individuals employment is either guaranteed (as in the case of the well off individuals) or preclusive (in the other extreme), thus uncertainty in employment is irrelevant. To this end, in most cases the dataset has been trimmed to remove the top and bottom five percent of observations in terms of two socioeconomic indicators, high school achievement rates and income. Detailed notes are included beneath each table.

6.4 Time-Series Data

Time series estimates are conducted using information collected by Hacker (2001) and by the author. Hacker collected information on income variation over time using the PSID. Values are calculated using the Gottschalk and Moffitt (1994) method. Assuming the process

$$y_{it} = \mu_i + \nu_{it}$$

where y_{it} denotes income at time t, μ_i is the permanent component and ν_{it} the transitory. Convert all values to logs. Variances of μ_i and ν_{it} are σ^2_μ and σ^2_ν respectively. Assume the two are uncorrelated, and write the variance of income as: $\sigma^2_y = \sigma^2_\mu + \sigma^2_\nu$. Then, σ^2_μ is equal to the covariance of log earnings between two distant time periods, $cov\left(y_{it}, y_{it'}\right) = \sigma^2_\mu$ if $cov\left(\nu_{it}, \nu_{it'}\right) = 0$. Now, one can calculate $\sigma^2_\nu = \sigma^2_y - \sigma^2_\mu$.

This paper uses these estimates as well as information on bankruptcy rates and unemployment rates over time.

7 Estimation and Results

7.1 Replication of existing studies

In this section, the paper covers a few sets of results. To begin, it summarizes and replicates the results from the empirical literature on bankruptcy to provide a baseline to support the claim that there is a great deal of unexplained variation in bankruptcy rates. Existing explanations from risk factors, changes in supply of credit to social networks have been shown to be relevant, but of small magnitude.

To correspond to existing empirical work this paper estimates a reduced form specification of the bankruptcy rate as follows:

$$B_{is} = a + bX_i + cY_g + J_s m_s + \varepsilon_{ig} \tag{9}$$

where B_{is} is the bankruptcy decision of individual i in state s, X_i are individual-specific credit characteristics taken from the credit file. These include age of the account holder, revolving credit line and utilization rates for revolving credit, mortgage line, as well as an aggregate measure of credit quality (the internal credit score). These variables correspond to the risk-controls used in the Gross & Souleles (2002) model, and capture differences in risk compositions of borrowers. This paper also includes community-level controls to proxy for local economic conditions and demographic composition of the neighborhood and the county, labeled Y_g. This vector includes controls for neighborhood race, education, and marital status composition, together with median household income and unemployment rate in the county of residence, average income growth in the neighborhood between 2000 and 2005, the percentage of people without health insurance in the state of residence, and the percentage of people on public assistance in the neighborhood. Finally, this paper can include the bankruptcy rate for the state of residence, computed using sample averages from the credit bureau data, and labeled m_s

Table 3 presents the results from this exercise in each of the dated observations (June 2006 and December 2007). In each of the time periods, almost all of the credit risk controls are significant. For example, the Transunion score is significant and is in line with expectations: people with higher credit scores are less likely to file for bankruptcy. Individuals with higher limits (revolve_cred) are less likely to default, and increased utilization in the extremes (credit_utilsq), leads to increased bankruptcy probabilities. The age variables are also in line with expectations, where probability of default increases with age but then flattens out. Interestingly, communities with higher proportions of Black populations are less likely to default, which is consistent with evidence found in prior work (Cohen-Cole, 2008) that access to credit is differentiated by location, implying that only relatively higher quality borrowers in minority areas have access to credit.[8] The effect of income is as expected: bankruptcy rates are lower in neighborhoods with higher income growth. Demographic and economic factors seem to dominate in magnitude the effects of risk controls, such as outstanding debt balances. These results also show that social context and aggregate behavior indeed play a significant role in individuals' bankruptcy decisions: the coefficients of the average bankruptcy rate in the state are all highly significant and positive, as in Fay *et al.* (2002) and Gross and Souleles (2002).[9]

Similar to previous findings, this paper also shows that the neighborhoods with high unemployment rates also seem to have a higher proportion of individuals that become bankrupt. More complete specifications below will show the coefficients on the unemployment variables will change once the model is expanded to include controls for macroeconomic risk. This is discussed in more depth below.

[8] See Cohen-Cole (2008) for a discussion of redlining in credit cards.

[9] It is worth noting that our baseline results show similar directional social effects as the other two papers. However, we find much larger impacts. We attribute this finding to differences in data and specification. Principally, we noted a great deal of sensitivity in the magnitude of the coefficient in this specification, particularly with respect to the inclusion of nonlinear credit score terms. Inclusion of the squared or cubed credit score leads to a drop in the magnitude of the social coefficient. Since credit scores are ordinal scales, nonlinear terms are akin to rescaling of the variable. This may or may not be appropriate, but requires much more information on the nature of the variable than is typically available. This sensitivity is much lower in our detailed specifications below. Once we look at lower levels of aggregation, our coefficient magnitudes are broadly in line with the literature.

7.2 Baseline Cross-Section Results

Here, this paper shows empirical results that form the core of the paper. This paper begins by predicting the bankruptcy choice in the manner of prior work.[10] The baseline includes measures of exposure to risk that might be reasonable proxies for the α and σ parameters. To start, the paper looks at the variance of unemployment. Some additional measures are discussed below. Each is a reasonable proxy for the variation that an individual faces in determining the optimal time to declare bankruptcy. Variance here is measured as the cross-section dispersion across neighborhoods of the variable in question for individuals in a given group. For example, one can calculate the cross-section dispersion in unemployment for individuals across neighborhoods g of income group j as $var\left(U_{jg}\right) = E\left[U_{jg} - \mu_j\right]^2$. Table 7 shows the results from the estimation:

$$B_{ig} = a + bX_i + cY_g + J_s m_s + \tau_1 U_g + \tau_2 varU_{jg} + \tau_3 kurtU_{jg} + \varepsilon_{ig}$$

where B_{ig} is the bankruptcy decision of individual i in area g, and X_i are again individual-specific credit characteristics. The variable Y_g again indicates shared community levels or environmental factors and $var\left(U_{jg}\right), kurt\left(U_{jg}\right)$ are the variance of unemployment and kurtosis of unemployment in area g calculated across all similar areas j. For the results in Table 7, the similar areas are defined as the income and education quantiles used in Tables above. Table 7 shows a series of 6 regressions including variations of the regressors above.

There are three points worth noting here. First, the coefficients on the unemployment rate are very significant, relatively small magnitude, and positively correlated with the bankruptcy decision (perc_unemp). That is, increased local unemployment leads to more bankruptcies. Note that doubling the local unemployment rate will increase the bankruptcy rate only from 5.90% to 5.98%.

Second, the coefficient on the variance of unemployment is large, positive and significant. This is both consistent with intuition and with the model. The constructed cross-sections are done according to socioeconomic grouping. Cross-sectional unemployment rates are a proxy for heterogeneity in risk faced by individuals of this social grouping. The working hypothesis is that this is heterogeneity in permanent shocks. That is a high variance implies larger potential differences between individuals across location in exposure to risk; this suggests that some greater fraction of these individuals will enter bankruptcy. From the model, the paper showed above that increased in α_i are associated with increases in bankruptcy.

Third, the coefficient on the kurtosis term is negative, significant though of small magnitude. As suggested, this is consistent with an interpretation of this variable as the variance of the stochastic innovations of the bankruptcy benefit process. Increase this variation (σ), and individuals will choose bankruptcy less often. This occurs for the now well known reason that there is some 'real' option to wait longer. A look at Figure 1, Panel B shows the impact of a mean-preserving spread of σ_i in the real options model above (thus an increase in kurtosis) on the expected bankruptcy rate. The mean and median of the solid line indeed decreases (albeit only slightly) from the dotted case.

[10] Because the dataset used has locations of residence, this paper can use lower levels of aggregation than the state. For most variables, information at the level of census block is available.

This is reflected in the regressions. However, the asymmetry present suggests that higher moments may also be relevant in this type of model.

Columns 4 and 8 further subdivide the population into deciles of income and education — leading to 100 socioeconomic groupings. The specification in columns 3 and 7 are repeated with largely similar results.

7.3 Time Series Results

In this section, the paper outlines the relationship between the bankruptcy rate and individual level income variation. Indeed, while the model above is useful in thinking about proxies for risk, ideally, one would like a measure of individual-specific income variance. As discussed above, there is a voluminous literature on this topic. Authors have collected data on individual income changes over time from the PSID as well as other sources. Turning the information into a panel of panels, they calculate the change in income variance over time. With this information, one can then decompose the variance into permanent and transitory components. In the context of the bankruptcy decision, the variance of permanent income in the time series data is a national measure of the dispersion of income over time.

Recall that one can make an argument that the permanent variance should show some relationship to the bankruptcy rate. Indeed, one might expect that this relationship would be observed with a lag; once an individual faces some permanent shock, he may not declare bankruptcy for a period of time afterward as he attempts to manage the financial situation and uncover whether the shock is indeed permanent. For example, an employment shock might initially be perceived as temporary. Until the individual realizes the long-term nature, he may not declare bankruptcy. However, notice that because permanent variance is calculated as a long-run covariance in earnings: $cov\left(y_{i,t}, y_{i,t-\tau}\right)$ for τ large, a one or two period lag may not change the measurement of the permanent variance. As such, one may not observe much difference between contemporaneous and lagged regressors.[11]

Table 8 shows the results of a number of specifications of the bankruptcy rate over time regressed against the two measures of variance. Column 1 regresses bankruptcies against total variance of income. The table shows a strong positive correlation between the two. Column 2 shows the disaggregation from the income variance literature. Now, the regression shows an R2 over 90% and a strong positive coefficient on the permanent variance. Temporary variance is insignificant. Column 3 includes the national unemployment rate, which is indistinguishable from zero in this regression. Column 4 adds two lags of the permanent variance and column 5 two lags of the temporary variance term. None of these are significant when included alongside the contemporaneous measure. When included without the current year variances, the two lags of the permanent variance are themselves highly significant (not shown).

Overall, in each of these cases, the permanent component is significant and the temporal variance is not. While it can be hard to draw inference from a relatively short sample of data, it is

[11] Another way of making this point is that there is some imprecision in ‘dating’ permanent variance changes.

reasonably strong confirmation of the intuition that increased variance of shocks to permanent income will have a negative effect on bankruptcy.

7.4 Functional Form

Taking the heterogeneity in the permanent income model seriously, one needs to allow the relationship between the α,σ terms and bankruptcy to vary across individuals. The most direct way to accomplish this is to allow μ_i to change across groups. This is accomplished via a random effects model.[12] It is assumed that groups, i, are defined as above — across income and education groups.

Table 9 begins with a linear probability model (OLS) that repeats the baseline in Table 7. These are available in columns 1 and 3, for 2006 and 2007 respectively and find results that are largely consistent with the probit model in Table 7. Columns 2 and 4 show the results of the random effects specification. The results are similarly unchanged. Both methodologies reveal a stronger effect for the each of the coefficients.

7.5 Nonlinearity in cross-sectional variance

To this point, the paper has emphasized evidence that the permanent income cum real-option model of bankruptcy is supported in the data. To do so, Tables 7 and 9 show results using variance and kurtosis of unemployment. Each of these are measures of the distribution of unemployment rates across a given socioeconomic group. That is, one can construct a distribution of local unemployment rates for each individual in the first quintile of income and education across a range of locations. The paper argues that this provides a measure of the dispersion around the trend rate of unemployment (see Figure 3).

One can also observe an additional nonlinearity from the data in Table 6, plotted against the bankruptcy rate by group in Figure 4. It shows a strong concavity when measured across groups. This, of course, can be captured by including the square of the variance term. Table 10 adds this information. As Figure 4 suggests, the squared term is strongly negative and dramatically increases the magnitude of the relevant coefficients.

7.6 Credit and Bankruptcy

The Livshits *et al.* (2007b) paper as well as now widespread opinion hold that a change in the credit market environment, in particular a widespread relaxation of credit standards is in some part responsible for the increasing bankruptcy rate. Indeed, improvements in underwriting technology could allow issuers to make loans to more individuals with low credit quality while maintaining profitability. This could lead to an increase in defaults at the macro level. If true, one would expect that indicators of credit quality, such as credit scores and high utilization rates should be important

[12] In fact, one can further allow α_i and σ_i to differ across i. This is the so-called random coefficients model. Unfortunately, the large dataset useful here for the decomposition by socio-economic groups makes estimation of a random coefficients model impractical.

in explaining the cross-section of bankruptcy rates. Unfortunately, as observed in Table 3, this is not the case. While the credit risk factors are significant, largely due to the enormous sample size, some even have unexpected signs. The empirical literature from Gross and Souleles (2002) to Cohen-Cole and Duygan-Bump (2008) have concluded that this is evidence that credit factors are not as important as previously thought.

While one would imagine that individual credit histories should be sufficient to determine individual bankruptcies from a credit quality perspective, recent events and research have suggested that credit availability may be a function of location or other aggregate characteristics. For example, Cohen-Cole (2008) finds evidence that local racial composition may impact credit access. As well, recent events have seen credit issuers restrict credit based in part on factors that are not captured by individual histories.[13]

Perhaps then, the intuition in Livshits *et al.* (2007b) can be corroborated empirically, but not directly through information in individual credit quality. To evaluate this, Table 11 adds information on the cross-sectional variance, across one's demographic group, of credit. For credit, the table uses the variance of total credit lines across each income and education group. The results are positive and significant; higher variance of credit availability leads to more bankruptcy. These results suggest that further evaluation of group-level and indirect determinants of credit may be important.

Columns 2 and 4 add the square of the variance to capture nonlinearities across demographic groups (see section above). In these columns, the negative coefficient captures the fact that the highest income and education groups have very high variances of credit but relatively low bankruptcy rates.

8 Conclusion

A range of authors have uncovered changes in the permanent variance of income. This paper has aimed to relate these permanent income processes to the individual bankruptcy decision. By casting the bankruptcy decision as a real option, it is possible to determine a relationship between economic shocks (risk) and the bankruptcy decision. Further, the model encourages the use of proxies for the income process that are explicitly related to the permanent component of income. Using cross-sectional variance of unemployment, the paper shows that economic risk is an important determinant of bankruptcy rates.

The intuition behind this finding is that local measures of demographic and sociopolitical composition appear to be poor measures of economic risk, at least vis-a-vis the bankruptcy decision. Among the possible reasons for this is heterogeneity in risk exposure at the local level. While census blocks are relatively small areas, they can nonetheless encompass individuals that work in distinct industries and at a range of income and education levels. Cross-sectional measures, in the way constructed here may be better proxies for risk. While potentially relevant for various economic decisions, income and education cross section may be particularly relevant for the bankruptcy choice.

[13] See Atlanta Journal and Constitution Dec 21, 2008.

Hacker (2006) finds a large increase over the past couple decades in the risk borne by individuals by virtue of institutional changes to retirement plans, health insurance, and other factors. These largely coincide with the temporal rise in bankruptcy.

References

[1] Athreya, K., 2002. Welfare Implications of the Bankruptcy Reform Act of 1999. Journal of Monetary Economics, 49, 1567-1595.

[2] Athreya, K., 2004. Shame As It Ever Was: Stigma and Personal Bankruptcy. Federal Reserve Bank of Richmond Economic Quarterly, 90(2), 1-19.

[3] Barron, J., Elliehausen, M., Staten, M., 2000. Monitoring the Household Sector with Aggregate Credit Bureau Data. Business Economics, January.

[4] Brockman, P., Turtle, H., 2003. A barrier option framework for corporate security valuation. Journal of Financial Economics, 67, 511-529.

[5] Cameron, S., Tracy, J., 1998. Earnings Variability in the United States: An Examination Using Matched-CPS Data. Mimeo.

[6] Carroll, C., 1992. The Buffer-Stock Theory of Saving: Some Macroeconomic Evidence. Brookings Papers on Economic Activity, 2, 61-135.

[7] Chatterjee, S., Corbae, D., Nakajima, M., Rios-Rull, J., 2007. A Quantitative Theory of Unsecured Consumer Credit with Risk of Default. Econometrica, 75(6), 1525-1589.

[8] Cohen-Cole, E., 2008. Credit Card Redlining. Federal Reserve Bank of Boston, mimeo.

[9] Cohen-Cole, E., Duygan-Bump, B., 2008. Pariahs or Pals:Understanding Peer Influences on the Bankruptcy Decision. Federal Reserve Bank of Boston, mimeo.

[10] Cohen-Cole, E., Duygan-Bump, B., Montoriol-Garriga, J., 2009. Forgive and Forget, Who Gets Credit After Bankruptcy and Why? Federal Reserve Bank of Boston, mimeo.

[11] Dahl, M., DeLeire, T., Schwabish, J., 2008. Year-to-Year Variability in Worker Earnings and in Household Incomes: Estimates from Administrative Data. Mimeo.

[12] Daly, M., Valleta, R., 2008. Cross-National Trends in Earnings Inequality and Instability. Economics Letters, 99(2), 205-209.

[13] Dixit, A., Pindyck, R., 1994. Investment Under Uncertainty. Princeton University Press, Princeton.

[14] Fay, S., Hurst, E., White, M., 2002. The Household Bankruptcy Decision. American Economic Review, 92(3), 706-718.

[15] Geske, R., Johnson, H., 1984. The American Put Option Valued Analytically. Journal of Finance 39(5), 1511-1524.

[16] Gottschalk, P., Moffitt, R., 1994. Growth in Earnings Instability in the U.S. Labor Market. Brookings Papers on Economic Activity.

[17] Gottschalk, P., Moffitt, R., 2002. Trends in the Transitory Variance of Earnings in the United States. The Economic Journal, 112(478), C68-C73.

[18] Gottschalk, P., Moffitt, R., 2008. Trends in the Transitory Variance of Male Earnings in the United States, 1970-2004. Mimeo.

[19] Gross, D., Souleles, N., 2002. An Empirical Analysis of Personal Bankruptcy and Delinquency. The Review of Financial Studies, 15(1), 319-47.

[20] Hacker, J., 2006. The Great Risk Shift: The Assault on American Jobs, Families, Health Care, and Retirement—And How You Can Fight Back. Oxford University Press, New York.

[21] Haider, S., 2001. Earnings Instability and Earnings Inequality of Males in the United States: 1967-1991. Journal of Labor Economics, 19(4), 799-836.

[22] Li, W., Sarte, P., 2006. U.S. Consumer Bankruptcy Choice: The Importance of General Equilibrium Effects. Journal of Monetary Economics, 53(3), 613-631.

[23] Livshits, I., MacGee, J.,Tertilt, M., 2007a. Consumer Bankruptcy: A Fresh Start. American Economic Review, 97, 402-418.

[24] Livshits, I., MacGee, J.,Tertilt, M., 2007b. Accounting For The Rise In Consumer Bankruptcies. NBER Working Paper, no. 13363.

[25] Mason, J., 2005. A Real Options Approach to Bankruptcy Costs: Evidence from Failed Commercial Banks During the 1990s. Journal of Business, 78(4), 1523-1553.

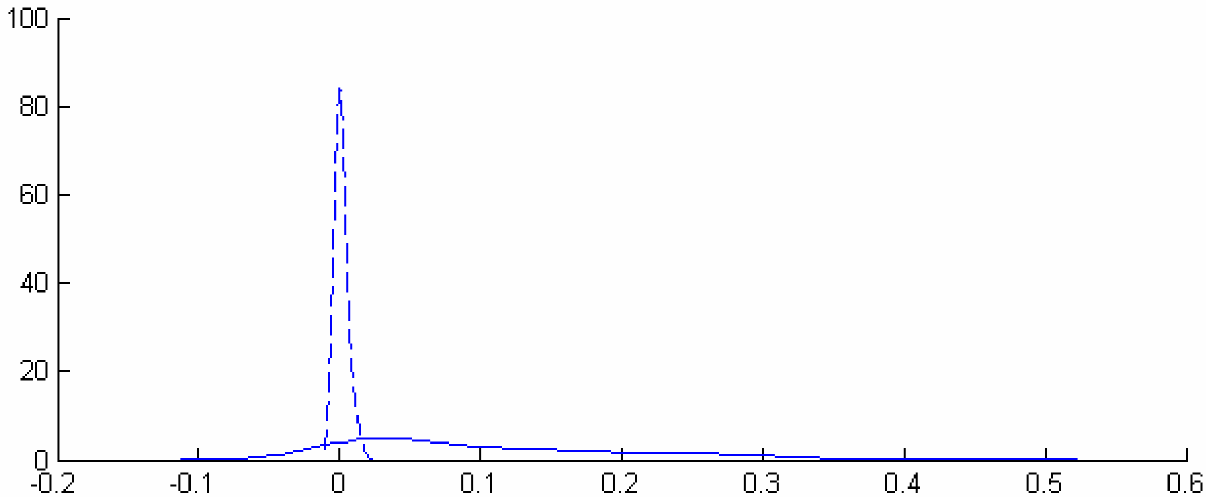
[26] McDonald, R., Siegel, D., 1986. The Value of Waiting to Invest. Quarterly Journal of Economics, 4, 707-727.

[27] Sullivan, T., Warren, A., Westbrook, J., 2000. The Fragile Middle Class. Yale University Press, New Haven and London.

[28] White, M., 2007. Bankruptcy Reform and Credit Cards. Journal of Economic Perspectives, 21(4), 175-199.

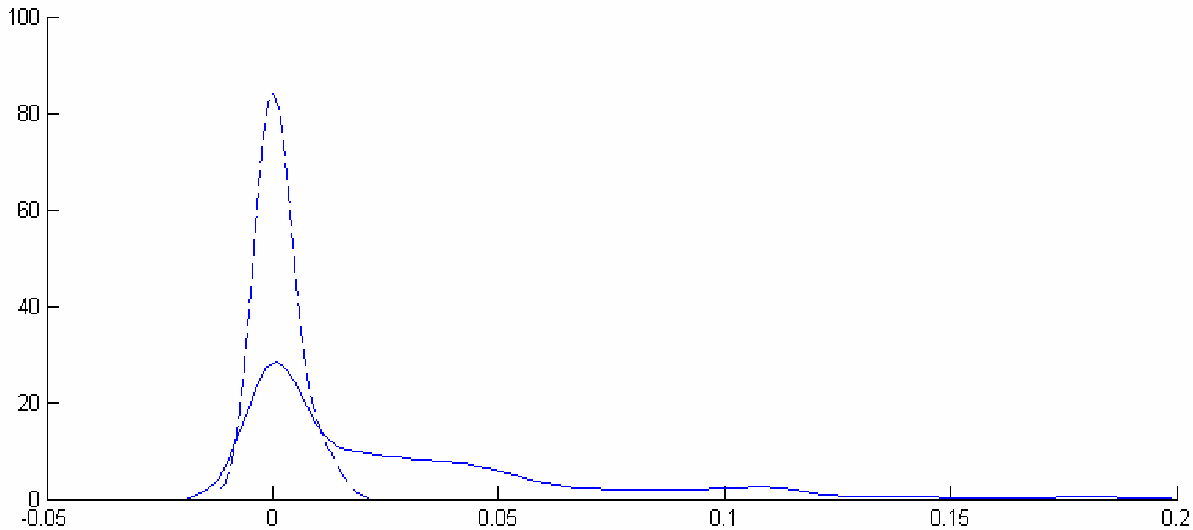
[29] Warren, E., Warren Tyagi, A., 2003. The Two Income Trap: Why Middle-Class Mothers & Fathers Are Going Broke (With Surprising Solutions That Will Change Our Children's Futures). Basic Books, New York.

FIGURE 1a: DISTRIBUTION OF BANKRUPTCY RATE BY VARIANCE OF α_i



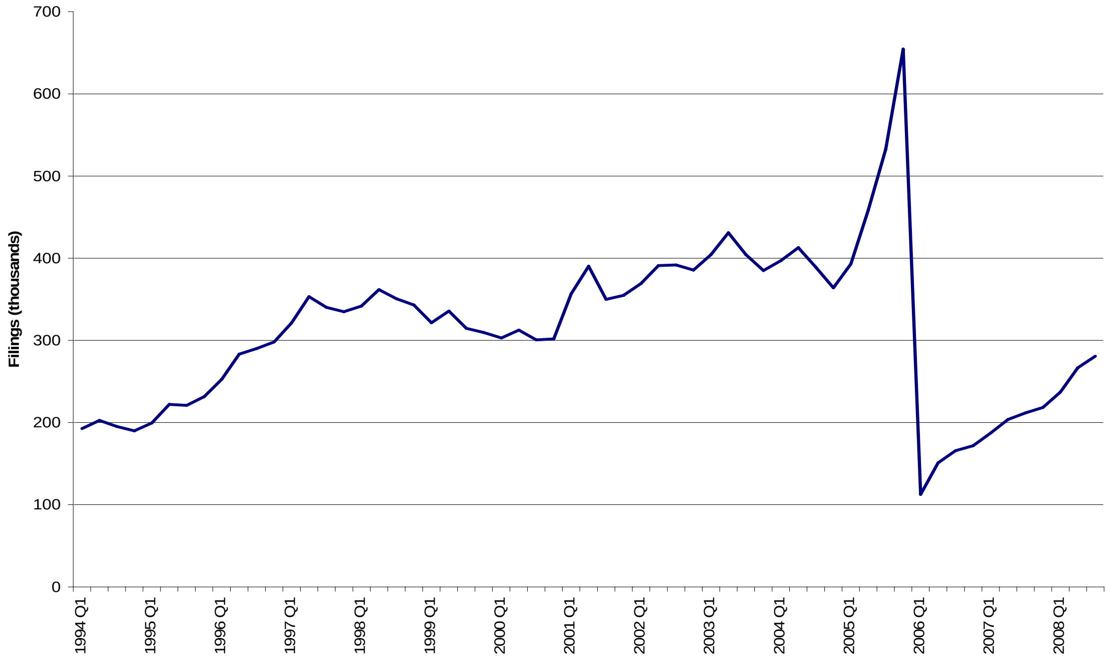
Notes: The figure shows the kernel density estimates of two populations, each with 100 people. Each underlying data point is the sample average bankruptcy rate of the population over a 1-year time period. The bankruptcy event is defined as the GBM crossing the optimal stopping point, as defined in the model. Model parameters are defined for this example as $\omega = 0.25, \beta = 0, \eta = 0.005, \rho = 0.6$. The dotted line indicates an economy in which each individual faces a $\phi = 0.04985, \alpha = 0.04985$. The solid line represents a mean preserving spread of phi over the other population. These range from $\phi = [0.04985, 0.050345]; \alpha = [0.04985, 0.050345]$.

FIGURE 1b: DISTRIBUTION OF BANKRUPTCY RATE BY VARIANCE OF σ_i



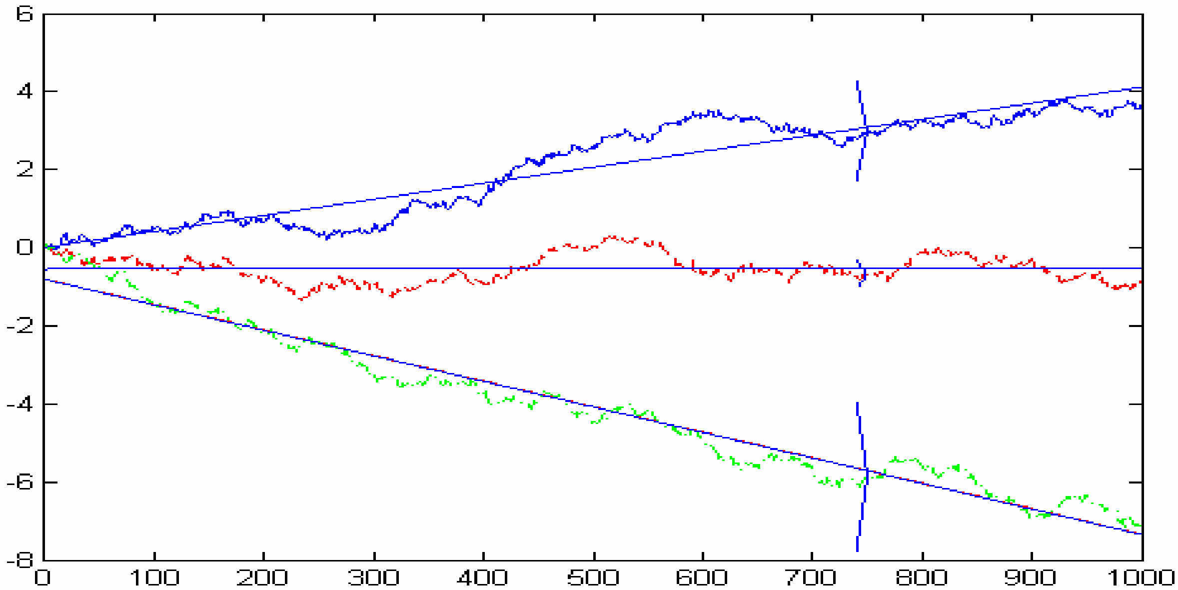
Note: The figure shows the kernel density estimates of two populations, each with 100 people. Each underlying data point is the sample average bankruptcy rate of the population over a 1-year time period. of 100 people. The bankruptcy event is defined as the GBM crossing the optimal stopping point as defined in the model. Models parameters are defined for this example as $\phi = 0.04985, \beta = 0, \eta = 0.005, \rho = 0.6$. The dotted line indicates an economy in which each individual faces an $\omega = 0.25; \sigma = 0.061025$. The solid line represents a mean preserving spread of omega over the other population. These range from $\omega = [0.2, 0.3]; \sigma = [0.038825, 0.088225]$.

FIGURE 2: QUARTERLY NONBUSINESS BANKRUPTCY FILINGS (IN THOUSANDS)



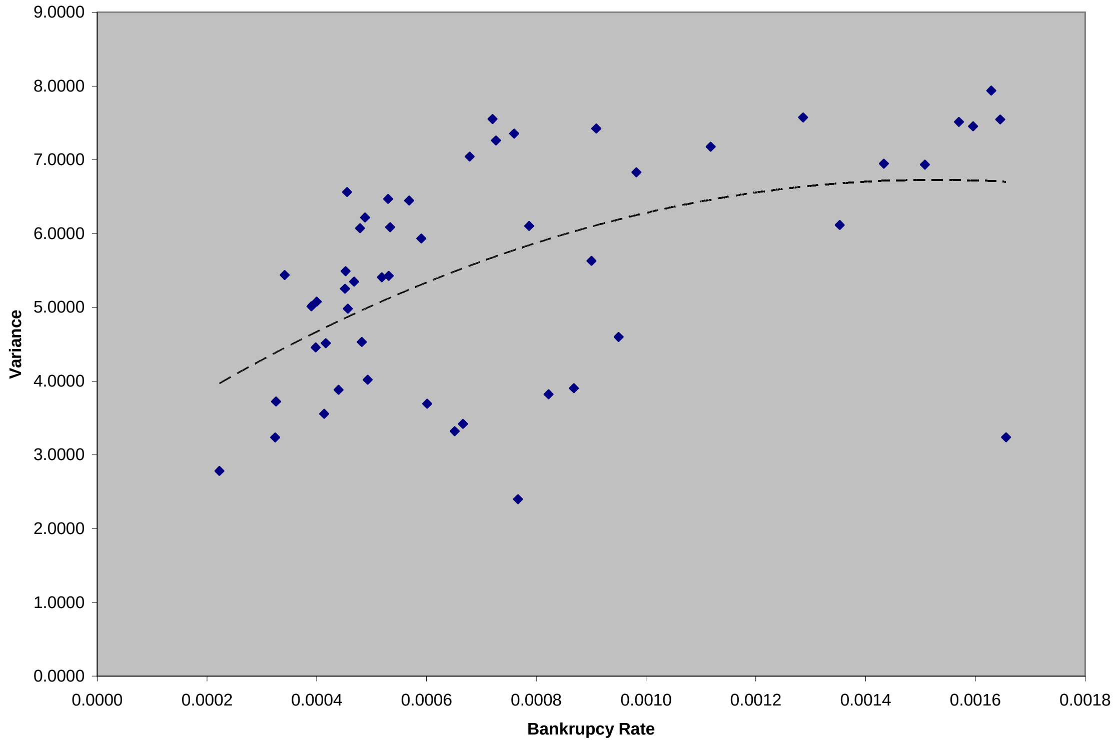
Source: American Bankruptcy Institute.

FIGURE 3: ALTERNATE PATHS OF BANKRUPTCY PROCESS



Notes: This figure shows three alternate paths of a Geometric Brownian Motion with parameters as follows: $\phi = 0.05, \beta = 0, \eta = 0.005, \rho = 0.6$. The innovation for each of the three process are different in the alpha term. The top, middle and lower line have $\alpha = 0.05, 0, -0.05$ respectively. The linear trends are included for comparison, as are bands which indicate the variance of each path at observation 750.

FIGURE 4: BANKRUPTCY VS VARIANCE OF UNEMPLOYMENT



Note: The scatter plot of bankruptcy rate vs. variance of unemployment indicates a strong positive relationship between the two variables.

TABLE 1: VARIABLE DEFINITIONS

VARIABLES	DEFINITION	SOURCE
age2	age of individual squared	author's calculation based on credit bureau data
avgbkrpt_state	average number of bankruptcies filed in the state	author's calculation based on credit bureau data
BRP_ind	indicator of public record bankruptcies	author's calculation based on credit bureau data
mortgage_limit	mortgage high credit/credit limit	author's calculation based on credit bureau data
credit_util	credit utilization, in thousands of dollars	author's calculation based on credit bureau data
credit_utilsq	credit utilization, in thousands of dollars, squared	author's calculation based on credit bureau data
age	age of individual	credit bureau data
avail.credit	total high credit/credit limit, in thousands of dollars	credit bureau data
revolve_cred	total revolving high credit/credit limit, in thousands of dollars	credit bureau data
c.score	internal credit score	credit bureau data
gt_eq_HS_01	percentage of residents in a one mile radius who have achieved high school equivalency or greater	author's calculation based on data from U.S. Census 2000
married_01	percentage of residents in a one mile radius who are married	author's calculation based on data from U.S. Census 2000
divorced_01	percentage of residents in a one mile radius who are divorced	author's calculation based on data from U.S. Census 2000
perc_black_01	percentage of residents in a one mile radius who are black	author's calculation based on data from U.S. Census 2000
perc_hispanic_01	percentage of residents in a one mile radius who are Hispanic	author's calculation based on data from U.S. Census 2000
public_assistance_01	percentage of residents in a one mile radius who receive public assistance	author's calculation based on data from U.S. Census 2000
incgrowth_inflation	income growth between 2000 and 2005, adjusted for inflation	author's calculation based on data from ACS 2000 & 2005
median household income	median household income in county of residence	U.S. Census 2000, 2005-2006 American Community Survey
poverty_rate	percentage of people below poverty level in county of residence	U.S. Census 2000, 2005-2006 American Community Survey
unemployment	percentage of unemployed residents in county of residence	Bureau of Labor Statistics: Local Area Unemployment Statistics
uninsured	percentage of residents in the state who are uninsured	U.S. Census Bureau: Current Population Survey
perc_unemployed	percentage unemployed residents in block group of residence	author's calculation based on data from U.S. Census 2000
variance unemployment	variance of 'perc_unemployed', across the twenty-five income/education groupings	author's calculation based on data from U.S. Census 2000
kurtosis unemployment	kurtosis of 'perc_unemployed', across the twenty-five income/education groupings	author's calculation based on data from U.S. Census 2000
variance unemployment.2	'variance unemployment' squared	author's calculation based on data from U.S. Census 2000
variance avail.credit	variance of 'avail.credit', across the twenty-five income/education groupings	author's calculation based on data from U.S. Census 2000 and credit bureau data
variance avail.credit.2	'variance avail.credit' squared	author's calculation based on data from U.S. Census 2000 and credit bureau data

TABLE 2: SUMMARY STATISTICS

	2006			2007		
VARIABLES	**Raw**	**5%**	**10%**	**Raw**	**5%**	**10%**
BRP_ind	0.058	0.060	0.061	0.053	0.055	0.056
mortgage_limit ($ thousands)	75.81	73.63	71.67	86.55	83.79	82.35
revolve_cred ($ thousands)	41.31	40.77	40.10	44.25	43.68	43.04
credit_util ($ thousands)	7.599	7.549	7.476	8.339	8.310	8.244
credit_utilsq ($ thousands)	425.4	399.0	372.4	520.9	489.6	462.4
c. score	693.4	694.4	694.7	689.3	690.5	690.9
age	37.92	38.17	38.28	37.74	38.01	38.07
age2	1,561	1,580	1,588	1,551	1,572	1,576
perc_blac~01	0.099	0.095	0.089	0.095	0.089	0.086
perc_hisp~01	0.123	0.103	0.098	0.123	0.102	0.098
gt_eq_HS_01	0.826	0.837	0.842	0.828	0.839	0.843
divorced_01	0.096	0.099	0.101	0.097	0.100	0.101
public_as~01	0.030	0.028	0.027	0.031	0.029	0.028
incgrowth_inflation	1.152	1.003	0.997	1.129	1.015	0.978
median_HH_inc	50.48	49.85	49.33	53.04	52.44	51.78
unemployment (state)	0.050	0.050	0.050	0.046	0.046	0.046
poverty_rate	12.56	12.29	12.21	12.53	12.21	12.22
uninsured	15.82	15.66	15.57	15.69	15.46	15.39
avgbkrpt_state	0.058	0.058	0.058	0.053	0.053	0.053
unemployment (local)	0.032	0.031	0.030	0.032	0.031	0.030
variance unemployment	0.0008	0.0006	0.0006	0.0008	0.0006	0.0006
kurtosis unemployment	113.6	117.8	119.7	162.1	92.8	100.2
variance unemployment.2	6.530E-06	5.130E-07	4.380E-07	5.250E-06	4.820E-07	4.210E-07
variance avail.credit	41,864	38,854	35,974	52,628	47,709	44,882
variance avail.credit.2	2.510E+09	2.020E+09	1.650E+09	4.250E+09	3.200E+09	2.720E+09
Number of observations	12,402,079	10,079,984	8,013,214	12,620,044	10,291,352	8,179,964

Notes: Based on author's calculations using credit bureau data, Census and other information as described in the data section, and Table 1.

TABLE 3: BASELINE SPECIFICATION

	2006	2007
mortgage_limit ($ thousands)	-0.000016***	-0.0000179***
	(0.000000408)	(0.000000354)
revolve_cred ($ thousands)	-0.0002***	-0.0002***
	(0.00000122)	(0.00000108)
credit_util ($ thousands)	-0.0012***	-0.0007***
	(0.00000486)	(0.00000424)
credit_utilsq ($ thousands)	0.00000141***	0.000000799***
	(0.00000000872)	(0.00000000671)
c.score	-0.0005***	-0.0004***
	(0.000000468)	(0.000000439)
age	0.0151***	0.0142***
	(0.000032)	(0.0000299)
age2	-0.0002***	-0.0002***
	(0.00000039)	(0.000000369)
perc_black_01	-0.0283***	-0.0205***
	(0.0004)	(0.0004)
perc_hispanic_01	-0.0134***	-0.0149***
	(0.0006)	(0.0006)
gt_eq_HS_01	0.0008	-0.0033***
	(0.0009)	(0.0009)
divorced_01	0.111***	0.1146***
	(0.0021)	(0.002)
public_assistance_01	0.1217***	0.1088***
	(0.003)	(0.0028)
incgrowth_inflation	0.0002***	0.0001***
	(0.0000224)	(0.0000221)
median_HH_inc	0.00000319	-0.0000111
	(0.00000926)	(0.00000941)
unemployment	0.0001**	0.0007***
	(0.0001)	(0.0001)
poverty_rate	-0.0006***	-0.0005***
	(0.0000238)	(0.000025)
uninsured	-0.0005***	-0.0004***
	(0.0000181)	(0.0000163)
avgbkrpt_state	0.7259***	0.6959***
	(0.005)	(0.0052)
Number of observations	12,402,079	12,620,044

Notes: The numbers reported are the marginal effects based on coefficients estimated using a probit model. See Table 1 for a detailed description of each of the variables. A constant term was also included but is not reported here. Standard errors are reported in parentheses, and we adopt the usual convention: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

TABLE 4: BANKRUPTCY RATES ACROSS INCOME AND EDUCATION GROUPS

2006

Bankruptcy Rate:	**Income Quintile**				
	1	2	3	4	5
Education					
1	7.94	7.45	7.58	7.52	5.63
2	7.55	7.42	7.26	7.18	5.25
3	6.45	6.56	6.22	6.09	4.51
4	5.41	5.49	5.44	4.98	3.72
5	3.90	3.69	4.02	3.24	2.78

2007

Bankruptcy Rate:	**Income Quintile**				
	1	2	3	4	5
Education					
1	7.55	6.94	6.12	6.95	4.60
2	7.36	7.04	6.10	6.83	4.53
3	6.47	6.07	5.35	5.93	3.88
4	5.43	5.08	4.46	5.02	3.23
5	3.82	3.55	3.32	3.42	2.40

2006

% of Total Bankruptcies:	**Income Quintile**				
	1	2	3	4	5
Education					
1	14.62	4.41	0.75	0.16	0.05
2	3.78	9.04	5.44	1.40	0.35
3	0.93	4.83	7.75	5.14	1.35
4	0.37	1.38	4.94	8.26	5.05
5	0.30	0.34	1.12	5.04	13.21

2007

% of Total Bankruptcies:	**Income Quintile**				
	1	2	3	4	5
Education					
1	14.62	4.39	0.76	0.17	0.06
2	3.80	9.03	5.39	1.42	0.36
3	0.96	4.85	7.70	5.12	1.36
4	0.35	1.39	5.00	8.23	5.03
5	0.27	0.33	1.15	5.06	13.20

Notes: The first panel above contains the bankruptcy rates particular to the cross section of individuals in each of two dimensions, lowest to highest income quintiles (based on aggregate household income in a zero to one mile radius) and lowest to highest education quintiles (based on percentage of residents with high school equivalency or greater in a zero to one mile radius). The second panel contains the percentage of all bankruptcies in our sample, for the years 2006 and 2007, attributable to each income/education group. The values are similarly aggregated across the two dimensions.

TABLE 5: CROSS TABULATIONS

	Income Growth	Variance Income	Variance Credit
Inc-1/Edu-1	-0.021	13952	64.87
Inc-1/Edu-2	-0.175	17588	82.64
Inc-1/Edu-3	-0.229	20311	98.42
Inc-1/Edu-4	-0.183	23384	115.0
Inc-1/Edu-5	-0.156	28045	135.8
Inc-2/Edu-1	1.195	14753	69.03
Inc-2/Edu-2	0.405	17831	84.41
Inc-2/Edu-3	0.326	20304	97.46
Inc-2/Edu-4	0.384	23689	117.9
Inc-2/Edu-5	0.980	30581	147.0
Inc-3/Edu-1	1.774	14601	94.89
Inc-3/Edu-2	1.522	19272	111.9
Inc-3/Edu-3	1.366	22263	128.4
Inc-3/Edu-4	1.309	26241	156.4
Inc-3/Edu-5	1.535	33573	196.3
Inc-4/Edu-1	1.941	16408	95.43
Inc-4/Edu-2	1.190	20115	112.5
Inc-4/Edu-3	1.324	22906	134.1
Inc-4/Edu-4	1.426	26551	159.6
Inc-4/Edu-5	1.933	35581	193.1
Inc-5/Edu-1	2.987	18401	121.1
Inc-5/Edu-2	2.221	23616	141.7
Inc-5/Edu-3	2.001	26622	162.8
Inc-5/Edu-4	2.007	30427	190.8
Inc-5/Edu-5	2.100	38191	244.5

Notes: Based on author's calculations using credit bureau and Census data. The socio-economic categories in the row headings represent the cross section of individuals in each of two dimensions, lowest to highest income quintiles (based on aggregate household income in a zero to one mile radius) and lowest to highest education quintiles (based on percentage of residents with high school equivalency or greater in a zero to one mile radius). The first column contains data on income growth between 2000 and 2005 in thousands of dollars. The second column contains data on income variance (in thousands of dollars). The third column contains the variance of total available credit in 2006 (in thousands of dollars).

TABLE 6: CROSS TABULATIONS OF UNEMPLOYMENT

2006

Variance	Income				
	1	2	3	4	5
Education					
1	0.0016	0.0016	0.0013	0.0016	0.0009
2	0.0007	0.0009	0.0007	0.0011	0.0005
3	0.0006	0.0005	0.0005	0.0005	0.0004
4	0.0005	0.0005	0.0003	0.0005	0.0003
5	0.0009	0.0006	0.0005	0.0017	0.0002

2007

Variance	Income				
	1	2	3	4	5
Education					
1	0.0016	0.0015	0.0014	0.0014	0.0009
2	0.0008	0.0007	0.0008	0.0010	0.0005
3	0.0005	0.0005	0.0005	0.0006	0.0004
4	0.0005	0.0004	0.0004	0.0004	0.0003
5	0.0008	0.0004	0.0007	0.0007	0.0008

2006

Kurtosis	Income				
	1	2	3	4	5
Education					
1	31.15	123.9	32.00	38.45	28.90
2	31.79	279.9	39.38	163.3	27.25
3	50.16	71.58	28.08	61.24	55.53
4	116.8	86.97	19.64	117.8	307.5
5	172.0	198.0	331.3	340.8	67.64

2007

Kurtosis	Income				
	1	2	3	4	5
Education					
1	40.78	93.91	32.91	45.5	37.9
2	41.00	204.7	51.97	121.07	21.5
3	43.80	73.74	34.61	63.57	52.8
4	123.09	74.4	43.05	104.1	257.9
5	167.04	341.76	321.11	406.0	811.7

Notes: Based on author's calculations using Census data. The socio-economic categories are as described in Table 4. The data in the top two panels are the variance of the unemployment (local) variable and the data in the lower two panels are the kurtosis of the unemployment (local) variable.

TABLE 7: VARIANCE REGRESSIONS

	2006				2007			
	1	2	3	4	5	6	7	8
unemployment (state)	-0.00349***	-0.00421***	-0.00222***	-0.01***	0.0225***	0.0184***	0.0157***	0.0182***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.00282)	(0.0028)	(0.0028)	(0.0028)
unemployment (local)	0.0153***	0.0122***	0.011***	0.0134***	0.017***	0.0128***	0.0127***	0.015***
	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0012)	(0.0012)	(0.0012)	(0.0012)
variance unemployment		2.7214***	2.9063***	7.0816***		3.7265***	3.7157***	9.6526***
		(0.1408)	(0.1409)	(0.2298)		(0.1441)	(0.1441)	(0.3618)
kurtosis unemployment			-0.00000709***	-0.00000829***			-0.00000241***	0.000000166
			(0.000000309)	(0.000000414)			(0.000000409)	(0.000000701)
Observations	10,079,984	10,079,984	10,079,984	10,079,984	10,291,352	10,291,352	10,291,352	10,291,352

Notes: The numbers reported are the marginal effects based on coefficients estimated using a probit model. Individuals who live in the top/bottom five percent of neighborhoods, as determined by lowest to highest income (based on aggregate household income in a zero to one mile radius) and lowest to highest educational attainment (based on percentage of residents with high school equivalency or greater in a zero to one mile radius), are removed from the sample for reasons discussed in the paper. See Table 1 for a detailed description of each of the variables. The dependent variable in each regression is an indicator variable for any public record bankruptcy on file in the year indicated. The innovation in the fourth and eighth columns is the introduction of ten income and ten educational groups, as opposed to five gourpings of each in the preceding columns. The baseline controls were also included but are not reported here, full results are available upon request. Standard errors are reported in parentheses, and we adopt the usual convention: *** p<0.01, ** p<0.05, * p<0.1.

TABLE 8: TIME SERIES REGRESSIONS

Variance of Income (000s)	1.2237***				
	(0.3217)				
Variance of Permanent Income (000s)		4.3496***	4.0669***	3.9701***	5.312**
		(0.3176)	(0.4183)	(1.0916)	(2.0252)
Variance of Temporary Income (000s)		-0.2364	-0.1930	-0.0641	-0.0457
		(0.2099)	(0.2164)	(0.349)	(0.3945)
Unemployment Rate			-0.0231	-0.0191	0.0141
			(-0.0143)	(-0.0117)	-0.0355
Lag (1 period) Variance of Permanent Income				-1.2013	-0.9694
				(1.5578)	(2.6311)
Lag (2 period) Variance of Permanent Income				1.1197	1.5983
				(1.285)	(1.8588)
Lag (1 period) Variance of Temporary Income					-0.3464
					(0.6196)
Lag (2 period) Variance of Temporary Income					-0.5640
					(0.3448)
Observations	18	18	18	17	17
R-squared	0.537	0.920	0.925	0.899	0.918

Notes: The dependent variable for each regression is the total number of bankruptcies (millions) in a particular year. All results have Newey-West heteroskedastic and autocorrelation consistent standard errors. See Table 1 for a detailed description of each of the variables. Similar results using the household bankruptcy *rate* are available from the author on request. Standard errors are reported in parentheses, and we adopt the usual convention: *** p<0.01, ** p<0.05, * p<0.1.

TABLE 9: OLS AND RANDOM EFFECTS REGRESSION

	2006		2007	
	OLS	Random Effects	OLS	Random Effects
unemployment (state)	-0.0002***	-0.0003***	0.0004***	0.0003***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
unemployment (local)	0.0278***	0.0245***	0.0352***	0.033***
	(0.0029)	(0.0029)	(0.0028)	(0.0029)
variance unemployment	7.6279***	8.4264***	9.843***	9.8554***
	(0.3259)	(0.9063)	(0.3449)	(0.7086)
kurtosis unemployment	-0.00000725***	-0.0000059**	-0.00000505***	-0.00000399
	(0.000000637)	(0.00000241)	(0.000000882)	(0.00000247)
Observations	10,079,984	10,079,984	10,291,352	10,291,352

Notes: The numbers reported are the coefficients of interest for two different regression methods. Individuals residing in the top/bottom five percent of neighborhoods, as described in Table 7 and in the paper, are removed from the sample. The first and third column contain results from an OLS model with an identical regression specification as Table 7. The second and fourth columns employ a random effects regression. See Table 1 for a detailed description of each of the variables. The baseline controls were also included but are not reported here, full results are available upon request. Standard errors are reported in parentheses, and we adopt the usual convention: *** p<0.01, ** p<0.05, * p<0.1.

TABLE 10: NONLINEARITY IN CROSS-SECTION VARIANCE

	2006		2007	
unemployment (local)	0.011***	0.0118***	0.0127***	0.0123***
	(0.0013)	(0.0013)	(0.0012)	(0.0012)
variance unemployment	2.9063***	13.54***	3.7157***	15.87***
	(0.1409)	(0.7296)	(0.1441)	(0.6384)
kurtosis unemployment	-0.00000709***		-0.00000241***	
	(0.000000309)		(0.000000409)	
variance unemployment.2		-6754***		-7758***
		(447)		(397.1)
Observations	10,079,984	10,079,984	10,291,352	10,291,352

Notes: The numbers reported are the marginal effects based on coefficients estimated using a probit model. Individuals residing in the top/bottom five percent of neighborhoods, as described in Table 7 and in the paper, are removed from the sample. See Table 1 for a detailed description of each of the variables. The baseline controls were also included but are not reported here, full results are available upon request. Standard errors are reported in parentheses, and we adopt the usual convention: *** p<0.01, ** p<0.05, * p<0.1.

TABLE 11: VARIANCE IN AVAILABLE CREDIT

	2006		2007	
unemployment (local)	0.0108***	0.011***	0.0126***	0.0128***
	(0.0013)	(0.0013)	(0.0012)	(0.0012)
variance unemployment	2.8829***	3.3515***	3.5564***	3.94***
	(0.1542)	(0.1623)	(0.1502)	(0.1509)
kurtosis unemployment	-0.00000705***	-0.00000556***	-0.00000229***	-0.0000022***
	(0.000000318)	(0.000000356)	(0.00000041)	(0.00000041)
avail.credit (000s)	-0.0001***	-0.0001***	-0.0000186***	-0.0000184***
	(0.00000128)	(0.00000128)	(0.00000112)	(0.00000112)
variance avail.credit (000s)	0.00000000129	0.0000000906***	-0.0000000052***	0.000000122***
	(0.00000000249)	(0.0000000099)	(0.00000000163)	(0.0000000056)
variance avail.credit.2 (000s)		-7.9E-13***		-8.98E-13***
		(8.47E-14)		(3.8E-14)
Observations	10,079,984	10,079,984	10,291,352	10,291,352

Notes: The numbers reported are the marginal effects based on coefficients estimated using a probit model. Individuals residing in the top/bottom five percent of neighborhoods, as described in Table 7 and in the paper, are removed from the sample. See Table 1 for a detailed description of each of the variables. The baseline controls were also included but are not reported here, full results are available upon request. Standard errors are reported in parentheses, and we adopt the usual convention: *** p<0.01, ** p<0.05, * p<0.1.