The Credit Market Consequences of Job Displacement*

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Abstract

This paper studies the role of job displacement in the household bankruptcy decision. Using an event-study methodology, I find that households in the NLSY are over three times more likely to file for bankruptcy in the year immediately following a job loss. Heightened bankruptcy risk then declines in magnitude but persists for two to three years. These findings are conditional on the financial benefit to filing and consistent with a dynamic forward-looking model where persistent negative income shocks increase a household’s likelihood of filing for bankruptcy both immediately and in the future. Aggregate patterns in job loss and bankruptcy are also consistent with the micro model. Using county-level data and a shift-share instrument for demand-driven job changes, I similarly find that 1,000 job losses are associated with a tripling of the county bankruptcy rate. In addition, the loss of a manufacturing job, a proxy for a more persistent separation, is 40 percent more likely to lead to bankruptcy than the loss of a non-manufacturing job. The results suggest that unemployment spells can have significant long-term consequences on households’ credit market outcomes.

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I Introduction

The length of unemployment spells in the United States reached historical highs during the Great Recession, with average unemployment durations of more than 40 weeks reported in 2011 and 2012 (Bureau of Labor Statistics). Unemployment spells resulting from job displacement have been shown to have considerable and persistent negative impacts on earnings (Jacobson et al. 1993). More broadly, recent research has documented decreased consumption, greater marital discord, and even heightened mortality risk as a result of job loss (Stephens 2001; Browning and Crossley 2008, 2009; Charles and Stephens 2004; Sullivan and von Wachter 2009). Notably, the decline in consumption around job displacement is attenuated relative to the decline in earnings, which must be accommodated by reduced savings and/or increased indebtedness. This paper explores the impact of job displacement and persistent income shocks on credit markets through the household bankruptcy decision.

More than two-thirds of bankruptcy filers cite the loss of a job or other source of income as the main reasons for filing, by far the most commonly provided motive (Sullivan, Warren, and Westbrook 1999, Warren and Tyagi 2003). These survey findings form the basis for the claim that unanticipated “adverse events” such as job loss, divorce, or health crises cause bankruptcy. Yet empirically there exists only limited well-identified evidence linking household shocks to personal bankruptcy. For instance, Domowitz and Sartain (1999) and Fay, Hurst, and White (2002) find limited or no support for income shocks influencing the likelihood or timing of bankruptcy filing. In this paper, I provide a formal test of the adverse events hypothesis using individual-level data from the National Longitudinal Survey of Youth (NLSY) and county aggregate data collected from the U.S. Courts.

The panel design of the NLSY allows for careful control of the timing of income shocks in an event-study framework, while detailed information on respondents’ assets, debts, and state of residence provides a high-quality estimate of the financial benefit of filing. Unlike previous research on bankruptcy, this event-study methodology explicitly addresses the source of exogenous variation and allows for estimation of pre-shock differences in bankruptcy likelihoods. Using this approach, I find that households are more than three times as likely to file for bankruptcy in the year imme-
diately following a job displacement. This heightened likelihood is equivalent in regression terms to increasing indebtedness by $24,000, or 1.1 standard deviations of the financial benefit to filing. Bankruptcy risk then declines in magnitude but persists for two to three years.

In the context of a forward-looking model, having enough debt such that there is a financial benefit to filing for bankruptcy is a necessary but not sufficient condition for filing. Similarly, even in a model with adverse event shocks, forward-looking individuals may optimally delay their response until uncertainty about the permanence of the shock is resolved. Thus, a dynamic model of personal bankruptcy provides three key predictions: First, two households may respond to the same shock differently depending on their financial benefit to filing. Second, the bankruptcy decision crucially depends on both the magnitude and the expected persistence of the income shock, conditional on the financial benefit of filing. Third, job separations and other income shocks can lead to lagged responses of bankruptcy filing.

The persistence of heightened bankruptcy risk after displacement documented in the NLSY is consistent with these dynamic models, which formalize the option value to delaying filing. I further show that the bankruptcy response to income shocks is most pronounced for those with the largest financial benefit of filing and the largest outstanding amounts of debt. Although the results confirm that individuals with a greater financial benefit to file are more likely to do so, the timing of their decision depends crucially on the timing of income shocks. These findings complement and extend previous static research on the personal bankruptcy decision (e.g. Domowitz and Sartain 1999; Gan and Sabarwal 2005).

To explore further the implications of the model and to test additional hypotheses raised by the “adverse events” empirical literature, I investigate the impact of disability and divorce on the household bankruptcy decision. Use the same event-study methodology, I find that the timing of disability onset is related (albeit noisily) to the timing of bankruptcy. However, in contrast to previous research, I find that divorce is not a proximate cause of bankruptcy: The likelihood of filing for bankruptcy rises significantly prior to divorce, likely due to unobserved drivers of both financial and marital distress. Overall, the evidence suggests that plausibly exogenous job displacement and

\[^1\text{In recent related work, Dobkin, Finkelstein, Kluender and Notowidigdo (2016) find hospitalization increases the likelihood of bankruptcy, especially for the uninsured non-elderly population.}\]
negative health shocks play a role in predicting future bankruptcies among those at-risk.

Although the NLSY is the best available panel data to study bankruptcy, its small sample size does not yield the statistical power necessary to distinguish the heterogeneous effects of job loss based on the expected duration of the displacement. To examine these issues, I use county-level data from the last three decades to estimate the aggregate relationship between bankruptcy and job loss. Using a Bartik-style shift-share instrument of industry composition for demand-driven changes in jobs, I find that 1,000 additional (net) job losses are associated with a four-fold increase in the county-level bankruptcy rate, and that the effects of job loss persist for two years, consistent with the model and corroborating the individual-level results using the NLSY.

To examine the model’s prediction that more permanent income shocks are more likely to lead to bankruptcy, I decompose county-level job changes into manufacturing and non-manufacturing jobs. Manufacturing jobs are generally associated with longer tenure relationships and greater industry-specific and firm-specific human capital. Losing a manufacturing job often leads to deeper and more persistent earnings shortfalls (Carrington 1993). Consistent with the model’s predictions, I find that the loss of a manufacturing job is 40 percent more likely to lead to bankruptcy than the loss of a non-manufacturing job. This is the first empirical evidence that the structural shift away from the manufacturing sector has contributed to increases in personal bankruptcy, and confirms that the micro foundations of dynamic default models are supported by the macro patterns in the data.

To assess the magnitudes of the estimates, I use data from mass layoffs to conduct a back-of-the-envelope calculation of the impact of insured displacements on creditors’ balance sheets. Controlling for county and year fixed effects and county-specific time trends, I find that 1,000 mass layoffs are associated with 14 additional bankruptcies. Based on this estimate, along with the fact that the average amount of debt discharged in bankruptcy is $140,000, I calculate that each insured displacement costs creditors about $2,000, and that the 377,000 mass layoffs of 2004 cost creditors about $740 billion through bankruptcy discharge.

These two complementary empirical analyses at the micro and aggregate levels contribute to the literature on job loss by providing new evidence that the consequences of displacement extend into the macro economy.
the broader macroeconomy through the credit market (Hsu, Matsa, and Melzer 2014). In a similar context, Sullivan (2008) finds that households increase their unsecured borrowing via credit cards in response to a short-term earnings shock. Although unemployment spells are traditionally brief (on average eight weeks between 1980 and 2004 in the NLSY), these short-term shocks can have large long-term consequences on a worker’s well-being. This is especially true when the associated income shocks are more persistent than anticipated. The results presented here raise the question of why households are unable to fully insure against or smooth consumption around these shocks.

In addition, the paper clarifies the sometimes-misleading dichotomy between adverse events and strategic incentives to file for bankruptcy. A considerable amount of research has established that households respond “strategically” (or “optimally”) to changes in the insurance value of the bankruptcy option when making some choices (see, e.g. Gross and Notowidigdo 2011, Mahoney 2015 on health insurance; Traczynski 2011, Burns and Stoddard 2012 on divorce), despite limited evidence that these changes in the insurance value affect actual bankruptcy filings (Agarwal et al. 2005, Lefgren and McIntyre 2009). Furthermore, by limiting the downside risk associated with borrowing, bankruptcy laws create an incentive for individuals to increase their indebtedness. This paper takes the potential moral hazard as given, and instead focuses on documenting the role of adverse events in the likelihood and timing of personal bankruptcy conditional on financial benefit, as well as showing that individuals with greater financial benefit to filing are indeed more likely to do so. Notably, these findings do not rule out strategic behavior on the part of borrowers or bankruptcy filers.

By 2004, over 11 percent of the NLSY cohort aged 39-48 had filed for personal bankruptcy. Understanding the drivers of this behavior is crucial for policymakers who determine the generosity of the bankruptcy system, as well as for researchers who seek to better model household decision-making in the presence of a default option. As households optimize in the face of shocks related to job displacement, this paper finds that filing rates rise both immediately and in the near future. These responses are consistent with strategic explanations often provided for filing behavior, as the value of filing rises based on downward revisions to expectations. The evidence suggests that

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3 Relatedly, Mohanan (2013) finds increases in debt to smooth consumption through exogenous health shocks (in the context of bus accident injuries in India).
households respond to adverse events by filing for bankruptcy, not in simple myopic fashion, but rather timed to maximize the value of filing.

The next section describes the institutional details of filing for bankruptcy and provides intuitive predictions from a dynamic forward-looking model about whether and when households choose to file. Section III describes the data, the NLSY, and the event study methods used to identify the relationship between the timing of job loss and the timing of bankruptcy. An analysis of aggregate trends in bankruptcy using county-level data and a shift-share instrument is presented in section IV. Section V concludes with policy implications and directions for future research.

II Institutional Details and Conceptual Framework

II.A The Costs and Benefits of Filing for Bankruptcy

The empirical analysis of this paper focuses on the time period prior to the passage of the Bankruptcy Abuse Prevention and Consumer Protection Act of 2005 (BAPCPA), which reformed United States bankruptcy law.\(^4\) Between 1980 and 2004, when the bankruptcy code was largely unchanged and the insurance value of personal bankruptcy in the U.S. was considered one of the most generous in the world, filing rates increased from 2.0 per thousand working-age adults in 1980 to 8.5 per thousand in 2004. Households were able to choose between two different options for resolving outstanding debts in bankruptcy court.\(^5\) The first, known as Chapter 7, permitted full discharge of allowable debts after deducting non-exempt assets. Back taxes, alimony, child support, and student loans are generally not dischargeable liabilities, but all other unsecured debts are discharged under Chapter 7 rules.\(^6\)

\(^4\)See Ashcraft et al. (2007) for more on the reforms of BAPCPA. Notably, some households no longer have the choice of chapter due to “means-testing,” which prohibits high-income filers from receiving a full discharge. However, the new bankruptcy rules have not altered the fundamental choices made by the vast majority of at-risk households regarding the timing of the filing decision (Cornwell and Xu 2014). Other statutory changes include residency requirements for access to state homestead and property exemptions, greater documentation requirements, and mandatory financial counseling.

\(^5\)Outside of the legal system, households can simply cease making payments, thereby forcing creditors to garnish wages or attach liens to property. See Dawsey and Ausubel (2004) for more details on this “informal bankruptcy” option.

\(^6\)Prior to 1998, government-guaranteed student loans were eligible for discharge if they were in repayment for more than seven years. Private student loans made by for-profit lenders were dischargeable in bankruptcy until the 2005 BAPCPA.
In theory, under Chapter 7 any non-exempt assets are forfeited to pay off these debts. In practice, however, non-exempt assets usually amount to less than 5% of all debts recovered by creditors (Livshits, MacGee, and Tertilt 2007). Exemption rules vary by state, but generally protect retirement plans such as IRAs and 401(k)s, provide a homestead exemption up to a dollar amount (unlimited in a few states), and grant additional exemptions for automobiles and personal belongings such as clothing (Gropp et al. 1997).

The alternative to filing for discharge is a reorganization of debts, Chapter 13. Under Chapter 13, households agree to a repayment plan of a portion of their debts, worked out through the bankruptcy court with their creditors. These repayment plans are usually scheduled for three to five years, however most Chapter 13 filers fall behind and many re-file in Chapter 7 (see Eraslan et al. 2016). An AOUISC report found that between 1980 and 1988, only 36% of Chapter 13 filers completed their repayment plan (GAO 1999). Individuals are not allowed to file again for seven years if filing Chapter 7, but can re-file sooner if filing Chapter 13.7

In addition to the discharge of eligible debts, another benefit to filing is the suspension of all garnishment and other debt collection techniques. Aggressive collection tactics, such as harassing phone calls, as well as wage garnishment and repossession efforts are often cited as a last straw in leading households to file (Luckett 2002). The tangible costs of filing are legal and processing fees on the order of $500 to $1500, a portion of which must be paid up front (Gross et al. 2014). The most costly aspect of bankruptcy is the flag placed on one’s credit report, which is present for up to ten years and has a strong impact on both access to credit and the price of credit (Musto 1999; Fisher and Filer 2007; Fisher and Lyons 2010; Han and Li 2011).

An often-discussed intangible cost of filing is the role of “stigma,” the emotional punishment inflicted by oneself or one’s peers for filing for bankruptcy.8 While there have been claims that declining stigma can explain some of the recent growth in bankruptcy filing (Fay, Hurst, and White 2002; Gross and Souleles 2002), subjective survey research indicates that individuals’ distaste for bankruptcy has been relatively constant over time (NORC, as cited in Sullivan et al. 2006). In fact, Sullivan et al. (2006) point out that the increased transparency of searchable online public records

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7 This time between filings has been extended to nine years by the passage of BAPCPA in 2005.
8 For more on the role of social capital and social spillovers in personal bankruptcy, see Agarwal et al. (2010) and Dick et al. (2008).
databases has, if anything, made filing for bankruptcy a more stigmatizing experience.

Thus households with negative wealth net of exemptions must weigh the benefits (debt discharge) and costs (access and price of future credit, forfeiture of assets, stigma) against the alternative of not filing and repaying their outstanding debts. Intuitively, households that experience a sufficiently large negative deviation from average lifetime expected earnings such that debt repayment is more painful than the costs of filing should optimally file for bankruptcy. The decision is heavily influenced both by the amount of outstanding debt and the magnitude and persistence of the income shock. This intuition is described in more detail in the next section.

II.B Conceptual Framework

A number of recent papers have solved dynamic structural models of the bankruptcy decision, which have improved our understanding of the behavior of borrowers and banks in a lending environment that includes the possibility of default. In Online Appendix A, I provide a simplified synthesis of these types of models, focusing on income shocks and the default decision. The models are general equilibrium in the sense that the decisions of both banks and households are endogenous.9 Livshits et al. (2007, 2010) assess potential determinants of the increase in bankruptcy rates and find support for an explanation based on a declining cost of filing for bankruptcy. In contrast, Chatterjee et al. (2007) use their model to examine the welfare implications of a counterfactual policy experiment where means-testing is imposed as in the post-BAPCPA regime, and find large welfare benefits attributed to decreased interest rates on unsecured debt.

Dynamic forward-looking models along these lines yield two key predictions: First, job separations and other income shocks can lead to lagged responses of bankruptcy filing, in addition to the obvious immediate filing response. Second, the bankruptcy decision depends crucially on both the magnitude and the expected persistence of the income shock. Simply put, strategic agents respond to adverse events optimally, both in their borrowing patterns and in the likelihood and timing of bankruptcy. Thus, in a framework with optimizing forward-looking borrowers, every default has elements of both “strategic borrowing” and “adverse events” behavior. However, shocks that predict prolonged periods of low income are more likely to lead to defaults than more transitory shocks.

9See the thorough summary by Athreya (2005).
This dynamic perspective clarifies the policy implications of increased bankruptcy filing and the potential role for intervention, as discussed in section VI.¹⁰

Depending on a household’s asset position and the size of the income shock, following displacement the household either files immediately, borrows while waiting to see the next period’s draw, or implicitly plans to never file by saving. These responses are consistent with both the “strategic” and “non-strategic” explanations for filing in the empirical literature, as those who file immediately respond to the adverse unemployment shock, while those who accumulate debt intend to maximize the value of filing in a later period. In contrast to existing empirical work which analyzes a one-year horizon (e.g. Fay, Hurst, and White 2002), these results imply that longer windows of observation around a job separation or other income shock are necessary to appropriately identify its full dynamic impact.

These dynamic models also reveal that changes in expectations can have a direct impact on the bankruptcy decision. Differences in expected earnings can allow for two households who appear similar in terms of indebtedness to behave very differently in making bankruptcy filing decisions. When unemployment is expected to be more persistent, a larger fraction of households are expected to file for bankruptcy. Measures used in previous studies to proxy for “stigma,” such as prior filing rates in the same state, may be contaminated by other households’ expectations about future earnings. Similarly, Gross and Souleles (2002) argue that a change in the fit of a model could represent a shift in the underlying distaste for debt. However, the decrease in the goodness of fit also may be indicative of changing expectations about future earnings.

The central prediction of dynamic models of personal bankruptcy is that the timing and likelihood of bankruptcy are determined by both the expected and realized magnitude and persistence of income and employment shocks. Thus negative household shocks can have delayed effects on the bankruptcy decision. These insights have been recognized in the context of general equilibrium models, but have not been taken directly to the data.¹¹ The next two sections investigate this central prediction empirically, using both individual and aggregate data as tests of the relationship

¹⁰See Online Appendix A for simulations of this style of model, albeit simplified, to qualitatively highlight these two predictions.
¹¹An exception is Livshits et al. (2007), which explores long-term changes in shock persistence in simulation exercises to explain recent increases in personal bankruptcy.
between job separations and bankruptcy.

III Microdata Analysis

III.A The NLSY

The National Longitudinal Survey of Youth initiated a panel study of young people aged 14-21 in 1979. The survey was conducted annually until 1994, and has been biennial thereafter. Questions about education, employment, family formation and dissolution, and respondents’ health have been asked in every wave of the survey. When the respondents had all reached the legal age of adulthood in 1985, they were asked about their assets and debts (independent of their parents’ resources). These questions have expanded as the respondents have aged and accumulated diverse assets and debts, such as 401(k)s, stock portfolios, outstanding auto loans, and mortgages.

The rich set of detailed questions on assets and debts can be used to estimate the financial benefit to filing for bankruptcy for each respondent in each year. I obtained the restricted-license NLSY data in order to identify the respondents’ state of residence which determines the relevant bankruptcy exemptions, as discussed above. State-level measures of the amounts and types of exemptions (home, auto, other) were collected from various annual issues of Nolo bankruptcy publications. I combine information on secured and unsecured debts to measure household indebtedness, as well as the respondents’ exempt and non-exempt assets to measure household wealth. Thus the benefit of filing for bankruptcy in any given year can be estimated for each individual by deducting a respondent’s assets (net of state-specific exemptions) from her discharge-eligible debts. Throughout the paper, I use the benefit of filing lagged one year to measure the pre-shock value of bankruptcy protection.

In the wave of the survey conducted in 2004, respondents were asked if they had ever filed for bankruptcy.

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12 For more information on the wealth questions in NLSY79, see Zagorsky (1999).
13 Asset and debt variables have been top-coded for confidentiality purposes and I apply the lowest consistent top-code to all wealth variables. This affects many but not all of the questions regarding asset and debt variables. Unfortunately the uncensored wealth responses are not available, even with the restricted license dataset. All dollar value variables are adjusted by the CPI-U to real values with the year 2000 as the base year.
14 The restricted license application can be obtained through the BLS website. I thank the BLS staff for their assistance.
personal bankruptcy and if so, in what year.\textsuperscript{15} Respondents also provided the chapter of filing and whether the filing was due to a business failure. In the analysis that follows, I combine Chapter 7 and Chapter 13 filings in the baseline micro-level analysis. This choice is made because of small sample sizes for a given chapter, but separating the analysis by chapter (shown in the appendix) yields essentially identical event-study patterns.\textsuperscript{16} In addition, I focus exclusively on non-business filings by omitting any filings classified as a Chapter 11 business reorganization or where the respondent reported that filing was due to the failure of a business.

The two main critiques of retrospective survey data on bankruptcy are that bankruptcies may be underreported and that individuals may not remember the precise timing of their filing date. First, it is possible that respondents do not report events which may have a negative stigma attached to them. In Appendix Figure 7, I compare the national bankruptcy rate with those implied by survey respondents in the NLSY, the PSID, and the SCF. Although the NLSY only follows one cohort over time, the level and trend of the filing rate is consistent with aggregate patterns, albeit slightly below the national rate and slightly above that of the PSID.

To examine the question of whether respondents accurately remember the timing of their filing, I compare respondents' retrospective date of bankruptcy with their debt and asset levels reported in each survey year. If the bankruptcy information provided in 2004 can predict a trend break in the asset and debt data provided in each survey, then the timing of the reported bankruptcy is sensible. In Figure 1, I confirm that respondents accurately remember the year in which they filed for bankruptcy. Figure 1 shows the total debt reported by bankruptcy filers, plotted against the relative years before or after bankruptcy, relative to the debts of those who never filed. The figure shows that total debts fall by $15,000 upon discharge, consistent with accurate recall. In Appendix B, I provide further assessment of the quality of participants' retrospective responses to the bankruptcy questions, including evidence that bankruptcy filers lose their homes around the time of filing.

The lack of representative panel data on shocks and bankruptcies has made understanding the

\textsuperscript{15}Because of the timing of this question, my sample consists of respondents who answered the NLSY survey in 2004.

\textsuperscript{16}During the period of analysis the choice of chapter was unrestricted, with two-thirds of filers reporting that they filed for Chapter 7, with the remainder filing Chapter 13. I show the event study results separately by Chapter in Appendix Figure 3 and distinguish between chapters in the aggregate analysis in Section IV. Recent work by Dobbie and Song (2015) has emphasized potentially different welfare consequences of bankruptcy chapters.
household decision particularly challenging. For instance, evidence based solely on surveys of filers lack a control group of individuals who have experienced shocks but have not filed for bankruptcy. Unlike previous research that has relied on the PSID, this paper uses the NLSY to investigate the timing and financial determinants of bankruptcy. Although the wealth questions in the PSID have more detail than those in the NLSY, respondents answer them only every five years (and now biennially). Estimating wealth between PSID supplements would require interpolating wealth data across five-year periods when a bankruptcy may have occurred in the interim. In addition, the sample size of bankruptcy filers in the PSID is much smaller than in the NLSY. The PSID only has 200 bankruptcy cases, whereas the NLSY has nearly five times as many cases, which allows for more precise estimates of the household response to “non-strategic” income shocks.

III.B An Event Study Approach to the Bankruptcy Decision

To carefully identify the timing of filing for bankruptcy around plausibly exogenous shocks, I follow the event study framework of Jacobson, LaLonde, and Sullivan (1993), which has been used in many contexts related to job loss (see, e.g., Sullivan and von Wachter 2009). In this framework, the regressions take the form:

\[ Y_{it} = \sum_{j=-s}^{s} \alpha_j \times 1[(t - \tau_i) = j] + \beta X_{it} + \gamma_t + \epsilon_{it}, \]

where \( Y_{it} \) is an indicator for whether or not the respondent filed for bankruptcy in year \( t \), \( \gamma_t \) are year fixed effects, the vector \( X_{it} \) is a set of individual-level characteristics. The coefficients of interest are a vector of relative time dummies, \( \alpha_j \), which reflect the time pattern of the response to the shock \( \tau_i \). During the observation window \((-s, s)\), each \( \alpha_j \) represents the effect on bankruptcy \( j \) years before or after the shock.

An event study methodology is a natural approach to studying the impact of adverse events

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17See Livshits et al. (2010) for a summary of surveys of bankruptcy filers (Appendix B).
19The difference in the number of bankruptcies across the PSID and NLSY samples can be attributed in part to the timing of the retrospective bankruptcy questions, which was asked in an earlier wave of the PSID, and in part to potential under-reporting. See Appendix B for details.
on the likelihood of filing for bankruptcy. This approach extends beyond a difference-in-difference estimator to reflect that the precise timing of discrete shocks conveys useful information in predicting household decisions. With a binary shock, such as job displacement, rather than omitting a time period we can estimate all event-time coefficients relative to those who never experienced a shock.\(^{20}\) The event study framework, in addition to examining the response to shocks and the information content in those shocks, allows for formally testing for the presence of pre-trends. In what follows I report both the estimated coefficients and a test of equality among the pre-shock bankruptcy coefficients.

The above equation is estimated using a logit model, and average marginal effects are reported in the tables and figures.\(^{21}\) The individual-level characteristics, \(X_{it}\), are a full set of age dummies, race, and education.\(^{22}\) The core results presented below also include a complete set of state and year fixed effects, as well as a quadratic in pre-shock financial benefit to filing (defined above).\(^{23}\) Pre-shock values of the financial benefit to filing were included because of their potential endogeneity to the income shock (see, e.g. Charles and Stephens 2004), and concern that simultaneous measures of financial benefit may instead reflect post-bankruptcy outcomes. Standard errors are clustered to allow for arbitrary heteroskedasticity and correlation of errors over time for individuals.\(^{24}\)

### III.B.1 Job Displacement Predicts Bankruptcy

Figure 2 shows the pattern of the relative year coefficients for male job losses, defined as the first time on Unemployment Insurance (UI), with the coefficients reported in Column 1 of Table 1.\(^{25}\)

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\(^{20}\)Because the sample of individuals who never experience a UI-shock is different than those who have, I include individual-level controls. These are not strictly necessary for the event study approach, and have no qualitative impact on the results. An identification approach which relies only on the set of households who experienced a shock yields qualitatively similar patterns, results available upon request.

\(^{21}\)I also discuss the log-odds ratios where applicable, results are shown in Appendix Table A-1. See Fisher (2004) and Gross and Souleles (2002) for examples of duration analysis of personal bankruptcy. Results using a linear probability model are quantitatively similar (and, if anything, statistically stronger) and available upon request.

\(^{22}\)Rather than including controls for health and marital status, I examine these potential determinants separately. In results not shown, including these variables as controls in the job loss specifications has little effect.

\(^{23}\)In results not shown, simply using households’ net financial position, rather than calculating a financial benefit to filing based on state exemption laws, yields qualitatively similar findings.

\(^{24}\)Because of the clustered sampling structure of NLSY, it may be desirable to allow for unspecified correlation at the level of the sampling stratum. Estimates of the main results using standard errors clustered by the sampling strata yield almost identical confidence intervals and are available upon request.

\(^{25}\)I focus on the first displacement because of the potential endogeneity of subsequent displacements. See Stevens (1997) for a careful analysis of the role of additional displacements on earnings and wage losses, which likely drives my finding of heightened bankruptcy risk in the out-years.
The sample consists of all respondents with a male household member who worked full-time in the year previous to a UI spell, with the control group of full-time male workers who never experienced a UI spell (and worked at least 45 weeks). Note that if a worker experiences a job separation but then quickly finds work without UI receipt, then this separation will be coded as “untreated.” In addition, individuals that are fired for cause are unable to collect UI; These types of separations that may be indicative of broader problems (health, financial, or otherwise) faced by the displaced worker are not included in this analysis. The marginal effect coefficients are relative to the group of respondents who have never received UI benefits (never experienced job loss while covered by Unemployment Insurance), and have a baseline bankruptcy filing rate of 4 per 1000 individuals.26

There is a clear spike in the relative time coefficient in the year in which the job loss is experienced: Households with a male worker experiencing a job displacement are more than three times as likely to file for bankruptcy. The heightened likelihood of bankruptcy remains significantly different from zero in the 2-3 years after bankruptcy. Subsequent years are no longer significantly different from the group who never experienced a job loss.27

To put this increased likelihood in perspective, it is useful to compare the regression coefficient on the financial benefit to filing (not shown) with the coefficient on the relative year of job displacement. The effect of the relative year of job loss on the likelihood of filing for bankruptcy is equivalent in regression terms to an increase in indebtedness of $24,000, or about 1.1 standard deviations of the financial benefit to filing measure. Thus, the shock of job separation represents a substantial heightening of bankruptcy risk, on the same order of magnitude as large negative shocks to household net worth.

In addition, prior to job separation there is no difference in the likelihood of filing for bankruptcy between future job losers and the never-unemployed. Although the coefficient for the period prior is close to statistically significant, this is likely due to the presence of measurement error in ret-

26 Marginal effects for these dummy variables are calculated using the “margins” command, “dydx” option in STATA. See Williams (2012) for details.

27 Note that in the out-years, many years both before and after job displacement, the displaced have a higher filing rate than the non-displaced. This finding suggests that, not surprisingly, the non-displaced are not a perfect control group for the displaced, and that other determinants of bankruptcy are omitted from this analysis. The non-displaced are used to pin down the fixed effects and financial benefit coefficients, but regressions using only the displaced (with an omitted relative time category) yield qualitatively similar time-patterns around the displacement event. Results are available upon request.
rospective survey responses (see Appendix B for more detail). The estimated coefficients of the pre-displacement relative time indicators are not significantly different from zero, as shown by the joint test in the next-to-last row of Table 1 ($p = 0.93$). Furthermore, the coefficient for the period immediately prior to job loss (-1 to -2 years) is statistically different from the time of job loss (year 0 and 1).  

With a marginal coefficient twice as large and a t-statistic over five (relative to the non-displaced), the effect is clearly largest at the time of job displacement. Thus the bankruptcy hazard in the year of job separation is not only significantly different from the non-separation control group, but is also different from the years prior to job separation. This result highlights the advantages of the event study methodology: The years prior to job separation serve as a “placebo” test of the impact of job displacement on bankruptcy, confirming that job separations are indeed a ‘shock’ to these households based on the timing of bankruptcy filing.

Figure 3 shows the relative job loss year coefficients for female job separations. These coefficients exhibit a similar pattern to those of men, with double the likelihood of filing in the year of job displacement and the year following displacement relative to those who are never displaced. However, the test of pre-separation coefficients is weaker for women, as the test of the null of equality of the pre-separation coefficient and the year of separation ($\alpha_0 = \alpha_{-1}$) cannot be rejected ($p=0.34$). While the statistical relationship is weaker, the pattern of coefficients is consistent with the timing of bankruptcy depending on the timing of job loss.

The results for job separations confirm that the timing of bankruptcy is strongly related to the timing of job displacement, particularly for male workers. Unlike the previous empirical methodology on bankruptcy, the event study framework allows for estimation of pre-shock differences in bankruptcy likelihoods, and to test the coefficients across years. The results support the dynamic forward-looking model described above, which predicts that households who suffer large negative shocks would file immediately upon receiving information about future employment and permanent income, while other households will delay filing as its effect on permanent income may not be immediately known. 

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28 The last row of Table 1 reports the p-value from an F-test of the null $\alpha_0 = \alpha_{-1}$. In this case, $p = 0.02$.

29 As discussed in Appendix B, the presence of measurement error in the retrospective response to the year of filing may induce some of the “delayed” effect, and lead to imprecision in the comparisons of the coefficients before and
III.B.2 Heterogeneity of the Bankruptcy Response

Given that indebtedness is a necessary condition to filing for bankruptcy, I next explore heterogeneous responses to unemployment shocks based on the level of the household’s indebtedness. An advantage of the NLSY data, given the rich questions on household assets and liabilities, as well as state of residence, is the ability to estimate each household’s financial benefit to filing for bankruptcy in each wave of the survey. As shown in Figure 4, households with a positive financial benefit to filing for bankruptcy are much more responsive to a male unemployment shock, with a relative time coefficient in the year of the shock twice as large as the coefficient for households with no benefit to filing.\textsuperscript{30} That some households with no estimated financial benefit nonetheless file for bankruptcy suggests that financial distress can occur relatively quickly, as the measure of financial benefit is from one or two years prior. It should also be re-iterated that measurement error in the timing variables (UI shock and bankruptcy decision) and assets and debts variables also leads to noisier estimates. Splitting the sample by financial benefit, not done elsewhere in the literature, yields a clear pattern in the bankruptcy likelihoods around the timing of a job displacement.

Similarly, in Figure 5, households above the top quartile of indebtedness (in the survey, $40,000), are much more likely to file for bankruptcy in response to an unemployment shock than those households who are less indebted. This heterogeneity is consistent with the theoretical framework in which households file for bankruptcy when it is advantageous to do so, but respond to new information about current and future income prospects. In addition, these heterogeneous patterns may be consistent with recent evidence of differential declines in the stigma associated with bankruptcy filing among higher-debt and higher-income households (Cohen-Cole and Duygan-Bump 2008). The timing of male unemployment shocks is a strong predictor of the timing of the personal bankruptcy decision, especially among those who benefit most from filing.

Do the bankruptcy response patterns vary along other dimensions of potential heterogeneity, including help from spouses and the deviations from income expectations? First, as shown in Appendix Figure 1, married households appear to respond more strongly to a male unemployment shock.\textsuperscript{30} The coefficient estimates from Figures 4 and 5 are presented in Table 2. Twenty-nine percent of person-years have a positive benefit to filing, exclusive of filing costs, for the purposes of this sample stratification. Using SCF data from 1992, White (1998) estimates that at least 15% of households had a positive benefit to filing.
shock than a single male household, which may reflect differences in consumption commitments (Chetty and Szeidl 2007) or differences in the severity of the job separation. As a proxy for the severity of the separation relative to expectations, Appendix Figure 2 splits the sample by the size of the pre-shock average income. Relative to other below-median earners, those who suffer an unemployment shock experience a large and persistent increase in the probability of filing for bankruptcy, which lasts four to five years after separation. In contrast, above-median earners who suffer an unemployment shock have a similar likelihood of filing for bankruptcy in the immediate aftermath, but the effects are much less persistent in the two to three years after filing. Finally, Appendix Figure 3 shows that the relative time coefficients are similar for both Chapter 7 (debt discharge) and Chapter 13 (debt reorganization) filers, supporting the decision to combine the two types of filers. If anything, Chapter 7 filers are slightly more responsive to unemployment shocks relative to those who file for a Chapter 13 debt renegotiation.

### III.B.3 Do Divorce or Disability Shocks Predict Bankruptcy?

Proponents of the adverse events hypothesis also suggest that divorce and health problems lead directly to bankruptcy.\(^{31}\) I test these additional claims in Figures 6 and 7 (with the coefficients reported in Table 1). Figure 6 presents the effect of relative time of divorce or separation, defined here as being married in year (t-1) and unmarried in year t. The control group is those individuals who have been married and never divorced or separated.

Although significantly different from those who never filed for divorce, the bankruptcy likelihood begins increasing one to two years prior to divorce. Further, we cannot reject the test of equality of the pre-divorce and year of divorce coefficients \((\alpha_0 = \alpha_{-1})\). Thus while bankruptcy is correlated with marital separation, the results presented here suggest that divorce is also related to money problems on their own.\(^{32}\) We can only conclude that divorce both precedes and follows bankruptcy, but it is not clear that causality runs in either direction, as there could be omitted drivers of both

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\(^{31}\)For related work in these areas, see Fisher and Lyons (2006) on divorce and Himmelstein et al. (2005) and Dobkin et al. (2016) on health shocks.

\(^{32}\)Separately estimating the impact of divorce for men and women yields similar magnitudes of the effects, but the timing is more immediate for women than men. There is no evidence that women are more likely to file than men after divorce, however. Results are available from the author upon request.
divorce and bankruptcy.\textsuperscript{33}

There is less power in the NLSY to detect an impact on bankruptcy from a disability shock, as the NLSY cohort is (for the most part) young and healthy. Nonetheless, 36% of the sample has experienced a health limitation that reduced their ability to work at some point. Following Burkhauser and Daly (1996), I define a disability shock as the first time a respondent reports being healthy for one period and then limited for two consecutive periods.\textsuperscript{34} The results based on this negative health shock, shown in Figure 7, show an increased likelihood of bankruptcy at the time of the shock, with unhealthy individuals more than twice as likely to file for bankruptcy than those who never experienced this pattern of health (at a rate of 5 bankruptcies per 1,000 disability cases). An F-test for the equality of the pre-shock and year-of-shock coefficients ($\alpha_0 = \alpha_{-1}$) can be rejected at the 6\% level. However, other time periods appear to have similar coefficients and significance in an unpredictable pattern. These results, which are presented in the fourth column of Table 1, suggest that the timing of disability shocks are weakly related to the timing of bankruptcy, independent of income and wealth.\textsuperscript{35} This finding is consistent with a disability shock permanently reducing expectations regarding lifetime income.

To isolate heterogeneous responses to divorce and disability based on the level of household indebtedness, Figures 8 and 9 stratify the sample by whether the household has a positive financial benefit to filing for bankruptcy. Households with a positive financial benefit to filing are much more responsive to both divorce (Figure 8) and disability (Figure 9), with much larger relative time coefficients in the year of the shock compared to households with no estimated benefit to filing. The patterns across relative time periods are generally consistent with the results for the full sample, as divorce both precedes and follows bankruptcy, with significant coefficients between two years before to five years after divorce. In contrast, the bankruptcy response to disability for households with a positive financial benefit to filing is sharpest in the first three years following the onset of disability.

\textsuperscript{33}Similarly, Hankins and Hoekstra (2011) find no impact of exogenous income shocks (in the form of large lottery winnings) on divorce rates.

\textsuperscript{34}This stricter definition of health shocks applies to 10\% of respondents.

\textsuperscript{35}In related recent research, Morrison, Gupta, Olson, Cook and Keenan (2013) and Gupta, Morrison, Fedorenko and Ramsey (2015) identify the financial consequences of car crashes and cancer diagnoses, respectively.
IV Aggregate Analysis

While the results above suggest a strong relationship between job loss and bankruptcy in the cross-section, the NLSY follows only one cohort over time, and the sample is not large enough to detect differences in the effects of job loss based on the severity of the displacement. I thus turn to an aggregate analysis to investigate the relationship between job losses and bankruptcy using county-level data. This alternative empirical approach corroborates and extends the evidence provided using the individual-level panel data.

The bankruptcy data are collected from the Administrative Office of the U.S. Courts. The dataset contains the number of business and non-business filings, by chapter, for each county for each year from 1980-2004, but no information is collected on the causes of bankruptcy or the characteristics of the filer at this level.\(^{36}\) Data on employment at the county level is collected from County Business Patterns (CBP) from 1980-2004. As described earlier, the bankruptcy code was essentially unchanged during this time period.\(^{37}\) I construct county-level measures of manufacturing, non-manufacturing, and total employment for 1980-2004, and use population data from three decennial censuses.\(^{38}\)

The theoretical framework described in Section II.B suggests that the bankruptcy decision should be made on the basis of new information. As such, in the specifications that follow the change in the number of jobs is the independent variable of interest, rather than the stock of jobs at a given time. I regress the total non-business bankruptcy rate (measured per 1000 residents) in county \(c\) in year \(t\), \(Y_{ct}\), on the annual net change in the number of jobs per person, \(\Delta Jobs_{ct} = Jobs_{ct} - Jobs_{ct-1}\), in the same county:

\[
Y_{ct} = \beta \Delta Jobs_{ct} + \gamma_c + \mu_t + \lambda_c \times t + \epsilon_{ct}
\]

To control for time and location differences, I include year dummies (\(\mu_t\)), fixed effects for all 3,135

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\(^{36}\)To the best of my knowledge, these county-level data have only been used in the recent literature to address the consequences of expanded access to casino gambling (Evans and Topoleski 2002; Barron, Staten, and Wilshusen 2002). Bankruptcy data from the AOUSC has been used more generally, see, e.g. Dick and Lehnert (2010).

\(^{37}\)Amendments have modified some exemption rules, and changes were made in 1984 intended to limit write-offs from debts incurred immediately prior to bankruptcy, so-called “bad faith” debts.

\(^{38}\)These measures use the appropriate NAICS and SIC codes (2-digit classifications), which have changed over time. Some employment values in the CBP data are coded as a range for confidentiality purposes. I impute using the midpoints of the ranges provided. Data limitations prevent the use of finer sub-classifications, as well as alternative precise indicators of the severity of job loss.
counties \((\gamma_c)\), and county-specific time trends \((\lambda_c \times t)\).\(^{39}\) The year dummies remove any trends in bankruptcy filing at the national level, as well as any cyclical aggregate variation. The county-specific fixed effects partial out the time-invariant characteristics of counties to account for the fact that some counties may have more bankruptcies (per capita) or a higher share of Chapter 7 filings due to factors unrelated to employment shocks, while the county-specific time trends capture any local long-run patterns in filing rates.\(^{40}\)

Thus the identifying variation in this equation is within-county variation in job growth over time relative to both county-specific and year-specific averages as well as within-county trends. By measuring bankruptcies as a per-person rate, and including county-level trends along with both time and county fixed effects, rather than solely using fluctuations in the business cycle, this specification is a particularly demanding test of the hypothesis that local fluctuations in employment have an impact on the local bankruptcy rate. Note that the coefficients from this regional analysis are not directly comparable to the microdata coefficients in Section III, as there are important differences in the available measures of job displacement (individual losses vs. net changes in a county).

To address the concern that labor supply shocks may both affect bankruptcy rates and employment, I employ a Bartik-style shift-share instrument to isolate the component of the annual change in net jobs that can be attributed to labor demand. For example, an unobserved local health shock could lead to both a decline in employment and an increase in personal bankruptcy filing. The instrument is based on the pre-existing industry share of jobs in a county (with 1980 as the base year) and the national percentage change in that industry from year to year. The Bartik (1991) procedure has been used extensively in labor economics (for a recent example, see Notowidigdo 2011), but to my knowledge has not been used to test for bankruptcy responses to local labor demand shocks.

The results from the aggregate analysis are presented in Table 3. All else equal, counties that experience more job losses have a greater number of bankruptcies. Column 1 shows that 1,000 additional jobs lost in a county lead to a doubling of the bankruptcy rate (an additional 4.3 bankruptcies

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\(^{39}\)A small number of counties have changed boundaries over this period, so I construct consistent county definitions across all 25 years where necessary.

\(^{40}\)Because of concerns related to heteroskedasticity across counties with different population sizes, all regressions using this specification are weighted based on the inverse of the estimated variance of the error term for the population in each county-year observation (see Solon, et al. 2013). Results without weights are qualitatively similar and available upon request. All standard errors are clustered to allow for arbitrary correlation at the county level.
on a base rate of 2.7 per 1,000 residents), even after accounting for the fixed attributes of the county and the macroeconomic conditions in the year of observation. Column 2 uses the shift-share measure as an IV (with a first-stage F-statistic of 71.4, p-value < 0.001), and estimates a larger but noisier impact of job changes on local bankruptcy rates.\footnote{In results not shown, I cannot reject a symmetric bankruptcy response to job gains and job losses. Given the fixed effects and time trends in the specification, the estimates are best interpreted as deviations from trends.} The coefficient implies that 1,000 additional job losses attributed to labor demand shocks from the county’s industrial composition are associated with a relative quadrupling of the per capita bankruptcy rate.

The larger coefficient in the IV specification relative to the OLS estimate may be a result of attenuation bias, but may also reflect underlying bias in the OLS regression. In particular, the results from the OLS specification may in part reflect a broader negative local shock that influences both employment and bankruptcy. The IV estimate is intended to address this concern, and the fact that the IV estimate is larger than the OLS estimate supports the view that OLS specifications of this relationship without a plausible instrument may be biased.

As a proxy for severe separations, I partition job changes into separate measures for the manufacturing and non-manufacturing sectors. Manufacturing jobs are generally more likely to be unionized, have longer tenures, and provide better health care and pensions than non-manufacturing jobs (Anderson and Meyer 1994, Brown 1989).\footnote{Note that the heightened stability of manufacturing jobs may also encourage lenders to offer more credit, such as mortgages, to workers in the manufacturing sector.} These are also jobs where the accumulation of specific human capital may be particularly important in determining the costs of job separation (Topel 1990, Carrington 1993). Column 3 of Table 3 separates the county-level changes in jobs by manufacturing and non-manufacturing job changes. Manufacturing job losses are 40 percent more likely to lead to bankruptcy than non-manufacturing jobs, and a test of equality of the coefficients is rejected with a p-value < 0.05. These results suggest that the changing structure of employment, towards shorter-tenure jobs and away from manufacturing industries, which provided steadier employment and better benefits, has been a contributing factor to the growth in consumer bankruptcies. In terms of the framework discussed in Section II.B, manufacturing losses have been both more severe (in terms of dollar magnitude) and more persistent (in terms of future earnings) than non-manufacturing job displacements.
Columns 4 through 7 of Table 3 explore whether county job changes have a larger impact on Chapter 7 or Chapter 13 filing rates. Using both OLS and IV methods described above, the results suggest that most of the local bankruptcy response to employment changes is associated with an increase in Chapter 7 filings. This finding supports the view that the rate of Chapter 7 filings, which are the “fresh start” liquidation chapter of filing, and often an indication of more extreme hardship compared to a Chapter 13 “restructuring” of debt, may be most affected by local labor market conditions.

The county-level data can be used to explore heterogeneity across the business cycle and across county-level characteristics in the responsiveness of the bankruptcy rate to job losses. Table 4 presents regression results where the net job change (per 1,000 residents) variable is interacted with characteristics of the time period or county. The first column shows that the responsiveness in the bankruptcy rate to job losses is higher in years with weaker macroeconomic conditions and elevated unemployment rates. Columns 2 through 7 show that the bankruptcy rate in counties that are less educated, have a larger share of minorities, and are more populous is more strongly associated with job losses. These results are consistent with the view that less affluent and more indebted households are the marginal bankruptcy filers, and that economic downturns have the most pronounced effects on these groups in terms of both unemployment and bankruptcy filing.

In Table 5, I use mass layoffs as an alternative measure of regional job losses. Starting in 1995, the BLS provides county-level totals of individuals who were laid off from an establishment that experienced at least 50 initial claims for unemployment insurance during a 5-week period. Although I do not have the same data coverage in terms of years and counties, mass layoffs are a cleaner measure of job separations relative to a net change in jobs that may reflect migration, second jobs, or secondary earners entering the workforce. Table 5 uses the total number of mass layoffs per 1,000 individuals in the county as the independent variable, and continues to control for county, year, and county-specific time trends. I find that 1,000 additional mass layoffs leads to 14 additional bankruptcies, sharply increasing the bankruptcy rate by a factor of more than five. Notably, as shown in columns (2) and (3), Chapter 7 filing rates appear to be much more strongly related to

\[^{43}\text{Notably, when comparing the bankruptcy effect in counties that experience net job gains with those that experience net job losses, the coefficients are nearly identical (result available upon request).}\]
mass layoffs than Chapter 13 filing rates.

These results on mass layoffs can be used for a back-of-the-envelope estimate of the economic impact of job losses on creditors’ balance sheets. Consider that the average bankruptcy filing discharges roughly $140,000 in debt. According to the BLS data, there were about 377,000 individuals displaced through a mass layoff in 2004. Based on the estimated increase of 14 bankruptcies per 1,000 mass layoffs, this would lead to a total increase of 5,300 bankruptcies that could be attributed to mass layoffs through this methodology, and a total debt discharge of $740 million. Each mass-layoff-displaced individual costs creditors roughly $2,000 through bankruptcy discharge, which in the aggregate can lead to substantial losses.

An important caveat to this aggregate analysis is that the individuals in the county who file for bankruptcy are not necessarily the same people who suffered the loss of a job as reflected in the net change in jobs or mass layoffs in the county. Thus, job losses could have both direct and indirect effects on bankruptcy in this aggregate analysis. In the direct case, the household losing the job also files for bankruptcy. If the job losses have an indirect effect on other members of the regional economy (through the service sector, or the housing or credit markets, for instance) then these general equilibrium effects would also be included in the county-level estimates. In addition, if individuals live and work in different counties, this will attenuate any observed relationship between job losses and personal bankruptcy.

Comparing the results from the county-level data and the individual-level data, the county-level estimates are larger than the individual-level estimates. There are a few reasons why this might be the case. First, the measures of job separation are different, as the individual-level data focuses only on insured unemployment spells, while the county-level data relies on a measure of net aggregate job changes. Next, as discussed in Section III.A, there may be under-reporting or mis-timed reporting of bankruptcy filings in the individual data, which would lead to attenuation. Finally, as discussed above, the county-level data may capture indirect effects of job losses on other participants of the local economy.

The results from the county-level data confirm the predictions of the dynamic framework and

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[44] See the US Court’s annual BAPCPA report to Congress for more details. This figure is the average “net scheduled debt,” which is the best available approximation of the amount of debt discharged.
corroborate the findings using the individual-level panel data of the NLSY. Both approaches suggest that more job losses lead to additional personal bankruptcy filings, especially Chapter 7 filings, all else equal. In particular, job displacement sharply increases the likelihood of bankruptcy and has persistent effects over two to three years after separation, and the effects are strongest when displacement is likely the source of permanent negative income shocks.

V Conclusion

Filing for personal bankruptcy has become so common that over 11% of NLSY households aged 39-48 have experienced it at some point in their lives. And yet economists know very little about the determinants of bankruptcy, due in large part to the lack of representative micro-level data with information on debts, assets, adverse events, and bankruptcies. This paper takes advantage of a new retrospective bankruptcy question in the NLSY to identify the role which adverse events in general, and job loss in particular, play in the timing and likelihood of filing for bankruptcy.\footnote{Two datasets, the PSID and the NLSY, are the only longitudinal surveys available for research on bankruptcy that contain information on household shocks as well as rich detail on assets and debts in order to accurately calculate households’ financial benefit to filing. Note that even matching administrative records on employment (e.g. the LEHD) to administrative bankruptcy records would not allow for estimates of the financial benefit of bankruptcy.}

The results from both individual- and county-level analyses suggest a pattern of bankruptcy filing in response to negative labor market shocks which is consistent with a dynamic forward-looking model of the household bankruptcy decision. In particular, although the duration of the unemployment shocks analyzed in this paper are brief, they potentially signal changes in expected permanent income. Although easing credit constraints should theoretically improve households’ ability to smooth consumption, there has been a marked increase in consumption volatility over the last 25 years (Keys 2008; Gorbachev 2011). For some households, credit expansion clearly has not kept pace with the growth in earnings volatility as documented by Moffitt and Gottschalk (2002) and Shin and Solon (2011). Some income shocks are sufficiently large that households must file for bankruptcy and select a new consumption path.

Households’ bankruptcy response to unemployment spells further suggests that households use credit markets as a form of unemployment insurance. The results demonstrate a complementarity
between unemployment insurance programs and personal bankruptcy, and thus examinations of
the optimality of the UI system should include its impact on credit markets. Furthermore, the
insurance value of the “bankruptcy floor” in the event of job loss can help to explain the attenuated
consumption response to job loss (Stephens 2001). Understanding how imperfect insurance markets
interact with credit markets remains an area worthy of further investigation. For instance, a tripling
of a region’s bankruptcy rate due to a labor demand shock is likely to affect lenders’ willingness to
provide access to low-cost credit.

Overall, the results support the view that labor market shocks are crucial to understanding the
timing and likelihood of personal bankruptcy. Back-of-the-envelope calculations suggest that each
displacement costs creditors’ about $2,000 in discharged debt through bankruptcy, with the mass
layoffs of 2004 being associated with a quarter of a billion dollars in discharged debt. Consistent with
the approach of Hsu, Matsa, and Melzer (2014) to describe the benefits to creditors from unemploy-
ment insurance as a “positive externality” in terms of repaid debts, the results here establish that
the employment shock itself serves as a “negative externality” from a creditor’s standpoint. Fur-
thermore, this figure is based on insured displacements, and direct discharge (as opposed to indirect
charge-offs), but the impact of all displacements on creditors’ balance sheets could be substantially
larger.

In addition, the effects of job displacement in both the NLSY and the county-level data are
of comparable magnitude and duration, an empirical regularity across independent datasets and
different estimation methodologies. These results reinforce the importance of dynamic micro-
foundations in interpreting both household decision-making and aggregate patterns in unemploy-
ment and bankruptcy. In sum, the findings suggest that the household bankruptcy decision relies
not only on current income and wealth, but also on expectations about future employment and
earnings possibilities.
References


Han, Song and Geng Li, “Household Borrowing after Personal Bankruptcy,” *Journal of Money, Credit, and Banking*, 2011, 43 (2-3), 491–517.


, “Do you have to be smart to be rich? The impact of IQ on wealth, income and financial distress,” *Intelligence*, 2007, 35, 489–501.

Figure 1: Total Debts of Bankruptcy filers Relative to Non-Filers, by Relative Time of Bankruptcy Shock

Note: Figure 1 presents relative time coefficients from an OLS regression of total debts on the timing of bankruptcy filing. See Appendix B for details. Controls include age, race, education, and state and year fixed effects. Dashed lines represent 95% confidence interval. Non-filer mean total debts are $36,961. The figure shows a clear break in indebtedness around the timing of reported bankruptcy filing.
Figure 2: Probability of Bankruptcy Filing for Men by Relative Time from UI Shock

Note: Figure 2 presents average marginal effect coefficients from a logit regression of bankruptcy filing on the timing of male unemployment shocks. See text for definitions of spells. The regression includes controls for age, race, education, state and year fixed effects, and a quadratic in financial benefit. Dashed lines represent 95% confidence interval. Coefficients are reported in Table 1.
Figure 3: Probability of Bankruptcy Filing for Women by Relative Time from UI Shock

Note: Figure 3 presents average marginal effect coefficients from a logit regression of bankruptcy filing on the timing of female unemployment shocks. See text for definitions of spells. The regression includes controls for age, race, education, state and year fixed effects, and a quadratic in financial benefit. Dashed lines represent 95% confidence interval. Coefficients are reported in Table 1.
Figure 4: Probability of Bankruptcy Filing for Men by Relative Time from UI Shock, by Financial Benefit to Filing

Note: Figure 4 presents average marginal effect coefficients from a logit regression of bankruptcy filing on the timing of male unemployment shocks, separately for whether the household has a positive financial benefit to filing for bankruptcy or not in the year prior to the shock. See text for definitions of spells. The regression includes controls for age, race, education, and state and year fixed effects. Coefficients are reported in Table 2.
Figure 5: Probability of Bankruptcy Filing for Men by Relative Time from UI Shock, by Indebtedness

Note: Figure 5 presents average marginal effect coefficients from a logit regression of bankruptcy filing on the timing of male unemployment shocks, separately for whether the household is in the top quartile of indebtedness (with debts exceeding $40,000) or not in the year prior to the shock. See text for definitions of spells. The regression includes controls for age, race, education, and state and year fixed effects. Coefficients are reported in Table 2.
Figure 6: Probability of Bankruptcy Filing by Relative Time from Divorce

Note: Figure 6 presents average marginal effect coefficients from a logit regression of bankruptcy filing on the timing of divorce. See text for definitions of spells. The regression includes controls for age, race, education, gender, state and year fixed effects, and a quadratic in financial benefit. Dashed lines represent 95% confidence interval. Coefficients are reported in Table 1.
Figure 7: Probability of Bankruptcy Filing by Relative Time from Disability

Note: Figure 7 presents average marginal effect coefficients from a logit regression of bankruptcy filing on the timing of disability. See text for definitions of spells. The regression includes controls for age, race, education, gender, state and year fixed effects, and a quadratic in financial benefit. Dashed lines represent 95% confidence interval. Coefficients are reported in Table 1.
Figure 8: Probability of Bankruptcy Filing by Relative Time from Divorce, by Financial Benefit to Filing

Note: Figure 8 presents average marginal effect coefficients from a logit regression of bankruptcy filing on the timing of divorce, separately for whether the household has a positive financial benefit to filing for bankruptcy or not. See text for definitions of spells. The regression includes controls for age, race, education, gender, and state and year fixed effects.
Figure 9: Probability of Bankruptcy Filing by Relative Time from Disability, by Financial Benefit to Filing

Note: Figure 9 presents average marginal effect coefficients from a logit regression of bankruptcy filing on the timing of disability, separately for whether the household has a positive financial benefit to filing for bankruptcy or not. See text for definitions of spells. The regression includes controls for age, race, education, gender, and state and year fixed effects.
Table 1: Estimated Impact of “Adverse Events” on the Probability of Filing for Bankruptcy

<table>
<thead>
<tr>
<th>By type of event</th>
<th>UI - Men</th>
<th>UI - Women</th>
<th>Divorce</th>
<th>Disability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Relative Time Coefficients</td>
<td>Coef.</td>
<td>SE</td>
<td>Coef.</td>
<td>SE</td>
</tr>
<tr>
<td>7 or more years before</td>
<td>0.0035</td>
<td>0.0018</td>
<td>0.0040</td>
<td>0.0022</td>
</tr>
<tr>
<td>5-6 years before</td>
<td>-0.0037</td>
<td>0.0043</td>
<td>-0.0134</td>
<td>0.0089</td>
</tr>
<tr>
<td>3-4 years before</td>
<td>-0.0020</td>
<td>0.0033</td>
<td>0.0032</td>
<td>0.0031</td>
</tr>
<tr>
<td>1-2 years before</td>
<td>0.0027</td>
<td>0.0022</td>
<td>0.0062</td>
<td>0.0024</td>
</tr>
<tr>
<td>year of event + 1 year after</td>
<td>0.0084</td>
<td>0.0015</td>
<td>0.0090</td>
<td>0.0020</td>
</tr>
<tr>
<td>2-3 years after</td>
<td>0.0044</td>
<td>0.0018</td>
<td>0.0010</td>
<td>0.0028</td>
</tr>
<tr>
<td>4-5 years after</td>
<td>0.0019</td>
<td>0.0021</td>
<td>0.0015</td>
<td>0.0029</td>
</tr>
<tr>
<td>6-7 years after</td>
<td>0.0015</td>
<td>0.0020</td>
<td>0.0034</td>
<td>0.0025</td>
</tr>
<tr>
<td>8-9 years after</td>
<td>0.0006</td>
<td>0.0021</td>
<td>0.0046</td>
<td>0.0024</td>
</tr>
<tr>
<td>10 or more years after</td>
<td>0.0043</td>
<td>0.0010</td>
<td>0.0019</td>
<td>0.0014</td>
</tr>
<tr>
<td>Additional Controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Individuals</td>
<td>5,396</td>
<td>5,210</td>
<td>6,492</td>
<td>7,560</td>
</tr>
<tr>
<td>Observations</td>
<td>60,644</td>
<td>46,724</td>
<td>99,839</td>
<td>116,733</td>
</tr>
<tr>
<td>Baseline (never shocked)</td>
<td>0.006</td>
<td>0.008</td>
<td>0.004</td>
<td>0.006</td>
</tr>
<tr>
<td>p-value for test of pre-shock coefs. = 0</td>
<td>0.93</td>
<td>0.99</td>
<td>0.06</td>
<td>0.43</td>
</tr>
<tr>
<td>shock year = previous year</td>
<td>0.02</td>
<td>0.34</td>
<td>0.27</td>
<td>0.06</td>
</tr>
</tbody>
</table>

Note: Table 1 presents average marginal effects from logit models for bankruptcy filing, see text for definition of spells. Standard errors clustered by individuals. Additional controls are race, age, education, state and year fixed effects, and a quadratic in the financial benefit to filing for bankruptcy. Respondents’ gender is included as a covariate in the last two specifications. Sample is restricted to those working full-time in the period prior to job loss (unemployment events), or those who ever married (divorce event).
Table 2: Heterogeneity of Impact of Male UI Shock on Bankruptcy Filing

<table>
<thead>
<tr>
<th>Relative Time Coefficients</th>
<th>No Financial Benefit</th>
<th>Positive Financial Benefit</th>
<th>Below $40k Debt</th>
<th>Above $40k Debt</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coef.</td>
<td>SE</td>
<td>Coef.</td>
<td>SE</td>
</tr>
<tr>
<td></td>
<td>Coef.</td>
<td>SE</td>
<td>Coef.</td>
<td>SE</td>
</tr>
<tr>
<td></td>
<td>Coef.</td>
<td>SE</td>
<td>Coef.</td>
<td>SE</td>
</tr>
<tr>
<td></td>
<td>Coef.</td>
<td>SE</td>
<td>Coef.</td>
<td>SE</td>
</tr>
<tr>
<td>7 or more years before</td>
<td>0.0023</td>
<td>0.0020</td>
<td>0.0052</td>
<td>0.0039</td>
</tr>
<tr>
<td>5-6 years before</td>
<td>-0.0006</td>
<td>0.0042</td>
<td>-0.0140</td>
<td>0.0116</td>
</tr>
<tr>
<td>3-4 years before</td>
<td>0.0002</td>
<td>0.0034</td>
<td>-0.0097</td>
<td>0.0086</td>
</tr>
<tr>
<td>1-2 years before</td>
<td>0.0018</td>
<td>0.0026</td>
<td>0.0034</td>
<td>0.0047</td>
</tr>
<tr>
<td>year of event + 1 year after</td>
<td><strong>0.0066</strong></td>
<td><strong>0.0016</strong></td>
<td><strong>0.0118</strong></td>
<td><strong>0.0035</strong></td>
</tr>
<tr>
<td>2-3 years after</td>
<td>0.0053</td>
<td>0.0017</td>
<td>0.0001</td>
<td>0.0050</td>
</tr>
<tr>
<td>4-5 years after</td>
<td>0.0020</td>
<td>0.0024</td>
<td>0.0006</td>
<td>0.0046</td>
</tr>
<tr>
<td>6-7 years after</td>
<td>0.0044</td>
<td>0.0020</td>
<td>-0.0064</td>
<td>0.0054</td>
</tr>
<tr>
<td>8-9 years after</td>
<td>0.0016</td>
<td>0.0023</td>
<td>-0.0023</td>
<td>0.0049</td>
</tr>
<tr>
<td>10 or more years after</td>
<td>0.0040</td>
<td>0.0010</td>
<td>0.0038</td>
<td>0.0023</td>
</tr>
<tr>
<td>Additional Controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Individuals</td>
<td>5,180</td>
<td>3,981</td>
<td>4,677</td>
<td>3,061</td>
</tr>
<tr>
<td>Observations</td>
<td>42,142</td>
<td>17,330</td>
<td>25,713</td>
<td>14,819</td>
</tr>
</tbody>
</table>

Note: Table 2 presents average marginal effects from logit models for bankruptcy filing, see text for definition of spells. Standard errors clustered by individuals. Additional controls are race, age, education, and state and year fixed effects. Sample is restricted to those working full-time in the period prior to job loss.
Table 3: County-level Estimates of Job Loss and Bankruptcy

<table>
<thead>
<tr>
<th>Dependent variable (per 1000 residents)</th>
<th>Total non-business bankruptcy rate</th>
<th>Chapter 7 bankruptcy rate</th>
<th>Chapter 13 bankruptcy rate</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OLS (1)</td>
<td>IV (2)</td>
<td>OLS (4)</td>
</tr>
<tr>
<td>Net Change in Jobs per person</td>
<td>-4.335***</td>
<td>-7.743***</td>
<td>-3.393***</td>
</tr>
<tr>
<td></td>
<td>(0.632)</td>
<td>(2.312)</td>
<td>(0.463)</td>
</tr>
<tr>
<td>Net Change in Manufacturing jobs per person</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Net Change in Non-manufacturing jobs per person</td>
<td>-3.811***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.701)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>County fixed effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Year fixed effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>County-specific time trends</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.815</td>
<td>0.908</td>
<td>0.816</td>
</tr>
<tr>
<td>Number of counties</td>
<td>3,135</td>
<td>3,135</td>
<td>3,135</td>
</tr>
<tr>
<td>Number of observations</td>
<td>75,172</td>
<td>75,172</td>
<td>75,172</td>
</tr>
</tbody>
</table>

Note: Table 3 presents OLS and IV coefficients from specifications exploring the relationship between county-level bankruptcy rates and changes in employment. Instrument in columns 3, 5, and 7 is a shift-share measure based on the pre-existing share of manufacturing and non-manufacturing jobs in a county and the national percentage change in manufacturing and non-manufacturing jobs. F-statistic on test of excluded instrument = 71.4. Regressions are efficiency-weighted based on a non-parametric estimation of the variance of the error terms as a function of the population of each county-year observation (Solon, et al. 2013). Standard errors clustered by county in parentheses. *** \( p < 0.01 \), ** \( p < 0.05 \), * \( p < 0.1 \).
Table 4: Heterogeneity in County-level Estimates of Job Loss and Bankruptcy

Dependent variable = number of non-business bankruptcies in a county per 1000 residents

<table>
<thead>
<tr>
<th>Interacted Covariate</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>High Unemp. Rate</td>
<td>Fraction w/HS diploma</td>
<td>Fraction w/college degree</td>
<td>% African-American</td>
<td>Median Age</td>
<td>County Population</td>
<td>Median Household Income</td>
</tr>
<tr>
<td></td>
<td>(0.571)</td>
<td>(0.475)</td>
<td>(0.362)</td>
<td>(0.461)</td>
<td>(0.727)</td>
<td>(0.493)</td>
<td>(0.400)</td>
</tr>
<tr>
<td>Net change in Total Jobs per person x Covariate</td>
<td>-1.190**</td>
<td>1.444**</td>
<td>0.907</td>
<td>-2.660***</td>
<td>0.279</td>
<td>-2.781***</td>
<td>0.324</td>
</tr>
<tr>
<td></td>
<td>(0.527)</td>
<td>(0.718)</td>
<td>(0.703)</td>
<td>(0.606)</td>
<td>(0.809)</td>
<td>(0.603)</td>
<td>(0.733)</td>
</tr>
<tr>
<td>County fixed effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Year fixed effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Number of counties</td>
<td>3135</td>
<td>3135</td>
<td>3135</td>
<td>3135</td>
<td>3135</td>
<td>3135</td>
<td>3135</td>
</tr>
<tr>
<td>Number of obs</td>
<td>75,175</td>
<td>75,175</td>
<td>75,175</td>
<td>75,175</td>
<td>75,175</td>
<td>75,175</td>
<td>75,175</td>
</tr>
</tbody>
</table>

Note: Table 4 presents OLS coefficients from specifications exploring the relationship between county-level bankruptcy rates and changes in employment. In each column the main effect of job changes is interacted with a covariate. In the first column, “high unemployment” is based on whether the national unemployment rate was greater than six percent, the median value for 1977-2004. In columns 2 through 7, each covariate takes on a value of 1 if the 1980 value is greater than the median for all 3,135 counties. Regressions are efficiency-weighted based on a non-parametric estimation of the variance of the error terms as a function of the population of each county-year observation (Solon, et al. 2013). Standard errors clustered by county in parentheses, *** p < 0.01, ** p < 0.05, * p < 0.1.
Table 5: County-level Estimates of Mass Layoffs and Bankruptcy

<table>
<thead>
<tr>
<th>Dependent variable (per 1000 residents)</th>
<th>Total non-business bankruptcy rate</th>
<th>Chapter 7 bankruptcy rate</th>
<th>Chapter 13 bankruptcy rate</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OLS</td>
<td>OLS</td>
<td>OLS</td>
</tr>
<tr>
<td>Mass Layoffs per person</td>
<td>14.723***</td>
<td>12.532***</td>
<td>2.204**</td>
</tr>
<tr>
<td></td>
<td>(2.202)</td>
<td>(1.677)</td>
<td>(1.061)</td>
</tr>
<tr>
<td>County fixed effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Year fixed effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>County-specific time trends</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>R²</td>
<td>0.660</td>
<td>0.654</td>
<td>0.507</td>
</tr>
<tr>
<td>Number of counties</td>
<td>3,091</td>
<td>3,091</td>
<td>3,091</td>
</tr>
<tr>
<td>Number of observations</td>
<td>30,905</td>
<td>30,905</td>
<td>30,905</td>
</tr>
</tbody>
</table>

Note: Table 5 presents OLS coefficients from specifications exploring the relationship between county-level bankruptcy rates and mass layoffs. Mass layoff data available for a subset of counties from 1995-2004. Regressions are efficiency-weighted based on a non-parametric estimation of the variance of the error terms as a function of the population of each county-year observation (Solon, et al. 2013). Standard errors clustered by county in parentheses, *** p < 0.01, ** p < 0.05, * p < 0.1.
VI FOR ONLINE PUBLICATION: Online Appendix A: A Conceptual Framework of the Household Bankruptcy Decision

This appendix provides simulated household responses to employment shocks in an environment with a bankruptcy option. Consider a multi-period model where household income, \( y_1, y_2, \ldots, y_T \), is random in all periods, and when employed, log earnings follow an AR(1) process: 
\[
\ln(y_t) = \rho \ln(y_{t-1}) + \epsilon_t.
\]
Households face a risk of unemployment, in which case they receive unemployment insurance benefits, \( z \).\(^{46}\) The risk of unemployment follows a Markov process, where the probability of staying employed, given employment in the previous period, is \( 0 \leq \eta_1 \leq 1 \) and the probability of staying unemployed, given unemployment in the previous period, is \( 0 \leq \eta_2 \leq 1 \). In other words, \((1-\eta_1)\) is the separation probability and \((1-\eta_2)\) is the job finding probability. The values of \( \eta_1 \) and \( \eta_2 \) shape households’ expectations of the length their employment and unemployment relationships.\(^{47}\)

In the first period all households begin in the employed state.

As most household debt is shared between spouses, and most bankruptcy petitions are jointly filed, bankruptcy is treated here as a household-level decision. Bankruptcy is not allowed in period 1 but is allowed in all subsequent periods. If a household chooses to file for bankruptcy, they face three punishments in the model. First, they are constrained from the credit market in the period they file and in subsequent periods, able neither to borrow nor to save.\(^{48}\) This assumption is broadly consistent with the bankruptcy flag which appears on the filer’s credit report for up to 10 years, and the potentially prohibitively high cost of obtaining credit (Musto 1999).

Second, the household pays a portion of their earnings, \( \phi \), to the bankruptcy court in the year in which they file. This garnishment is intended to represent the inability of households to hide their nonexempt assets from the bankruptcy courts. Finally, the third cost of filing is to repay a portion of the debt even in filing (\( S \) for debt service), which will be shown to be necessary for interior optimal borrowing behavior, i.e. not borrowing up to the credit limit in all periods. These costs are built into the model to best fit the real-world punishments from bankruptcy, and are adapted from previous models (see, e.g., Livshits et al. 2007). The model does not directly incorporate the bankruptcy “stigma” as an additional cost. If stigma was hypothesized to be proportional to household earnings, then a portion of \( \phi \) could be interpreted as such. Similarly, if stigma was considered proportional to the amount of debt discharged, then \( S \) would reflect the cost of stigma.

Let \( V_t(x_{t-1}, y_t, b_{t-1}) \) be the value function for a given debt \( (x > 0) \) or asset \( (x < 0) \) level in period \( t \), where \( b_{t-1} \) is an indicator for whether the household had previously filed for bankruptcy. The maximized value function for filing for bankruptcy is given by \( V^B \) and not filing given by \( V^N \).

---

\(^{46}\)In the simulations which follow, mean log earnings is chosen to be 4, so mean earnings are around 54 and range from 30 to 100, while unemployment benefits are set to \( z = 20 \). The qualitative results are not sensitive to the choice of these values, within reason.

\(^{47}\)When households are unemployed, they receive a “shadow” draw from the distribution of earnings to provide a basis for future earnings expectations if they exit unemployment.

\(^{48}\)The restriction on saving is included so that households are unable to preserve any liquid assets.
If households receive a positive income shock then they save, $x < 0$, and earn interest $r$. If they experience a negative income shock, either due to a low draw from the wage distribution or from an unanticipated unemployment spell, households accumulate debt, $x > 0$, with exogenously determined interest rate $R > r$ charged by the bank to offset write-offs from bankruptcies. Households are assumed to be borrowing constrained up to a fraction of current income.\footnote{This assumption is required so that households do not borrow an infinite amount and then attempt to file for bankruptcy. Even if the interest rate was a function of the amount borrowed, some households might borrow as much as they could until the interest rate were infinite with the full intention of defaulting in the subsequent period.}

The model can be solved by backwards induction. The essential features of the multi-period model are described most easily in a three-period setting. In period 3, the final period, the household chooses whether or not to file for bankruptcy, giving the value function in the last period:

$$V_3(x_2, y_3, b_2) = \max\{V_3^N(x_2, y_3, b_2), V_3^B(x_2, y_3, b_2)\}$$

where the household chooses to file only when optimal to do so, $V_3^B > V_3^N$. The payoff to not filing, $V_3^N$, depends on behavior in the second period and the assets or debts brought forward to the final period. If the household did not file in period 2, $b_2 = 0$, then it consumes its period 3 labor income minus interest payments on borrowing (or interest income from saving):

$$V_3^N(x_2, y_3, 0) = \begin{cases} u(y_3 - rx_2) & \text{if } x_2 < 0 \text{ (saving)} \\ u(y_3 - Rx_2) & \text{if } x_2 > 0 \text{ (borrowing)} \end{cases}$$

If the household did file for bankruptcy in period 2, it simply consumes its period 3 labor income:

$$V_3^N(x_2, y_3, 1) = u(y_3)$$

The payoff to filing, $V_3^B$, is period 3 wages net of garnishment minus the portion of debt which is not forgiven:

$$V_3^B(x_2, y_3, 0) = u((1 - \phi)y_3 - Sx_2)$$

In making the bankruptcy decision in period 3, the model’s final period, the household does not need to consider the lack of access to the credit market in future periods. The household chooses bankruptcy in period 3 when the punishment mechanisms, garnishment $\phi$ and debt service $S$, are less painful than repaying the debt accrued in period 2: $(1 - \phi)y_3 - Sx_2 > y_3 - Rx_2$. If the household saved in period 2, $x_2 < 0$, then there is no benefit to filing for bankruptcy, and the household consumes all of its income and savings, $y_3 - rx_2$.

In period 2 (and any additional “mid-life” periods in a multiple-period setting), the decision rule is more complicated; the household chooses the amount to consume, $c_2$, or equivalently the amount...
to borrow or save, $x_2$, as well as whether to file for bankruptcy:

$$V_2(x_1, y_2) = \max \{ V^N_2(x_1, y_2), V^B_2(x_1, y_2) \}$$

The payoff from not filing, $V^N_2$, is determined by the household’s income draw, $y_2$, amount of borrowing or saving in the previous period, $x_1$, and the expected payoff in period 3, represented by the integral term, which is determined by expectations about the distribution of future income, $F$:

$$V^N_2(x_1, y_2) = \begin{cases} \max_{x_2} u(y_2 + x_2 - rx_1) + \beta \int V_3(x_2, y_3, 0)dF(y_3|y_2) & \text{if } x_1 < 0 \\ \max_{x_2} u(y_2 + x_2 - Rx_1) + \beta \int V_3(x_2, y_3, 0)dF(y_3|y_2) & \text{if } x_1 > 0 \end{cases}$$

The payoff to filing for bankruptcy, $V^B_2$, also depends on expectations about future earnings. The bankrupt household consumes period 2 income net of garnishment, minus the portion of debt which is not forgiven:

$$V^B_2(x_1, y_2) = u((1 - \phi)y_2 - Sx_1) + \beta \int V_3(0, y_3, 1)dF(y_3|y_2)$$

In period 1, the preliminary period, the household chooses how much to borrow or save, $x_1$, based on their income draw, but cannot file for bankruptcy:

$$V_1(y_1) = \max_{x_1} u(y_1 + x_1) + \beta \int V_2(x_1, y_2)dF(y_2|y_1)$$

Despite the simplicity of this three-period model, the optimal $x^*_1$, $x^*_2$, and $b^*_2$ do not have analytical solutions. Thus it is necessary to select parameter values, functional forms, and simulate households’ responses.\(^{50}\)

The model is simulated to provide an understanding of the household response to income and employment shocks. The qualitative insights that I highlight are captured by the optimal Bellman equation in period 2. Periods 1 and 3 in this setting are discussed in less detail, as the choices made in these periods are designed to capture the dynamic aspects of the household’s period 2 decision.\(^{51}\)

The predictions from the model motivate the empirical methodology used in sections IV and V.

\(^{50}\)Household utility is assumed to exhibit constant relative risk aversion (CRRA): $u(c) = \frac{c^{1-\sigma}}{1-\sigma}$, where $1/\sigma$ is the degree of intertemporal elasticity of substitution. The parameters used in this simulation are: $\beta = 0.85$, $\phi = 0.4$, $S = 0.1$, $r = 1.05$, $R = 1.1$, $\sigma = 2$, $\rho = 0.15$, $\sigma_r = 0.15$, $\eta_1 = 0.95$, $\eta_2 = 0.4$, and an exogenous borrowing limit of 1.5 times current income. The main qualitative results of the model are not sensitive to the choice of parameters within reason.

\(^{51}\)Understanding banks’ optimal lending rules under incomplete information regarding the income and employment processes is an important extension of this model and is left for future research.
VI.A Optimal Borrowing and Bankruptcy Decisions

Figure A-4 shows the period 1 decision of how much to borrow or save, $x_1$, depending on the values of the income draw, $y_1$. The solid line represents the choices of households when bankruptcy is an available option in later periods. Households with low income borrow, but most borrow relatively small amounts. Households with the lowest income borrow such that the borrowing constraint binds, which leads to the flat portion of the borrowing curve. Because of the uncertainty of income and possible job separation in the subsequent periods, households with high income save a significant fraction of their income.

The decision whether to borrow or save in the first period is based not only on the income draw but also on expected future draws and the value of filing for bankruptcy (even though households cannot file in this period). As a counterfactual, the dashed line in Figure A-4 presents the optimal choices of households when there is no option to file for bankruptcy in later periods. Low-income households borrow much less than when they possess a default option in the future, and even wealthy households save more in a bankruptcy-free world than in a world which allows for a “fresh start.” The difference between the solid and the dashed lines highlights the strategic aspect of the optimal bankruptcy decision: borrowing (dis-saving) is everywhere higher when bankruptcy is available, and especially so for households in debt.

The amount borrowed or saved in period 1 is brought into period 2, where the most interesting decisions occur. The household chooses whether to file for bankruptcy or decide to wait and see the income realization in period 3 before filing. Thus delaying filing has an option value. If the household files in period 2, it cannot borrow or save to smooth consumption in the next period, and it must pay both the garnishment and the debt service penalties. On the other hand, if the household chooses to borrow, it has the option of filing in the subsequent period, so it will borrow more than if it was required to repay all debt in period 3.

Figure A-5 shows the borrowing and saving decision in period 2, based on the income draws in periods 1 and 2, $y_1$ and $y_2$, among the employed. Among employed households, as second period income increases (moving to the right in the graph), households first borrow more in anticipation of bankruptcy in the subsequent period, then begin saving. Those individuals with the worst draws are borrowing constrained and cannot borrow as much as they would like, leading to the flat part of the graph on the left hand side. The individuals with high income in the first period but low in the second choose to draw down their savings but not borrow (the flat part at “0” for the 80th percentile, the “high” income line). The individuals with relatively good income realizations in period 1 and bad income draws in period 2 borrow heavily in anticipation of bankruptcy in the next period. Given that the likelihood of employment in the next period is high for those who are currently employed, $\eta_1 = .95$, none of the employed file for bankruptcy in period 2 in this simulation. If plotted for all percentiles of the $y_1$ distribution, the graph would not be symmetric because the expected distribution of future income draws, $dF(y_3|y_2)$, depends only on $y_2$ and not on $y_1$. 
The only households who choose to file for bankruptcy in period 2 are those with bad income realizations while employed in period 1 and subsequently unemployed in period 2, who borrowed in period 1 in anticipation of a better outcome and now wish to default on their debts. Given the high value of \( \eta_1 \), unemployment was a relatively low-probability event. Figure A-6 shows the bankruptcy decision in period 2, depending on the expected persistence of the unemployment shock, \( \eta_2 \). Each point on the graph is from a separate simulation, and represents the maximum value of income in the first period, \( y_1 \), for which a household who is unemployed in period 2 would file for bankruptcy.

For low values of unemployment persistence, the household expects to return to the labor force quickly, so only those households with very low values of \( y_1 \) (and thus very high values of period 1 debt) file for bankruptcy in period 2. However, as the persistence of unemployment increases, more and more households file immediately in response to the unemployment shock. When \( \eta_2 = 1 \), and the unemployment spell is expected to be permanent, 50% more households file for bankruptcy. I test this prediction of the model directly in the county level analysis in Section IV. The simulated results highlight the important role which the persistence of shocks and the formation of expectations, only relevant in a dynamic context, play in shaping the household’s bankruptcy decision.
VII NOT FOR PUBLICATION: Online Appendix B: Evaluating the Quality of Retrospective Data

The two main critiques of retrospective survey data on bankruptcy are that bankruptcies may be under reported and that individuals may not remember the precise timing of their filing date. First, it is possible that respondents do not report events which may have a negative “stigma” attached to them. In their analysis of PSID data, Fay, Hurst, and White (2002) find that the bankruptcy rate in the sample is roughly one-half of the national rate. In other words, there is potentially 50% under-reporting of bankruptcy experiences. The PSID sample likely has fewer bankruptcies for two primary reasons: First, the retrospective question was not available for more recent waves during the period when bankruptcy filing rates have sharply increased. Second, the PSID respondents are older on average when asked about bankruptcy filing. Although this would give them potentially more years to file for bankruptcy, there are important generational differences in the composition of bankruptcy filers over time.

In Appendix Figure 7, I compare the national bankruptcy rate to the filing rate in the NLSY, the PSID, and the Survey of Consumer Finances (SCF), which asked a similar retrospective question of a nationally representative sample in 2004. The national rates are calculated by dividing the total number of non-business bankruptcies by the Census Bureau’s estimate of the total number of US households.

Although the NLSY only follows one cohort over time, the level and trend of the filing rate is consistent with aggregate patterns, albeit slightly below the national rate and slightly above that of the PSID. Turning to the overall rate of ever having filed, the NLSY cohort’s rate is 11.1%, whereas the rate in the SCF is 12.2% for respondents of the same age range (aged 39-48 in 2004). That the reported annual filing rates are lower in a retrospective survey such as the SCF and the NLSY is not surprising, as some individuals from the cohort interviewed would not have been old enough to file for bankruptcy in 1979, and some individuals who filed multiple times would only be counted as filing once. In the NLSY, 9% of filers say they have filed more than once, yet respondents were given the opportunity to report only one date of bankruptcy filing.

Alternatively, respondents may not remember the timing of their bankruptcy filing, which would lead to measurement error (and potentially inconsistent estimates) in all subsequent analysis. Without administrative confirmation, there is no way to exhaustively assess the magnitude of this problem. One approach is to compare the respondents’ reported retrospective date of bankruptcy with their debt and asset levels which were reported in each survey year. If the bankruptcy information provided in 2004 can predict a break in the asset and debt data provided in each survey, then the timing of the bankruptcy is sensible.\textsuperscript{53}

\textsuperscript{52} For confidentiality purposes the SCF assigned responses into two-year periods, which explains why the filing rates are the same in two-year intervals in the figure.

\textsuperscript{53} Also, if we believe that there is a significant stigma to bankruptcy, then it should be easy for respondents to recall the year in which the filing occurred.
In Figure 1 and Appendix Figures 8 and 9, I confirm that respondents accurately remember the year in which they filed for bankruptcy. The numbers from the figures are reported in Appendix Table 2. Figure 1 in the main text shows the total debt reported by bankruptcy filers, plotted against the relative years before or after bankruptcy, relative to the debts of respondents who never filed for bankruptcy.\footnote{54} Year 0 is the year of filing for bankruptcy, and the years to the left are years prior to bankruptcy; to the right are years since filing. The plotted points are relative to those who have never filed for bankruptcy to control for time effects (as described below in more detail), so the “0” on the y-axis is equivalent to the mean value of debts for non-filers, $36,961. The figure shows that total debts fall by $15,000 upon discharge, with a large drop in the year reported as the bankruptcy year. The figure also suggests that debts re-accumulate after bankruptcy, and almost as rapidly as prior to bankruptcy.

The increase in total debts in the years following bankruptcy is a surprising pattern in Figure 1 given the damage which bankruptcy does to one’s credit score. Other questions in the NLSY provide clear evidence that filing for bankruptcy has a large negative impact on post-bankruptcy credit access: over half of filers who applied for credit were rejected or received less than they asked for, compared to only 20% of non-filers who did not receive the loan they desired. This difference remains nearly thirty percentage points even after controlling for income, age, gender, race, marital status, family size, and education. Furthermore, 32% of bankruptcy filers were dissuaded from applying for credit because they anticipated rejection compared to only 13% of non-filers. Although some debts are re-accumulating well before the removal of the bankruptcy flag on the credit report (ten years), these are likely at a high cost of credit.\footnote{55}

Appendix Figure 8 presents the relative average amounts of “other” debts, as classified by the NLSY, which importantly includes credit card debt, around the time of bankruptcy filing. Again, these coefficients are relative to those who never filed for bankruptcy, so the “0” on the y-axis is equivalent to the mean value of debts for non-filers, $2,669. The amount of these “other” debts peaks in the two years prior to bankruptcy, and then falls by nearly $5,000. This component of debt does not re-accumulate in the six years following bankruptcy but begins to increase in years 8-10. In Appendix Figure 9, the homeownership rate of bankruptcy filers is plotted in a similar fashion, relative to those who never filed. As this is a young cohort, the mean homeownership rate for never-filers is only 33% (which should be interpreted as the “0” value on the y-axis in the figure). The fraction of bankruptcy filers owning a home falls by ten percentage points around the timing of bankruptcy. Homeownership does rebound in the years following bankruptcy, which likely contributes to the increase in total debts shown in Figure 1 (which includes mortgage debt). These graphs document the challenges to post-bankruptcy credit access and show that the dates reported retrospectively by respondents in 2004 accurately identify the inflection points in debt reported in earlier years.

\footnote{54}95% confidence intervals are plotted in dashes, based on standard errors clustered at the individual level. \footnote{55}Some lenders may eagerly lend to these poor-credit households because after filing they have no means of immediate discharge of their debts.
For completeness, Appendix Table 3 presents the summary statistics of the NLSY data. The top portion of the table shows the mean values of standard demographic characteristics such as age, race, gender, education and parents’ education. The bottom portion of the table provides a summary of what events respondents have experienced by the time of the 2004 survey. Using my definition of non-business bankruptcy, 11.1% of respondents have filed at some point in their lives. Many more households have experienced a displacement (a head or a spouse on UI), a health problem, or a divorce, with the proportion of the sample for each ranging from 30-48%. These shocks form the basis of the tests of the model, whether households respond to shocks in the timing and likelihood of filing for bankruptcy.

VII.A Adverse Events and Bankruptcy in Representative Panel Data

Prior work has used the PSID to explore the relationship between adverse events and personal bankruptcy. A simple assessment of the timing of filing and the incidence of shocks in the previous three years in the PSID and NLSY is presented in Appendix Table 4. The table shows the frequency of displacement, divorce, and disability shocks in the three years prior to bankruptcy filing for respondents of the PSID and the NLSY. The results confirm that these shocks are relatively common among those who never file for bankruptcy, but much more prevalent among those who do file.

In the three years prior to filing for bankruptcy, 23.6% of NLSY respondents have experienced a job loss, 19.5% have experienced a divorce, and 15.2% have experienced a health problem. The fraction of all bankruptcies that the survey literature would attribute to these shocks is thus 58.3%. For the PSID, the numbers are comparable: 18.8% have experienced a job loss, 14.1% have experienced a divorce, and 15.2% have experienced a health problem. The results suggest that the patterns in the PSID and the NLSY are not meaningfully different, and that the larger sample and cleaner methodology of the event study framework used here establishes the role of these “non-strategic” shocks in the timing of personal bankruptcy. Notably, the use of relatively narrow definitions of shocks leaves about 40% of bankruptcies “unexplained” by this methodology.

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56See Keys (2010) for a formal replication of earlier work using the PSID. Given the small number of bankruptcy filings in the PSID, the results are imprecise and sensitive to the inclusion of potentially simultaneously-determined control variables.
Figure A-1: Probability of Bankruptcy Filing for Men by Relative Time from UI Shock, by Marital Status

Note: Appendix Figure 1 presents average marginal effect coefficients from a logit regression of bankruptcy filing on the timing of male unemployment shocks, separately for whether the male was married or single in the pre-shock period. See text for definitions of spells. The regression includes controls for age, race, education, state and year fixed effects, and a quadratic in financial benefit. Dashed lines represent 95% confidence interval.
Figure A-2: Probability of Bankruptcy Filing for Men by Relative Time from UI Shock, by Income

Note: Appendix Figure 2 presents average marginal effect coefficients from a logit regression of bankruptcy filing on the timing of male unemployment shocks, separately for whether the household had above-median or below-median income in the pre-shock period. See text for definitions of spells. The regression includes controls for age, race, education, state and year fixed effects, and a quadratic in financial benefit. Dashed lines represent 95% confidence interval.
Figure A-3: Probability of Bankruptcy Filing for Men by Relative Time from UI Shock, by Chapter of Filing

Note: Appendix Figure 3 presents average marginal effect coefficients from a logit regression of bankruptcy filing on the timing of male unemployment shocks, separately for whether the household filed for Chapter 7 (discharge) or Chapter 13 (renegotiation). See text for definitions of spells. The regression includes controls for age, race, education, state and year fixed effects, and a quadratic in financial benefit. Dashed lines represent 95% confidence interval.
Figure A-4: The Borrowing and Saving Decision in Period 1

Note: Appendix Figure 4 shows the optimal net asset position $x^*$ for relevant values of $Y_1$ depending on the presence of a bankruptcy option. See Appendix A for details.
Figure A-5: The Borrowing and Saving Decision in Period 2

Note: Appendix Figure 5 shows the optimal net asset position $x^*$ for relevant values of $Y_2$ depending on the receipt of a low or high income draw in the first period. See Appendix A for details.
Figure A-6: The Bankruptcy Decision in Period 2

Note: Appendix Figure 6 shows the optimal bankruptcy threshold depending on the expected persistence of the unemployment shock, \( \eta_2 \). Each point on the graph represents the maximum value of income in the first period, \( Y_1 \), for which a household who is unemployed in period 2 would file for bankruptcy. See Appendix A for details.
Figure A-7: Comparison of Bankruptcy Filing Rates in NLSY, PSID, SCF Datasets relative to National Filing Rate, 1979–2002

Note: Appendix Figure 7 presents a comparison of the personal bankruptcy filing rates (measured per household) in the primary available micro data sources (NLSY, PSID, and SCF) relative to the national filing rate as recorded by the Administrative Office of the U.S. Courts (AOUSC) for 1979-2002. See Appendix B for details.
Figure A-8: “Other” Debts of Bankruptcy filers Relative to Non-Filers, by Relative Time of Bankruptcy Shock

Note: Appendix Figure 8 presents relative time coefficients from an OLS regression of “other” debts on the timing of bankruptcy filing. Other debts include credit card debt, medical debt, legal bills, and any outstanding debts. See Appendix B for details. Controls include age, race, education, and state and year fixed effects. Dashed lines represent 95% confidence interval. Non-filer mean other debts are $2,669. The figure shows a clear break in indebtedness around the timing of reported bankruptcy filing.
Figure A-9: Homeownership of Bankruptcy filers Relative to Non-Filers, by Relative Time of Bankruptcy Shock

Note: Appendix Figure 9 presents relative time coefficients from an OLS regression of homeownership on the timing of bankruptcy filing. See Appendix B for details. Controls include age, race, education, and state and year fixed effects. Dashed lines represent 95% confidence interval. Non-filer mean homeownership rate is 33%. The figure shows a clear break in homeownership around the timing of reported bankruptcy filing.
Table A-1: Estimated Impact of “Adverse Events” on the Probability of Filing for Bankruptcy: Log-Odds Ratios

<table>
<thead>
<tr>
<th>By type of event</th>
<th>Relative Time Coefficients</th>
<th>UI - Men</th>
<th>UI - Women</th>
<th>Divorce</th>
<th>Disability</th>
</tr>
</thead>
<tbody>
<tr>
<td>7 or more years before</td>
<td>1.614** (0.392)</td>
<td>1.584* (0.403)</td>
<td>0.981 (0.165)</td>
<td>1.242 (0.374)</td>
<td></td>
</tr>
<tr>
<td>5-6 years before</td>
<td>0.606 (0.354)</td>
<td>0.218 (0.219)</td>
<td>1.270 (0.291)</td>
<td>1.016 (0.584)</td>
<td></td>
</tr>
<tr>
<td>3-4 years before</td>
<td>0.763 (0.348)</td>
<td>1.435 (0.501)</td>
<td>1.230 (0.260)</td>
<td>2.259** (0.738)</td>
<td></td>
</tr>
<tr>
<td>1-2 years before</td>
<td>1.453 (0.436)</td>
<td>2.022*** (0.548)</td>
<td>1.554** (0.274)</td>
<td>0.707 (0.355)</td>
<td></td>
</tr>
<tr>
<td>year of event + 1 year after</td>
<td>3.131*** (0.619)</td>
<td>2.777*** (0.610)</td>
<td>1.955*** (0.291)</td>
<td>2.058** (0.596)</td>
<td></td>
</tr>
<tr>
<td>2-3 years after</td>
<td>1.828** (0.441)</td>
<td>1.118 (0.362)</td>
<td>2.052*** (0.314)</td>
<td>1.770** (0.501)</td>
<td></td>
</tr>
<tr>
<td>4-5 years after</td>
<td>1.299 (0.377)</td>
<td>1.188 (0.385)</td>
<td>1.733*** (0.284)</td>
<td>1.412 (0.477)</td>
<td></td>
</tr>
<tr>
<td>6-7 years after</td>
<td>1.228 (0.343)</td>
<td>1.467 (0.424)</td>
<td>1.053 (0.222)</td>
<td>2.098** (0.661)</td>
<td></td>
</tr>
<tr>
<td>8-9 years after</td>
<td>1.091 (0.316)</td>
<td>1.696* (0.467)</td>
<td>1.129 (0.230)</td>
<td>1.299 (0.504)</td>
<td></td>
</tr>
<tr>
<td>10 or more years after</td>
<td>1.798*** (0.231)</td>
<td>1.246 (0.205)</td>
<td>1.684*** (0.184)</td>
<td>0.982 (0.215)</td>
<td></td>
</tr>
<tr>
<td>Additional Controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Individuals</td>
<td>5396</td>
<td>5210</td>
<td>6492</td>
<td>7560</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>60644</td>
<td>46724</td>
<td>99839</td>
<td>116733</td>
<td></td>
</tr>
<tr>
<td>p-value for test of pre-shock coefs. = 0</td>
<td>0.72</td>
<td>0.84</td>
<td>0.06</td>
<td>0.43</td>
<td></td>
</tr>
<tr>
<td>shock year = previous year</td>
<td>0.07</td>
<td>0.15</td>
<td>0.27</td>
<td>0.06</td>
<td></td>
</tr>
</tbody>
</table>

Note: Appendix Table 1 presents average log-odds ratios from logit models for bankruptcy filing, see text for definition of spells. Standard errors clustered by individuals. Additional controls are race, age, education, state and year fixed effects, and a quadratic in the financial benefit to filing for bankruptcy. Respondents’ gender is included as a covariate in the last two specifications. Sample is restricted to those working full-time in the period prior to job loss (unemployment events), or those who ever married (divorce event).
Table A-2: Debts, Assets, and the Timing of Personal Bankruptcy

<table>
<thead>
<tr>
<th>Relative Time Coefficients</th>
<th>Total Debt</th>
<th>&quot;Other&quot; Debts</th>
<th>Own Home?</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coef.</td>
<td>SE</td>
<td>Coef.</td>
</tr>
<tr>
<td>9 or more years before</td>
<td>-9026</td>
<td>1226</td>
<td>765</td>
</tr>
<tr>
<td>7-8 years before</td>
<td>-7800</td>
<td>1860</td>
<td>1240</td>
</tr>
<tr>
<td>5-6 years before</td>
<td>-6136</td>
<td>1851</td>
<td>790</td>
</tr>
<tr>
<td>3-4 years before</td>
<td>-556</td>
<td>1968</td>
<td>2388</td>
</tr>
<tr>
<td>1-2 years before</td>
<td>2480</td>
<td>2334</td>
<td>3856</td>
</tr>
<tr>
<td>year of bankruptcy + 1 year after</td>
<td>-9042</td>
<td>2133</td>
<td>2788</td>
</tr>
<tr>
<td>2-3 years after</td>
<td>-15755</td>
<td>1768</td>
<td>-565</td>
</tr>
<tr>
<td>4-5 years after</td>
<td>-12333</td>
<td>2166</td>
<td>-397</td>
</tr>
<tr>
<td>6-7 years after</td>
<td>-9771</td>
<td>2451</td>
<td>-655</td>
</tr>
<tr>
<td>8-9 years after</td>
<td>-7491</td>
<td>3131</td>
<td>956</td>
</tr>
<tr>
<td>10 or more years after</td>
<td>-8368</td>
<td>3522</td>
<td>433</td>
</tr>
</tbody>
</table>

Individuals | 7661 | 7659 | 7661
Observations | 96354| 87735| 129198

Non-filer mean | $36,961 | $2,669 | 0.33

Note: Appendix Table 2 presents relative time coefficients from OLS models for debts, assets, and homeownership around the time of bankruptcy filing, see text for definition of spells. Standard errors clustered by individuals. Additional controls are race, age, education, state and year fixed effects. “Other” debts include credit card debt, medical debt, legal bills, and any outstanding debts.
Table A-3: Summary Statistics, NLSY in 2004

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Less than High School</td>
<td>7661</td>
<td>8.2%</td>
<td>0.27</td>
</tr>
<tr>
<td>High School</td>
<td>7661</td>
<td>42.0%</td>
<td>0.49</td>
</tr>
<tr>
<td>Some College</td>
<td>7661</td>
<td>23.2%</td>
<td>0.42</td>
</tr>
<tr>
<td>College and Up</td>
<td>7661</td>
<td>26.6%</td>
<td>0.44</td>
</tr>
<tr>
<td>Age</td>
<td>7661</td>
<td>43.3</td>
<td>2.32</td>
</tr>
<tr>
<td>Mother's highest grade completed</td>
<td>7188</td>
<td>11.6</td>
<td>2.78</td>
</tr>
<tr>
<td>Father's highest grade completed</td>
<td>6534</td>
<td>11.8</td>
<td>3.60</td>
</tr>
<tr>
<td>Male</td>
<td>7661</td>
<td>50.9%</td>
<td>0.50</td>
</tr>
<tr>
<td>African-American</td>
<td>7661</td>
<td>14.3%</td>
<td>0.35</td>
</tr>
<tr>
<td>Ever filed for bankruptcy</td>
<td>7661</td>
<td>11.1%</td>
<td>0.31</td>
</tr>
<tr>
<td>Ever on UI - male</td>
<td>7661</td>
<td>40.5%</td>
<td>0.49</td>
</tr>
<tr>
<td>Ever on UI - female</td>
<td>7661</td>
<td>28.0%</td>
<td>0.45</td>
</tr>
<tr>
<td>Ever had health problem</td>
<td>7661</td>
<td>8.8%</td>
<td>0.28</td>
</tr>
<tr>
<td>Ever divorced</td>
<td>7661</td>
<td>45.4%</td>
<td>0.50</td>
</tr>
</tbody>
</table>

Note: Appendix Table 3 presents summary statistics of the main variables used in the analysis as of the 2004 wave of the NLSY. Observations weighted using sample weights.
Table A-4: Incidence of “Adverse Events” to Bankruptcy Filers Relative to Non-Filers

<table>
<thead>
<tr>
<th></th>
<th>Filers</th>
<th>Non-filers</th>
<th>Filers</th>
<th>Non-filers</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>PSID</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Period of unemployment</td>
<td>18.8</td>
<td>10.9**</td>
<td>14.3</td>
<td>8.1**</td>
</tr>
<tr>
<td>Divorce</td>
<td>14.1</td>
<td>10.2</td>
<td>11.2</td>
<td>8.7</td>
</tr>
<tr>
<td>Health problems</td>
<td>15.2</td>
<td>14.4</td>
<td>9.8</td>
<td>9.9</td>
</tr>
<tr>
<td><strong>NLSY</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Any UI</td>
<td>23.6</td>
<td>17.3***</td>
<td>9.1</td>
<td>5.0***</td>
</tr>
<tr>
<td>Man UI spell (men)</td>
<td>23.3</td>
<td>16.0***</td>
<td>10.7</td>
<td>8.7</td>
</tr>
<tr>
<td>Woman UI spell (women)</td>
<td>14.7</td>
<td>10.7**</td>
<td>9.1</td>
<td>6.7**</td>
</tr>
<tr>
<td>Divorce</td>
<td>19.5</td>
<td>8.4***</td>
<td>13.3</td>
<td>6.6***</td>
</tr>
<tr>
<td>Work limitation</td>
<td>15.2</td>
<td>10.5</td>
<td>2.9</td>
<td>1.3***</td>
</tr>
</tbody>
</table>

Note: Appendix Table 4 presents summary measures of the incidence of adverse events to bankruptcy filers compared to non-filers using data from the NLSY and PSID. Stars indicate statistically significant difference across columns for filers and non-filers, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. 