# Do households jointly manipulate their debt and filing decisions? Personal bankruptcy with heterogeneous filing behavior

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**Abstract**

Personal bankruptcy can serve as insurance for large financial shocks, but may also provide an opportunity for abusive use. We identify two different filing behavior patterns using data from the Survey of Consumer Finances (SCF). For a first type of consumers the financial benefit is exogenous to the filing decision, which is consistent with a "non-strategic" behavior or "rational inattention" to a rare event. For a second type the financial benefit is endogenous, which is consistent, although not exclusive, with a "strategic" behavior. The second group also exhibits a higher probability of filing and a larger financial benefit. The higher prevalence of the first group supports the insurance function of bankruptcy.

**Keywords**: Personal bankruptcy, heterogeneous behavior, debt manipulation, non-strategic behavior
**JEL codes**: D14, D12, C32

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## 1. Introduction

The number of non-business or personal bankruptcy filings in the US are still high and there is a constant debate about the factors driving this phenomenon and the policy responses to address it. As shown in Figure 1, after the significant decline in the number of personal filings in 2006, following the Bankruptcy Abuse Prevention and Consumer Act (BAPCA) passed by the Congress in October 2005, filings surpassed the million in 2008 and reached 1.5 million in 2010, similar to the levels exhibited in the early 2000s.[1] While personal filings have started to decrease since 2011, the number of filers is still much higher than the business filings. In 2014, there were almost 910 thousand personal bankruptcy petitions compared to the 27 thousand of business petitions, which have also been much more stable over the last two decades regardless of the ups and downs of the US economy and the financial crisis of 2008. Despite the continuous efforts to limit fraudulent and abusive uses of the bankruptcy system, it is clear the need to further understand the elements and motivations associated with consumers' bankruptcy decisions and the prevalence of different types of filing behavior.

[Insert Figure 1]

This paper formally accounts for heterogeneous filing types in the bankruptcy decision. The types in the model comprise different bankruptcy behavior patterns resulting from different factors that are not necessarily observable. In particular, the bankruptcy and debt (financial benefit) decisions are conditional on each consumer type and may or may not be jointly determined, while the personal characteristics and adverse events driving these decisions are

[1] See Li, White and Zhu (2011) for a discussion of the 2005 bankruptcy reform.

allowed to vary by type.[2] The identified types can be further associated to a specific set of observable characteristics. We extensively discuss the model identification and provide evidence on the robustness of the model. We also show that the model helps to better identify, although marginally, potential bankruptcy filers and non-filers than traditional probabilistic models.

The existence of different filing types can be linked to different incentives and factors driving the filing decision. In their influential study, Fay, Hurst and White (2002) distinguish between "strategic" and "non-strategic" models of bankruptcy.[3] "Strategic" households are defined as forward-looking households who are more likely to file for bankruptcy when their financial benefit for filing is higher. "Non-strategic" households are not driven by a financial incentive in their filing decision and will only file in response to unanticipated adverse events like a divorce, health or employment shock, which reduce their ability to repay. In this sense, a positive correlation between the likelihood of filing and the financial benefit, all else equal, can be associated with a "strategic" behavior, while a positive correlation between the likelihood of filing and the occurrence of an adverse event can be associated with a "non-strategic" behavior.

Gross and Notowidigdo (2011) also divide the literature on consumer bankruptcy into two strands. A first strand that emphasizes the "strategic" nature and potential moral hazard behavior in the household bankruptcy decision and a second strand that focuses on the role of adverse, likely unforeseen events that may lead to bankruptcy. The authors document the relative importance of medical costs on the bankruptcy decision.

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[2] The financial benefit from filing is the amount of unsecured debt that can be discharged in bankruptcy. We provide further details below on the calculation of this variable for the analysis.

[3] This behavior distinction is motivated by the previous work of Sullivan, Warren and Westbrook (1989), Braucher (1993), Domowitz and Sartain (1999), Gross and Souleless (2002), among others.

More recently, Zhang, Sabarwal and Gan (2015) formalize the potential relationship between financial benefit, adverse events and different filing behaviors using a simple two-period model of decision-making following Gan and Sabarwal (2005). In the first period, individuals receive a noisy signal for experiencing a financial shock (adverse event) in the future and choose their debt level based on the signal; in the second period, the shock is realized and consumers decide whether or not to file. The authors define a "strategic" consumer as one who chooses her debt level based on her chances of filing for bankruptcy given the signal. In contrast, a "non-strategic" consumer is one who chooses her debt level without conditioning on the signal –she plans to repay her debt in the absence of an adverse event and may exhibit a "rational inattention" to a rare event.[4]

As a result, testing for the joint manipulation of the financial benefit and filing decision can provide better insight about potential different filing behaviors, although we cannot fully disentangle between "strategic" and "non-strategic" behaviors. The exogeneity of the financial benefit in the filing decision is consistent with a "non-strategic" behavior. Yet, the endogeneity of the financial benefit is consistent, but not exclusive, with a "strategic" behavior; while an individual who intends to abuse the law will consciously increase her unsecured debts before filing, an individual who does not intend to abuse the law may also rollover her debt when faced, for example, with an adverse event as long as there is a chance of future repayment. In fact,

[4] See Sims (2003) for a general discussion of rational inattention behavior and its implications. The basic idea is that individuals exhibit a limited amount of attention and must decide how to allocate it. Limited attention is assumed to impose a bound on the information flow or, equivalently, on the signal received by an individual concerning, for example, a financial shock.

personal bankruptcy models generally account for the possibility of a debt increase prior to filing, despite no intent to abuse the law.[5]

Besides variations in the financial benefit from debt discharge and the reaction to possible adverse events, different filing behaviors, whether "strategic" or not, can also be associated with other factors. These include variations in the social costs of filing (stigma), time preferences, risk aversion and other factors correlated with the debt attitude of an individual. Gross and Souleles (2002) define the social stigma of filing for bankruptcy as both pecuniary costs (e.g., the consequences of a bad reputation) and non-pecuniary costs (e.g., disgrace). These costs may differ across consumers; for example, richer households, which generally have a higher social status, are more likely to face higher pecuniary costs than poorer households. Consumers with different time preferences, i.e. "patient" versus "impatient" individuals, may also show different behavior patterns. Laibson, Repetto and Tobacman (2003) further argue that individuals might exhibit a quasi-hyperbolic discount function of the type proposed by Phelps and Pollack (1968), behaving patiently in their retirement accumulation and impatiently in the credit card market. On variations in the level of risk aversion, Athreya (2006) shows that a lower degree of risk aversion might increase or decrease the bankruptcy rate depending on the bankruptcy exemption level. Gan and Mosquera (2008) indicate that a more risk averse person

[5] Athreya (2005) provides a comprehensive survey of equilibrium models of personal bankruptcy. Recent work on consumer bankruptcy include Dubey, Geanakopolos and Shubik (2005), Athreya (2006), Li and Sarte (2006), Livshits, MacGee and Tertilt (2007, 2010), Chatterjee et al. (2007), Keys (2010), Han and Li (2011), Gross and Notowidigdo (2011), Traczynski (2011), Gross, Notowidigdo and Wang (2014), Dobbie and Song (2015), and Mahoney (2015). Keys (2010), for example, develops a dynamic, forward-looking model of bankruptcy behavior with income shocks and shows that "adverse events" and "strategic filing" perspectives are both essential and not necessarily mutually exclusive to understand the personal bankruptcy decision.

may or may not exhibit a higher probability of default depending on the ratio of her current and future income.

Ultimately, different filing attitudes may result from a combination of elements, both observable and unobservable. The types in our model summarize all these potential factors into different groups and we can correlate the identified types to specific observable characteristics. Disentangling these factors, however, is beyond the scope of the study.

The estimation results support the existence of two filing behaviors (types). We identify a first type of consumers whose financial benefit is exogenous to their bankruptcy decision and a second type of consumers whose financial benefit is endogenous. The filing behavior of the first group is in line with a "non-strategic" behavior or a "rational inattention" to a rare event while the behavior of the second group is consistent, but not exclusive, with a "strategic" behavior. The probability of filing for bankruptcy is more than 4.5 times higher among the second type of consumers relative to the first type, and the second group exhibits a larger financial benefit from filing. In addition, the factors associated with the filing decision appear to differ by type. The first type of filers seem to be mainly composed of households with a higher income and less risk averse. The higher proportion (61%) of the first type of individuals in the data, who do not jointly manipulate their debt and filing decision, also provides evidence for the insurance function of bankruptcy. Additional estimations support the robustness and predictive power of the model.

The contribution of the paper to the bankruptcy empirical literature is twofold. First, we implement a more general approach than previous related studies. The model permits to identify varying behavior types regarding the bankruptcy and financial benefit decisions, which may result, in turn, from a combination of factors. Fay, Hurst and White (2002) do not account for the potential endogeneity of the financial benefit in the filing decision. Zhang, Sabarwal and Gan (2015) test the endogeneity of financial benefit in the filing equation, but do not allow for the existence of different behavior types in the data. The study provides strong evidence for the existence of two unobserved filing types. Second, our model is more informative than traditional probabilistic models in that the factors driving the filing decision appear to differ by filing type and the model can help to better identify potential filers and non-filers given their likelihood of being of a certain type. This is critical in the absence of experimental and quasi-experimental data to unravel different filing attitudes, and in a context where reducing information asymmetries (moral hazard) can play a key role when evaluating bankruptcy provisions.

The model implemented in this study can also help to better uncover heterogeneous behaviors in other settings such as loan repayment, insurance, education and employment decisions. Gan, Hernandez and Liu (2013), for example, analyze heterogeneous behavior in group lending schemes in India, but do not allow for the potential endogeneity of some of the regressors in the repayment equation. Dong, Gan and Wang (2015) examine varying neighborhood effects on educational attainment, but do not formally test for the endogeneity of the moving choice on the schooling decision and just fix one type of individuals as endogenous movers and another type as exogenous movers.[6]

The remainder of the paper is organized as follows. Section 2 presents the empirical model implemented to account for heterogeneous filing behavior in the bankruptcy decision.

[6] Other studies that use mixture density specifications to model unobserved types include Keane and Wolpin (1997) to examine heterogeneous ability endowment in the career decision, Knittel and Stango (2003) to assess whether state-mandated price ceilings serve as focal points for tacit collusion among credit card companies, and Gan and Hernandez (2013) to model collusive and non-collusive regimes among clustered versus isolated hotels in Texas. These studies, however, do not formally test the identification of the mixture model proposed.

Section 3 describes the data used in the analysis. Section 4 reports and discusses the estimation results. Section 5 concludes.

## 2. Model

Consider first the following decision of filing for bankruptcy of individual *i*

$$file_i = 1\left(\kappa + \gamma \ln(fb_i + 1) + X_i\beta + AE_i\alpha + e_i > 0\right) \qquad (1)$$

where $file_i$ is the observed binary outcome equal to one if an individual files for bankruptcy, $\kappa$ is a constant term, $fb_i$ is the net financial benefit from filing defined below in equation (8), $X_i$ is a vector of observable controls, $AE_i$ is a set of dummy variables for different possible adverse events encountered by the individual prior to filing, and $e_i$ is an error term.

The specification in equation (1) is similar to the specification in Fay, Hurst and White (2002).[7] According to these authors, if filing for bankruptcy is mainly driven by a "strategic" behavior we should observe $\gamma > 0$ and $\alpha = 0$, i.e. individuals are more likely to file when their financial benefit from filing is higher, all else equal. In contrast, if filing for bankruptcy is mainly driven by a "non-strategic" behavior we should observe $\gamma = 0$ and $\alpha > 0$, i.e. individuals are more likely to file when an adverse event occurs which reduces their ability to repay.

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[7] The only difference is the inclusion of financial benefit ( $fb_i$ ) in logarithms while Fay, Hurst and White (2002) use this variable in levels. We apply a log transformation to $fb_i$ because this variable exhibits a distribution that is similar to a log-normal distribution, although left-censored at zero (see, e.g., Arabmazar and Schmidt, 1982; Powell, 1984). We particularly use $\ln(fb_i + 1)$ to capture the characteristics of censored data at zero.

However, as noted by Zhang, Sabarwal and Gan (2015), the financial benefit from filing may be jointly determined with the filing decision such that $fb_i$ could be endogenous in equation (1). For example, an individual's creditworthiness and attitude towards debt, which is unobserved, may determine how they accumulate debt (and thus their financial benefit) and whether they file for bankruptcy or not. Additionally, the financial benefit prior to filing for bankruptcy may increase irrespective of whether an individual is intending to take advantage of the bankruptcy law or not. A "strategic" consumer will consciously increase her unsecured debt before filing in order to increase the benefit from filing; a "non-strategic" consumer may also rollover her debt (i.e. through the use of credit cards) when faced, for example, with an adverse event as long as there is a chance of future repayment, thus also increasing her unsecured debt and measured financial benefit prior to filing.

Zhang, Sabarwal and Gan (2015) test for the potential endogeneity of the financial benefit by jointly modeling the filing and financial benefit decision using an extended discrete choice model and examining if both decisions are correlated. In their model, if the financial benefit is exogenous, the observed filings in the data are consistent with a "non-strategic" behavior while if the financial benefit is endogenous, the filings are consistent but not exclusive to a "strategic" behavior.

We implement an alternative, more general finite mixture specification, which allows for different filing behavior types when modeling the financial benefit and bankruptcy decisions. The unobserved consumer types may result from a combination of factors, including those associated with the filing and debt attitude of an individual. The financial benefit and filing decisions are conditional on the consumer type and may or may not be jointly determined. The personal characteristics and adverse events driving these choices are also allowed to vary by type. The identified individual types can be associated to a particular filing behavior based on testable model implications. Similarly, the types can be correlated to a set of observable characteristics.

We redefine the decision to file for bankruptcy as

$$file_i = 1\left(\kappa + \gamma \ln(fb_i + 1) + X_i \beta + T_i^* + u_i > 0\right) \tag{2}$$

where $T_i^*$ is the unobserved consumer type which can be correlated with $fb_i$ and $u_i$ is the new error term. Since the type is unobserved it can only be determined with a probability. We can assume that individuals can be one of two possible types with a particular probability such that $\Pr\left(T_i^* = T_i^1\right) = \Phi(W\lambda)$ and $\Pr\left(T_i^* = T_i^2\right) = 1 - \Phi(W\lambda)$, where $\Phi(\cdot)$ is the normal cumulative distribution function and $W_i$ is a set of type-determinant variables. We can think of $T_i^1$ as Type 1 individuals and $T_i^2$ as Type 2 individuals, and of $W_i$ as variables that help describe the filing and debt attitude of an individual. Certainly, we can allow for a wider set of types but our dataset supports a two-type model. We considered, for example, a three-type model but the two-type model shows a lower Schwarz-Bayesian information criterion than the three-type model; similarly, a Likelihood Ratio test indicates that the three-type model does not provide a better fit than the two-type model.[8]

The filing decision is then given by

[8] Further details are available upon request.

$$file_i = \begin{cases} 1(\kappa_1 + \gamma_1 \ln(fb_i + 1) + X_i\beta_1 + u_{1i} > 0) & \text{if } T_i^* = T_i^1 \\ 1(\kappa_2 + \gamma_2 \ln(fb_i + 1) + X_i\beta_2 + u_{2i} > 0) & \text{if } T_i^* = T_i^2 \end{cases}. \quad (3)$$

In the specification above the effect of $T_i^*$ is absorbed by the constant terms $\kappa_1$ and $\kappa_2$. The coefficients further vary across types, which permits to capture differentiated effects of individual characteristics and other factors on the filing decision by type.[9] Without loss of generality, we normalize the variances of the error terms of both types to one, i.e. $\text{Var}(u_1) = \text{Var}(u_2) = 1$.

The behavior in accumulating debt or financial benefit is also allowed to differ across types. The financial benefit for $T_i^* = T_i^1$ or Type 1 consumers is modeled as

$$\ln(fb_i^* + 1) = X_i\delta_1 + AE_i\mu_1 + v_{1it}, \quad \begin{cases} fb_i = fb_i^* & if \quad fb_i^* \geq 0 \\ fb_i = 0 & if \quad fb_i^* < 0 \end{cases} \quad (4a)$$

and for $T_i^* = T_i^2$ or Type 2 consumers is modeled as

$$\ln(fb_i^* + 1) = X_i\delta_2 + AE_i\mu_2 + v_{2i}, \quad \begin{cases} fb_i = fb_i^* & if \quad fb_i^* \geq 0 \\ fb_i = 0 & if \quad fb_i^* < 0 \end{cases}. \quad (4b)$$

where $fb_i^*$ is the latent financial benefit. The adverse events $AE_i$ help in this case to model the financial benefit of filing. Since adverse events are likely exogenous to a household's bankruptcy

[9] This flexibility is similar to Gan and Hernandez (2013) that use a mixture specification to model hotels' behavior across different demand regimes.

decision, they act more as a negative shock to an individual's wealth.

Consistent with this view, we may distinguish between different filing behaviors by testing whether consumers make their debt and filing decision jointly or not. Empirically, this is implemented by testing whether financial benefit is endogenous to the filing decision in equation (3). In particular, we let $u_{1i} = \theta_1 v_{1i} + \varepsilon_{1i}$ and $u_{2i} = \theta_2 v_{2i} + \varepsilon_{2i}$, where $\mathrm{Var}(\varepsilon_s) = 1 - \theta_s^2 \sigma_{vs}^2$ and $\mathrm{Var}(v_s) = \sigma_{vs}^2$ for $s = 1,2$. A direct test of the correlation between the error terms in equations (3) and (4) provides key insights about the potential filing behavior of the identified consumer types. More specifically, if $Cov(u_s, v_s) = 0, s = 1,2$ or, alternatively, $\theta_s = 0$, we can conclude that the financial benefit is exogenous to the filing decision in equation (3). Thus if $\theta_s = 0$, the corresponding *s*-type individuals are consumers who do not jointly manipulate their debt and filing decisions; if $\theta_s \neq 0$, consumers jointly manipulate their debt and filing decisions. The test is then critical to link the modeled types to particular filing behaviors like "strategic" (if $\theta_s \neq 0$) and "non-strategic" ($\theta_s = 0$), at least partially.

The variables considered in the $X_i$ vector include age, education, household size, if individual is self-employed or owns a business and if she is a home owner, as well as regional dummies to control for differences across locations. The adverse events accounted for include health problems, divorce, job loss and unemployment spell. These variables are generally similar to the control variables used in other previous empirical studies on consumer bankruptcy (e.g., Chakravarty and Rhee, 1999; Fay, Hurst and White, 2002; Zhang, Sabarwal and Gan, 2015). Note also that different adverse events may have a different impact on the modeled financial benefit and potential filing behavior. For example, a divorce may be more predictable than a health shock, and may have a different effect on debt and bankruptcy decisions.

Similarly, as indicated above, we can associate the identified consumer types to specific observable characteristics through $W_i$. The types intend to capture potential differences among individuals in, for example, their creditworthiness and debt attitude, which shape their filing behavior. We include in $W_i$ the household income, number of credit cards, the shopping attitude of the household head, a measure of risk aversion, and the gender and race of the head. Given that the filing and financial benefit decisions are conditional on the consumer type, all the variables included in the type-equation still affect these decisions, although indirectly, through the likelihood of being of a certain type.

While several of these variables serve as proxies of an individual's debt attitude, it is not clear a priori whether they will be positively or negatively correlated with a particular filing behavior and the likelihood of filing for bankruptcy. For instance, while a person with a higher income is generally more prudent, cares more about her reputation and is less likely to take debts and plan for bankruptcy, a person with several credit cards may signal either a high creditworthiness and low probability of abusing the law or, in contrast, may be more likely to file for bankruptcy given the higher number of credit cards (debts) she holds. Women are also considered to be more risk averse than men (Croson and Gneezy, 2009), but they are not necessarily more or less likely to file for bankruptcy. Risk-averseness itself may be associated with a lower or higher probability of filing (Athreya, 2006; Gan and Mosquera, 2008).

Overall, in the proposed model the vector of individual characteristics and other observable factors $X_i$ help us to model both the likelihood of an individual to file for bankruptcy and her behavior in accumulating debt or financial benefit. The occurrence of adverse events $AE_i$ in the previous period directly affect an individuals' financial benefit and indirectly her likelihood of filing. That is, we can recover the effect of adverse events on the filing probability through the channel of financial benefit. Similarly, the variables included in the type equation ($W_i$) indirectly affect the filing and financial benefit choices through the likelihood of being of a certain type. Certainly, there can be some discussion regarding which variables should be included in the different modeled equations, similar to the discussion when estimating a selection model. Yet, the specification above provides the best fit for the data and ultimately we can recover marginal effects (conditional or unconditional) of all the control variables on the filing decision.

The resulting joint density of the filing decision and financial benefit, $(file_i, \ln(fb_i + 1))$ with two consumer types, $T_i^1$ and $T_i^2$, is equal to

$$\begin{aligned} f\left(file, \ln(fb+1) \mid X, AE, W\right) = {} & f\left(file, \ln(fb+1) \mid T^* = T^1, X, AE, W\right)\Pr(T^* = T^1 \mid X, AE, W) \\ & + f\left(file, \ln(fb+1) \mid T^* = T^2, X, AE, W\right)\Pr(T^* = T^2 \mid X, AE, W) \end{aligned} \tag{5}$$

where we omit the subscripts to save space. This joint density consists of four observed cases: $(file = 1, \ln(fb+1) = 0)$, $(file = 0, \ln(fb+1) = 0)$, $(file = 1, \ln(fb+1))$ and $(file = 0, \ln(fb+1))$, where $\ln(fb+1)$ is positive and continuous in the last two cases.

The proposed model belongs to the class of finite mixture density models. The identification of these models has been extensively studied in recent years (see, e.g., Mahajan, 2006; Lewbel, 2007; Fox and Gandhi, 2008; Henry, Kitamura and Salanié, 2014; Gan, Huang and Mayer, 2015). A necessary identification condition of the model requires an exclusion restriction, i.e. that the set *W* is different from *X* and *AE*. Henry, Kitamura and Salanié (2014) show that the model is fully identifiable if $W$ is correlated with $T^*$ and $W$ is conditionally independent of the error terms ($u_1$ and $u_2$) in equation (3). Intuitively, the model identification is similar to that underlying a two-stage least squares (2SLS) procedure. Formally, the key identifying assumption in the proposed model is given by

$$f\left(file, \ln(fb+1) \mid T^* = T^1, X, AE, W\right) = f\left(file, \ln(fb+1) \mid T^* = T^1, X, AE\right). \tag{6}$$

$W$ only affects the probability of being of a certain type, but is not related to the conditional joint density $(file, \ln(fb+1) \mid T^*)$.

When $W$ includes more than one variable, Henry, Kitamura, and Salanié (2014) and Gan, Huang, and Mayer (2015) further show that either using the full set of $W$ or a subset of $W$ will produce consistent estimates of the parameters in the filing equation. A direct implication of the type-varying model is that we require some but not full information about the factors describing individual heterogeneity ($T^*$) to identify the parameters in the filing equation. A Hausman-type specification test can be then implemented comparing the estimated coefficients in equation (4) using the full set of $W$ versus the estimates using a subset of $W$. This test is similar to an overidentification test in an instrumental variables approach. Failing to reject the null hypothesis of no systematic differences between the estimated coefficients provides supporting evidence for the appropriateness of the model specification.

Overall, the joint densities for each of the four observed cases are given by

$$
\begin{aligned}
\Pr(file=1,\ln(fb+1)=0) &= \Pr\left(file=1,\ln(fb+1)=0 \mid T^*=T^1\right)\Pr\left(T^*=T^1\right) \\
&\quad+\Pr\left(file=1,\ln(fb+1)=0 \mid T^*=T^2\right)\left(1-\Pr\left(T^*=T^1\right)\right) \\
&=\Phi(W\lambda)\int_{-\infty}^{-X\delta_1-AE\mu_1}\Phi\left(\frac{\kappa_1+X\beta_1+\theta_1 v_1}{\sqrt{1-\theta_1^2\sigma_{v1}^2}}\right)\frac{1}{\sigma_{v1}}\phi\left(\frac{v_1}{\sigma_{v1}}\right)dv_1\,, \\
&\quad+\left(1-\Phi(W\lambda)\right)\Phi(\kappa_2+X\beta_2)\Phi\left(-\frac{X\delta_2+AE\mu_2}{\sigma_{v2}}\right)
\end{aligned}
\tag{7a}
$$

$$
\begin{aligned}
\Pr\left(file=0,\ln(fb+1)=0\right) &= \Pr\left(file=0,\ln(fb+1)=0 \mid T^*=T^1\right)\Pr\left(T^*=T^1\right) \\
&\quad+\Pr\left(file=0,\ln(fb+1)=0 \mid T^*=T^2\right)\left(1-\Pr\left(T^*=T^1\right)\right) \\
&=\Phi\left(W\lambda\right)\int_{-\infty}^{-X\delta_1-AE\mu_1}\Phi\left(-\frac{\kappa_1+X\beta_1+\theta_1 v_1}{\sqrt{1-\theta_1^2\sigma_{v1}^2}}\right)\frac{1}{\sigma_{v_1}}\phi\left(\frac{v_1}{\sigma_{v1}}\right)dv_1\,, \\
&\quad+\left(1-\Phi\left(W\lambda\right)\right)\left[1-\Phi(\kappa_2+X\beta_2)\right]\Phi\left(-\frac{X\delta_2+AE\mu_2}{\sigma_{v2}}\right)
\end{aligned}
\tag{7b}
$$

$$
\begin{aligned}
\Pr(file=1,\ln(fb+1)) &= \Pr\left(file=1,\ln(fb+1) \mid T^*=T^1\right)\Pr\left(T^*=T^1\right) \\
&\quad+\Pr\left(file=1,\ln(fb+1) \mid T^*=T^2\right)\left(1-\Pr\left(T^*=T^1\right)\right) \\
&=\Phi(W\lambda)\cdot\Phi\left(\frac{\kappa_1+X\beta_1+\gamma_1\ln(fb+1)+\theta_1\left(\ln(fb+1)-X\delta_1-AE\mu_1\right)}{\sqrt{1-\theta_1^2\sigma_{v1}^2}}\right) \\
&\quad\times\frac{1}{\sigma_{v1}}\phi\left(\frac{\ln(fb+1)-X\delta_1-AE\mu_1}{\sigma_{v1}}\right) \\
&\quad+\left(1-\Phi(W\lambda)\right)\Phi(X\beta_2+\gamma_2\ln(fb+1)) \\
&\quad\times\frac{1}{\sigma_{v2}}\phi\left(\frac{\ln(fb+1)-X\delta_2-AE\mu_2}{\sigma_{v2}}\right)
\end{aligned}
,\tag{7c}
$$

and

$$
\begin{aligned}
\Pr(file=0,\ln(fb+1)) &= \Pr\left(file=0,\ln(fb+1)\mid T^{*}=T^{1}\right)\Pr\left(T^{*}=T^{1}\right)\\
&\quad+\Pr\left(file=0,\ln(fb+1)\mid T^{*}=T^{2}\right)\left(1-\Pr\left(T^{*}=T^{1}\right)\right)\\
&=\Phi(W\lambda)\left[1-\Phi\left(\frac{\kappa_1+X\beta_1+\gamma_1\ln(fb+1)+\theta_1\left(\ln(fb+1)-X\delta_1-AE\mu_1\right)}{\sqrt{1-\theta_1^2\sigma_{v1}^2}}\right)\right]\\
&\quad\times\frac{1}{\sigma_{v1}}\phi\left(\frac{\ln(fb+1)-X\delta_1-AE\mu_1}{\sigma_{v1}}\right)\\
&\quad+\left(1-\Phi(W\lambda)\right)\left[1-\Phi(X\beta_2+\gamma_2\ln(fb+1))\right]\\
&\quad\times\frac{1}{\sigma_{v2}}\phi\left(\frac{\ln(fb+1)-X\delta_2-AE\mu_2}{\sigma_{v2}}\right)
\end{aligned}
\tag{7d}
$$

where $\phi(\cdot)$ is the normal density function.

## 3. Data

The data used in the analysis is obtained from the Survey of Consumer Finances (SCF), which is a national survey sponsored by the Federal Reserve Board in cooperation with the Department of Treasury and collected by NORC at the University of Chicago. While this cross-sectional survey is generally conducted every three years, key information such as the location (region) of the respondents has not been released to the public after 1998. We work with the 1998 dataset, which provides all the necessary variables to carry out the analysis.

The SCF is the most representative survey of household finances in the US.[10] The dataset has detailed information on households' balance sheets and their use of financial services, labor force participation, pensions and demographic characteristics. This includes data on bankruptcy

[10] For further details on the 1998 SCF refer to Kennickell, Starr-McCluer and Surette (1998).

filings, debts, assets, income, household size, as well as characteristics of the household head like age, sex, education, marital status and employment condition.[11]

Two key variables in our analysis are bankruptcy filings and the net financial benefit from filing. The filing rate in the 1998 SCF sample is 1.28% (55 out of 4,305 surveyed households). This figure is close to the 1.16% national bankruptcy filing rate reported by the US Courts in the corresponding year.[12] We cannot distinguish, however, between Chapter 7 and Chapter 13 filings as the SCF survey does not provide information on the chapter choice. While filing under Chapter 7 is a liquidation bankruptcy that usually takes between 3 and 5 months to receive a discharge, filing under Chapter 13 is a reorganization bankruptcy that takes between 36 and 60 months to receive a discharge. Still, as noted by Fay, Hurst and White (2002), households have a choice between the two filing procedures and the potential financial benefit from filing under Chapter 13 is related to that under Chapter 7.

Following Fay, Hurst and White (2002), the net financial benefit from filing is defined as

$$fb_i = \max\left[d_i - \max\left[w_i - ex_i, 0\right], 0\right] \tag{8}$$

where $d_i$ is the value of unsecured debt discharged in bankruptcy by household $i$, $w_i$ is the household wealth, and $ex_i$ is the value of bankruptcy exemption in the household's state of residence. In this equation, $d_i$ represents the gross benefits of filing while $\max\left[w_i - ex_i, 0\right]$,

[11] The Panel Study of Income Dynamics (PSID) also provides information on bankruptcy filings, wealth, income and demographic characteristics, but the wealth information is less detailed than the SCF for some variables of interest in this study and it is collected in 5-year intervals.

[12] There are, for example, only 254 bankruptcy filings in the PSID over the period 1984-1995, which is roughly half of the national filing rate during the same period (Fay, Hurst and White, 2002).

which measures the nonexempt assets that a filer loses in bankruptcy, represents the financial costs of filing. If $d_i - \max[w_i - ex_i, 0] < 0$, not filing dominates filing, so $fb_i$ is truncated at zero to yield the formula above.

Note, however, that this calculation does not capture the full economic costs of filing. A more complete measure of costs would include the future costs from filing such as more restricted (and costly) access to credit markets and the loss of profit streams from liquidated assets, as well as out-of-pocket filing costs.[13] Unfortunately, reliable data on these measures is not available and is also a limitation of previous related studies (e.g., Fay, Hurst and White, 2002; Zhang, Sabarwal and Gan, 2015).

We include as unsecured debt $d_i$ both credit card debts and installment loans. Credit card debts comprise both traditional credit card debts (e.g., Visa, Mastercard, Discover) and revolving debts from credit cards issued by stores (e.g., retail store cards, airline cards, gasoline cards). Installment loans refer to those loans obtained for purposes other than real estate and car purchases. The household wealth $w_i$ is the total financial and non-financial assets net of secured debts like mortgages and car loans. Financial assets include transaction accounts (checking, savings, money market and call accounts), deposit certificates, bonds, stocks, directly-held mutual funds, cash-value of life insurance, quasi-liquid assets (individual retirement accounts, thrift accounts and future pensions), and other managed assets (trust funds, annuities and management investment accounts with equity interest).[14] Non-financial assets include the value of all vehicles, primary residence, residential real estate and business interests.

[13] See, e.g., Berkowitz and Hynes (1999), Musto (2004) and Han and Li (2011).

[14] Other financial assets comprise, for example, loans given to other individuals, future proceeds, royalties, deferred compensations, non-public stocks and cash not elsewhere classified.

The construction of the bankruptcy exemption $ex_i$ requires certain adjustments as the SCF provides the Census region but not state where the household resides. First, we obtain the 1998 exemption levels for each state from Elias, Renauer and Leonard (1999). We recover exemption levels for homestead equity in owner-occupied homes, equity in vehicles, personal property and wildcard exemptions, and use the sum of these exemptions as the exemption variable for each state.[15] We then calculate a regional composite exemption measure based on the exemptions for each state in a region and using as weights the relative population of the state in the region.[16]

Table 1 presents descriptive statistics of all the variables used in the analysis. We observe, for example, that the calculated financial benefit is on average around 3,991 dollars for the full sample, yet filers show a financial benefit which is about five times higher than non-filers (18,680 versus 3,801 dollars). As noted above, the control variables include age and education of the household head, household size, whether the head is self-employed or owns a business, if the head is a homeowner, and regional dummies to capture local fixed effects. The adverse events, which are assumed to occur with an exogenous probability prior to the filing decision, include whether the household head (self-reported) health condition is poor, if the head is divorced, if the head was unemployed at any time during the prior twelve months and the

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[15] We adjust the exemptions for each state whenever possible. For example, if a state doubles the exemption for married households, we also double the exemption. When a state allows residents to choose between state or federal exemptions, which is the case of fifteen states, we consider the larger of the exemptions. For states with unlimited homestead exemptions, we use as the homestead exemption the average of the home values in our sample.

[16] The state population data is obtained from Regional Economic Information System (REIS) from the Bureau of Economic Analysis.

number of weeks unemployed over the prior twelve months.[17] The controls in the type equation comprise the household income, number of credit cards maintained by the household head, whether the head shops around for the best term, a measure of risk aversion, and the gender and race of the head.[18]

[Insert Table 1]

## 4. Results

This section presents and discusses the estimation results. For comparison purposes we first present the results of the Probit or pooled model, which does not account for unobserved filing types when modeling the bankruptcy decision. We then turn to our two-type model. We discuss the estimation results, test the model identification and evaluate the out-of-sample performance of the model.

### 4.1 Pooled model

Table 2 reports the estimation results of modeling the decision of filing for bankruptcy using a standard Probit model. The model specification in the first two columns is similar to the specification in Fay, Hurst and White (2002). The difference between the two columns is that in column (1) we include financial benefit in levels plus its squared term while in column (2) we

[17] The results are qualitatively similar when accounting instead for the poor health condition of either the head or partner.

[18] The shop around variable can take values between 1 and 5 after the individual is asked "When making major saving and investment decisions, some people shop around for the very best terms while others don't. What number would you be on the scale", where the higher the number the greater the shopping around. The risk averse variable takes a value of one if the individual simply responds "not willing to take any financial risks" when directly asked about "the amount of financial risk that you are willing to take when you save or make investments."

include financial benefit in logarithms. In column (3) we add the variables used to model the type equation.

[Insert Table 2]

We find that the direction of the effects of the control variables are generally comparable to those reported in Fay, Hurst and White (2002), when applicable. In particular, financial benefit affects the filing decision positively and at a decreasing rate in column (1). In columns (2) and (3) we also observe a positive correlation between financial benefit and the probability of filing. On average, a 1,000 dollars increase in the financial benefit (roughly a 25% increase in the sample mean) increases the likelihood of filing in 0.06 percentage points, which is equivalent to a 4.7% increase in the filing rate.[19] Among the adverse events, only being divorced is positively correlated with the decision to file. Family size is positively associated with filing across all specifications, while the number of credit cards seems negatively correlated with the filing decision in column (3).

As in Fay, Hurst and White (2002), using a standard Probit model provides little support for a "non-strategic" behavior since the financial benefit is positively correlated with the decision to file and among the adverse events only divorce is significantly correlated with the filing decision. As discussed above, however, this model does not account for different filing types and the potential endogeneity of financial benefit.

### 4.2 Two-type model

[19] Fay, Hurst and White (2002) find a 7% increase in the filing rate after a 1,000 dollars increase in the financial benefit.

Table 3 presents the estimation results of the type-varying model, which allows for two filing types (Type 1 and Type 2) and formally tests the exogeneity of financial benefit in the filing decision for each type. In the model, the effects of the variables included in the filing and financial benefit equations are allowed to vary by consumer type, while the adverse events are assumed to act as a negative shock to the household wealth and help to model the financial benefit of filing. We further correlate the probability of being of a certain type with specific observable characteristics.

[Insert Table 3]

Several important patterns emerge from the table. First, similar to the Probit or pooled model, we observe a positive correlation between the financial benefit and the likelihood of filing among the two consumer types. However, the financial benefit is exogenous to the bankruptcy decision for the first type and endogenous for the second type, as inferred from the reported correlations between the error terms in the filing and financial benefit equations. More specifically, $\theta_2$ = -0.81 (0.30) is statistically different from zero at conventional levels while $\theta_1$ = -0.07 (0.26) is not. In addition, the conditional probability of filing, reported at the bottom of the table, is considerably different between the two types. The chances of filing for bankruptcy is more than 4.5 times higher among Type 2 consumers relative to Type 1 consumers (3.5% versus 0.75%).

Hence, the model clearly distinguishes between two filing types with different probabilities of filing and different behavior in terms of the financial benefit and filing decisions. Type 1 individuals, who do not jointly manipulate their financial benefit and filing decisions and are less likely to file for bankruptcy, can be associated with "non-strategic" individuals who do not intend to abuse the law and who would repay their debt in the absence of an adverse event.

These are probably consumers who place a lot of value in their reputation as well as consumers who may simply exhibit "rational inattention" to a rare event. Type 2 individuals who seem to jointly manipulate their financial benefit (unsecured debt) and filing decisions and are more likely to file may comprise, in turn, "strategic" consumers who consciously increase their debt before filing to benefit from it. However, it may also include "non-strategic" consumers who do not intend to benefit from the law but simply rollover their debt when faced with an adverse event in the hope of future repaying it. That is, individuals who may appear "strategic" due to a "non-strategic" run-up of debt before filing. The nature of our data does not permit us to further disentangle between these potential opposite behaviors among Type 2 consumers, but the role of adverse events in the estimated model can provide some guidance on this matter as discussed next.

We observe a significant correlation between several adverse events and the financial benefit among Type 1 individuals, as opposed to Type 2 individuals. In particular, among Type 1 consumers, reporting being divorced and unemployment spell have a positive effect on the financial benefit while having been unemployed has a negative effect; among Type 2 consumers, only having been unemployed is negatively correlated with financial benefit. Intuitively, being divorced may lead to a larger amount of debt and a higher financial benefit, potentially including more debt being discharged such that both (ex) partners get a fresh start.[20] Transition to unemployment at some point over the past 12 months may lower the access to credit markets, decreasing the potential financial benefit. Yet, conditional on being unemployed, an increase in

[20] Traczynski (2011) shows that higher exemption levels can lead to higher divorce rates as the income protection (risk-sharing) offered by marriage is replaced by that offered by bankruptcy laws. This is similar to Mahoney (2015) who exploit multiple variations in asset exemption laws and shows that bankruptcy can serve as implicit health insurance given that most medical care is provided on credit, which can be discharged on bankruptcy.

the number of weeks under this condition may result in reaching credit limits on existing debt lines or an increase in outstanding debts (due to the non-servicing of the debt), which will increase the financial benefit.[21]

Hence, the varying role of adverse events by type support the association of Type 1 consumers with individuals who do not intend to abuse the law in the absence of an adverse event; certain adverse events affect their potential financial benefit, which may (or not) result in filing, but the financial benefit is not jointly manipulated with the filing decision. Similarly, while we cannot unravel "strategic" and "non-strategic" behaviors among Type 2 individuals, the lack of correlation between most of the adverse events and the financial benefit provide some support for a "strategic" behavior among Type 2 consumers relative to a "non-strategic" run-up of debt before filing. We further discuss below the (indirect) effect of adverse events on the filing decision by type, which is channeled through their impact on the financial benefit.

The variables included in the type equation permit, in turn, to correlate the likelihood of being of a certain filing type with particular characteristics. We find that income is positively correlated with the likelihood of being a Type 1 consumer. We interpret this finding in line with the fact that households with a higher income are generally more prudent and care more about their reputation, such that they are less likely to jointly manipulate their financial benefit and filing decision and file for bankruptcy. The costs of the social disapproval (social stigma) associated with filing, for example, can be relatively higher among richer than poorer households. Our proxy of risk aversion is, in contrast, negatively correlated with the probability

[21] Agarwal and Liu (2003) find that county unemployment rates in the US are significantly correlated with credit card delinquency and bankruptcy rates. Athreya and Simpson (2006) also argue that income interruptions, the receipt of public insurance like unemployment assistance and the incidence of personal bankruptcy are all closely related; the authors show that increases in the generosity of public insurance can lead to more bankruptcy.

of being a Type 1 consumer. This can be linked to the fact that less risk-averse consumers are more likely to exhibit "rational inattention" to rare events such that they choose their debt level without fully accounting for the occurrence of an adverse event.[22] Type 1 individuals are assumed to both not abuse the law and pay their debts in the absence of adverse events.

If we further segment our sample based on the likelihood of the household of being of a certain type, we can obtain additional insights about observed filing and financial benefit patterns within each type. Table 4 divides the sample between consumers with an estimated Type 1-probability of 0.5 or greater and consumers with a probability less than 0.5.[23] According to this criterion, 2,616 (61%) of the households are considered as Type 1 and 1,689 (39%) as Type 2. This indicates a higher prevalence of Type 1 households in the data. Notably, the sample average probability of filing among Type 1 consumers is 0.7% versus 2.1% among Type 2 consumers. More interesting, the potential financial benefit is significantly higher among Type 2 consumers and, on average, 36.6% of them have a strictly positive financial benefit relative to 13.7% of Type 1. This is consistent with the view of Type 2 consumers as individuals who consciously (or not) increase their debt before filing. These patterns also suggest that the types in the model are not purely identified by the functional form. We formally evaluate in the next section the model identification.

[Insert Table 4]

Finally, the estimated model is informative in terms of the effects of different control variables on the filing decision, which can vary by filing type. To better appreciate this, Table 5 shows the effects of hypothesized changes in particular variables on the probability of filing,

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[22] This measure of risk aversion, however, may be imperfect as it is not based on a standard lottery choice experiment.

[23] The sample average probability of being Type 1 is 58.9%.

evaluated at the sample means. We calculate both conditional and total (unconditional) marginal effects as the effects of these variables are allowed to vary by type; in the case of adverse events, the effect is channeled through the effect on financial benefit.[24] The table also reports the corresponding percentage changes in the filing rate.[25]

[Insert Table 5]

For example, if financial benefit increases by 1,000 dollars, the probability of filing increases by 0.23 percentage points among Type 1 consumers and by 0.26 percentage points among Type 2 consumers. Hence, the marginal effect of financial benefit on the filing decision is slightly smaller among the "non-strategic" individuals. Relative to the filing rate, the increase is equivalent to a 31.8% rise in the probability of filing for Type 1 individuals and 12.4% for Type 2 individuals. The total increase in the filing rate is 19.2%, which is much higher than the 4.7% increase estimated with the pooled Probit model. Similarly, an increase in family size by one member decreases the filing rate by 3.3% among Type 1 consumers, but increases the filing rate by 2.1% among Type 2 consumers. Regarding the adverse events, being divorced, which has a positive effect on the financial benefit, increases the likelihood of filing among Type 1 individuals by more than four times while it has a marginal effect among Type 2 individuals. One more week of unemployment spell also has a positive effect on the probability of filing among Type 1 consumers (11.6%) and a close to zero effect among Type 2 consumers. Recall

[24] The marginal effect for each type is the change in the conditional probability of filing. The total marginal change is the weighted average change using as weights the estimated average probabilities of being Type 1 and Type 2 (0.59 and 0.41).

[25] The change in the filing rate results from dividing the marginal effects by the corresponding average filing probabilities (0.0073, 0.0213 and 0.0128).

that Type 1 households, who do not seem to jointly manipulate their debt and financial benefit decision, are not expected to file for bankruptcy in the absence of facing an adverse event.

In sum, the results obtained show the importance of having a flexible, type-consistent model, which identify two different bankruptcy behavior patterns. The results permit to associate the identified types to specific characteristics and provides some insights about the possible factors driving the filing decision, which can differ by type. This is critical in a context where information asymmetries seem to play a critical role in bankruptcy.

### 4.3 Model identification

We now evaluate the identification of the estimated two-type model. As indicated above, when estimating a discrete mixture specification we require only partial information about the factors describing the consumer types ($T^*$) to identify the parameters in the filing equation (3). A subset of the variables included in $W$ used to model the type equation should still produce consistent estimates of the parameters in the filing equation.

Table 6 reports the corresponding Hausman test results when comparing our base (benchmark) model that uses the full set of variables in $W$ versus alternative specifications that exclude different variables in $W$. We observe that the sign and magnitude of the coefficients are generally not sensitive to the exclusion of different variables in the type equation. In all but one case there are no systematic differences at conventional statistical levels between the estimated coefficients across the models. This exercise supports the robustness of the implemented mixture model.

[Insert Table 6]

### 4.4 Predictive performance

Lastly, we assess whether allowing for different filing types offers a higher predicative performance on the likelihood of filing than standard probabilistic methods, which can help to identify potential filers and non-filers. For the assessment, we follow a standard cross-validation procedure and randomly partition our sample into a design subsample for estimation purposes (80% of the observations) and a test subsample for the out-of-sample prediction analysis (20% of the observations). Both samples naturally maintain the full-sample proportions of filers and non-filers. The idea is to test how the model will perform when using new information sets.[26] We acknowledge, however, that this exercise may be subject to some limitations due to the already small number of filers in the full sample and the subsequent reduction of this number in the data partitions.

We use two different procedures to calculate the probability of filing of an individual based on the two-type model estimates. The first method or "naïve" approach simply uses the unconditional probability of filing, which is equivalent to the weighted sum of conditional probabilities. The second method or "conservative" approach uses both the conditional and unconditional probability of filing based on the likelihood of being of a particular type. In particular, the "naïve" approach is given by

$$\begin{aligned} f\left(file=1,\ln(fb+1)\right) = {} & f\left(file=1,\ln(fb+1)\mid T^{*}=T^{1}\right)\Pr(T^{*}=T^{1}) \\ & + f\left(file=1,\ln(fb+1)\mid T^{*}=T^{2}\right)\left(1-\Pr(T^{*}=T^{1})\right) \end{aligned}$$

[26] An out-of-sample performance assessment is also more appropriate when comparing between a models that account for latent types versus standard models without such types.

while the “conservative” approach is defined as

$$f\left(file=1,\ln(fb+1)\right)=\begin{cases} f\left(file=1,\ln(fb+1)\mid T^{*}=T^{1}\right) & \text{if } \hat{\Pr}(T^{*}=T^{1}) \text{ in 5th quintile} \\ f\left(file=1,\ln(fb+1)\mid T^{*}=T^{1}\right)\Pr(T^{*}=T^{1})+ & \\ f\left(file=1,\ln(fb+1)\mid T^{*}=T^{2}\right)\left(1-\Pr(T^{*}=T^{1})\right) & \text{if } \hat{\Pr}(T^{*}=T^{1}) \text{ in 2nd - 4th quintile} \\ f\left(file=1,\ln(fb+1)\mid T^{*}=T^{2}\right) & \text{if } \hat{\Pr}(T^{*}=T^{1}) \text{ in 1st quintile} \end{cases}$$

where $\hat{\Pr}(T^{*}=T^{1})$ is the estimated probability of being a Type 1 individual.

Table 7 presents different performance indicators for the Probit and two-type model. The results are based on 200 repeated 80-20% partitions.[27] The indicators are the mean square predicted error and several performance indicators, including McFadden, Puig and Kirschner (1977) standard predictive performance measure and the correct filing and non-filing classification rates.[28] We observe that the two-type model generally exhibits a higher out-of-sample performance than the Probit model, although the pooled (Probit) model has a smaller mean square predicted error. In particular, the two-type “naïve” and “conservative” approach have an overall predictive performance of 78.4% and 78.8% versus 73.6% of the Probit model. Similarly, the two-type model outperforms the Probit model by 3-4 percentage points in both correctly identifying filers (sensitivity) and non-filers (specificity). Hence, besides being more informative in terms of uncovering different filing behavior patterns and associating them to

[27] The results are not sensitive to alternative data partitions (75-25% and 85-15%).

[28] The performance and classification rates are based on converting the estimated filing probabilities to the standard 0/1 binary regime prediction. McFadden, Puig and Kirschner (1977) predictive performance measure is equal to $p_{11}+p_{22}-p_{12}^{2}-p_{21}^{2}$ where $p_{ij}$ is the *ij*th entry in the standard 2x2 confusion matrix of actual versus predicted (0,1) outcomes in which the entries are expressed as a fraction of the sum of all entries.

some observable characteristics, the two-type model attains a marginally higher predictive power than the pooled model.

[Insert Table 7]

## 5. Conclusions

Personal bankruptcy has been extensively studied in the US, but there is still an ongoing discussion about the factors associated with filing. In a context where information asymmetries play an important role, further understanding the elements and motivations driving the filing decision is critical to better design bankruptcy policies and provisions. If filers are mainly consciously taking advantage of the law, then more stringent regulations should be implemented such as reducing the exemption levels, making bankruptcy more expensive or limiting the number of repeated filings (debt discharges). If filers are not deliberately taking advantage of the law, then policies that attenuate the impact of adverse events are recommended, including mitigation and preparedness strategies.

This paper examines the existence of different filing types in the bankruptcy decision. The types in the model represent different filing behaviors, which may result from a combination of factors. We find evidence of two filing types in the data. The financial benefit is exogenous to the filing decision among the first type of consumers and endogenous among the second type. We interpret the joint manipulation of the debt and filing decision in the second group as consistent, although not exclusive, with a "strategic" behavior, while the first group is in line with a "non-strategic" behavior or a "rational inattention" to a rare event. We further observe that the second type has a higher probability of filing and shows a larger financial benefit. The proposed model is informative in that the factors correlated with the filing decision seem to differ by type and we can associate each type to some observable characteristics. The data support the prevalence of the first type of filing behavior over the second one. Hence, a larger fraction of households seem to not jointly manipulate their financial benefit and filing decisions, which also supports the insurance function of bankruptcy.

Finally, we recognize that data limitations prevent us from studying in more detail the bankruptcy decision. The analysis is based on cross-section data with a small number of filings, while more comprehensive household data with bankruptcy information are not available. We are able to uncover two different filing types, but certainly a wider number of types could be identified with richer data and the model could be easily extended for such purpose. Tracing, for example, in more detail the sequence of actions taken by consumers prior to filing, would permit to distinguish among the second type of consumers between "strategic" individuals and consumers who may appear "strategic" due to a "non-strategic" rollover of debt prior to filing. Similarly, the model is simplified and does not consider other relevant aspects of the bankruptcy decision such as the timing of filing, the choice of the bankruptcy chapter and the potential correlation with other public programs, some of which have been addressed in other studies cited above. Future research should examine whether the prevalence of different filing attitudes have changed across time, when (hopefully) more recent data becomes open.

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**Table 1. Summary Statistics**

| Variable | Mean | Std. |
|---|---|---|
| If file for bankruptcy | 0.013 | 0.112 |
| Financial benefit (US dollars) | 3,991 | 26,001 |
| If filing for bankruptcy | 18,680 | 28,377 |
| If not filing for bankruptcy | 3,801 | 25,918 |
| Ln (financial benefit + 1) | 1.945 | 3.687 |
| Unsecured debts if financial benefit>0 (US dollars) | 9,550 | 38,319 |
| Nonexempt assets if financial benefit >0 (US dollars) | 1,981 | 29,429 |
| Age household head | 49.840 | 16.523 |
| Years of education head | 13.740 | 2.902 |
| Family size | 2.649 | 1.437 |
| If self-employed/own business | 0.254 | 0.435 |
| If owns home | 0.699 | 0.459 |
| Northeast: New England | 0.052 | 0.222 |
| Northeast: Middle Atlantic | 0.168 | 0.374 |
| South: South Atlantic | 0.178 | 0.383 |
| South: East South Central | 0.058 | 0.233 |
| South: West South Central | 0.093 | 0.291 |
| Midwest: East North Central | 0.160 | 0.366 |
| Midwest: West North Central | 0.069 | 0.254 |
| West: Mountain | 0.064 | 0.245 |
| West: Pacific | 0.158 | 0.365 |
| If head had health problems | 0.040 | 0.195 |
| If head divorced | 0.128 | 0.334 |
| If head is unemployed | 0.225 | 0.418 |
| Weeks of unemployment | 2.391 | 6.347 |
| Ln household annual income | 10.892 | 1.977 |
| Number of credit cards | 4.439 | 4.357 |
| If shops around | 3.031 | 1.377 |
| If risk averse | 0.303 | 0.460 |
| If head male | 0.781 | 0.414 |
| If head black | 0.096 | 0.295 |
| # observations | | 4,305 |

**Table 2. Pooled model results (Probit)**

| Variable | (1) | (2) | (3) |
|---|---|---|---|
| | Dependent variable: If file for bankruptcy | | |
| Financial benefit | 2.63e-05*** | | |
| | (7.20e-06) | | |
| Financial benefit squared | -1.53e-10* | | |
| | (8.47e-11) | | |
| Ln (financial benefit + 1) | | 0.0841*** | 0.0862*** |
| | | (0.0145) | (0.0157) |
| Age household head | 0.0158 | 0.0216 | 0.0305 |
| | (0.0302) | (0.0311) | (0.0299) |
| Age household head squared | -0.0002 | -0.0002 | -0.0003 |
| | (0.0003) | (0.0003) | (0.0003) |
| Years of education head | 0.2380 | 0.2270 | 0.2500 |
| | (0.1560) | (0.1630) | (0.1730) |
| Years of education head squared | -0.0103* | -0.0093 | -0.0085 |
| | (0.0061) | (0.0063) | (0.0067) |
| Family size | 0.0900*** | 0.0992*** | 0.0935*** |
| | (0.0322) | (0.0334) | (0.0333) |
| If self-employed/own business | -0.3250* | -0.2920 | -0.2730 |
| | (0.1880) | (0.1940) | (0.2010) |
| If owns home | -0.1630 | 0.0281 | 0.1250 |
| | (0.1420) | (0.1360) | (0.1590) |
| If head had health problems | 0.0272 | 0.0468 | -0.0257 |
| | (0.3200) | (0.3250) | (0.3260) |
| If head divorced | 0.5840*** | 0.5550*** | 0.5450*** |
| | (0.1440) | (0.1460) | (0.1570) |
| If head is unemployed | -0.1470 | -0.1230 | -0.1610 |
| | (0.2150) | (0.2200) | (0.2410) |
| Weeks of unemployment | 0.0055 | 0.0111 | 0.0028 |
| | (0.0315) | (0.0308) | (0.0301) |
| Weeks of unemployment squared | -0.0004 | -0.0005 | -0.0002 |
| | (0.0009) | (0.0009) | (0.0007) |
| Ln household annual income | | | -0.0184 |
| | | | (0.0363) |
| Number of credit cards | | | -0.1150*** |
| | | | (0.0390) |
| If shops around | | | 0.0515 |
| | | | (0.0413) |

*(Cont.)*

| Variable | (1) | (2) | (3) |
| --- | --- | --- | --- |
| | Dependent variable: If file for bankruptcy | | |
| If risk averse | | | 0.1530 |
| | | | (0.1350) |
| If head male | | | 0.1350 |
| | | | (0.1580) |
| If head black | | | -0.1620 |
| | | | (0.1980) |
| Constant | -4.5490*** | -5.1450*** | -5.7330*** |
| | (1.2410) | (1.3000) | (1.4240) |
| Log-likelihood | -247.0627 | -242.0859 | -227.8773 |
| Observations | 4,305 | 4,305 | 4,305 |

Note: Standard errors reported in parentheses. All regressions include region fixed effects. *** p<0.01, ** p<0.05, * p<0.1.

**Table 3. Two-type model results**

| Variable | Type 1 | Type 2 |
|---|---|---|
| | Bankruptcy equation: If file for bankruptcy | |
| Correlation between two errors $\theta$ | -0.0724 | -0.8067*** |
| | (0.2632) | (0.3032) |
| Ln (financial benefit + 1) | 0.1810*** | 0.2040*** |
| | (0.0659) | (0.0378) |
| Age household head | 0.1440 | 0.0683* |
| | (0.0989) | (0.0367) |
| Age household head squared | -0.0019 | -0.0005 |
| | (0.0012) | (0.0004) |
| Years of education head | 0.2530 | 0.1810 |
| | (0.3890) | (0.1810) |
| Years of education head squared | -0.0189 | -0.0050 |
| | (0.0158) | (0.0071) |
| Family size | -0.1810* | 0.1150** |
| | (0.1100) | (0.0542) |
| If self-employed/own business | 0.2650 | -0.2110 |
| | (0.3900) | (0.2850) |
| If owns home | -0.2110 | 0.1060 |
| | (0.2940) | (0.1550) |
| Constant | -4.900 | -9.1640 |
| | (3.360) | (9.1590) |
| | Financial benefit equation | |
| If head had health problems | 3.1240 | -0.3150 |
| | (4.8920) | (1.0130) |
| If head divorced | 7.0450*** | 0.9500 |
| | (1.6510) | (0.6380) |
| If head is unemployed | -8.6990* | -4.3920*** |
| | (5.0970) | (0.8200) |
| Weeks of unemployment | 1.1050* | -0.0212 |
| | (0.6540) | (0.1330) |
| Weeks of unemployment squared | 0.0091 | -0.0016 |
| | (0.0141) | (0.0043) |
| Age household head | 0.8730 | 0.4990*** |
| | (0.7770) | (0.1000) |
| Age household head squared | -0.0257** | -0.0056*** |
| | (0.0120) | (0.0010) |

*(Cont.)*

| Variable | Type 1 | Type 2 |
|---|---|---|
| | Financial benefit equation | |
| Years of education head | 2.3740 | -0.3700 |
| | (2.1380) | (0.3660) |
| Years of education head squared | -0.1150 | 0.0183 |
| | (0.0785) | (0.0165) |
| Family size | 0.4660 | 0.3050* |
| | (0.4710) | (0.1770) |
| If self-employed/own business | -13.8500*** | -3.7640*** |
| | (3.1250) | (0.8870) |
| If owns home | -3.4450** | -1.7280*** |
| | (1.4020) | (0.6440) |
| Constant | -12.6100 | -3.6330 |
| | (18.9900) | (3.4010) |
| Standard deviation of error $\sigma_V$ | 7.2146*** | 7.5350*** |
| | (0.0166) | (0.0032) |
| | Type equation: If Type 1 | |
| Ln household annual income | 0.9830*** | |
| | (0.1060) | |
| Number of credit cards | 0.0231 | |
| | (0.0143) | |
| If shops around | 0.0189 | |
| | (0.0422) | |
| If risk averse | -0.3880*** | |
| | (0.1350) | |
| If head male | -0.1300 | |
| | (0.1530) | |
| If head black | -0.3230 | |
| | (0.2150) | |
| Constant | -10.1500*** | |
| | (1.1340) | |
| Conditional predicted probability of filing | 0.75% | 3.50% |
| Log-likelihood | | -4,611.1394 |
| Observations | | 4,305 |

Note: Standard errors reported in parentheses. Regression includes region fixed effects. *** p<0.01, ** p<0.05, * p<0.1.

**Table 4. Comparison between types**

| Variable | Type 1 | Type 2 |
|---|---|---|
| Predicted probability of being Type 1 | 58.89% | |
| | Considered Type 1 if probability > 0.5 | |
| Observed probability of filing for bankruptcy | 0.73% | 2.13% |
| Ln financial benefit | 1.274 | 2.984 |
| % households with financial benefit > 0 | 13.69% | 36.59% |
| Number of households | 2,616 | 1,689 |

**Table 5. Marginal effects**

| Hypothesized change in variable | Marginal effect (% points) | | | % change in filing rate | | |
|---|---|---|---|---|---|---|
| | Type 1 | Type 2 | Total | Type 1 | Type 2 | Total |
| Financial benefit + $1,000 | 0.23 | 0.26 | 0.24 | 31.81 | 12.39 | 19.15 |
| | (0.012) | (0.016) | (0.014) | (1.67) | (0.74) | (1.12) |
| Age + 1 | -0.06 | -9e-5 | -0.04 | -8.26 | -0.004 | -2.77 |
| | (0.006) | (1.4e-4) | (0.002) | (0.76) | (0.007) | (0.19) |
| Family size + 1 | -0.02 | 0.04 | 0.004 | -3.27 | 2.06 | 0.32 |
| | (0.002) | (0.005) | (0.004) | (0.30) | (0.21) | (0.28) |
| Divorced from 0 to 1 | 3.02 | 0.05 | 1.80 | 415.30 | 2.31 | 140.62 |
| | (0.19) | (0.005) | (0.08) | (26.25) | (0.24) | (6.37) |
| Unemployed spell + 1 week | 0.08 | -0.001 | 0.05 | 11.57 | -0.05 | 3.84 |
| | (0.007) | (1.2e-4) | (0.005) | (1.00) | (0.006) | (0.34) |

Note: The hypothesized changes are calculated at the sample means. The marginal effect for each type is the change in the conditional probability of filing. The total marginal change is the weighted average change using as weights the estimated average probabilities of being Type 1 and Type 2 (0.5889 and 0.4111). The change in the filing rate results from dividing the marginal effects by the corresponding average filing probabilities (0.0073, 0.0213 and 0.0128). The standard errors, reported in parentheses, are computed using 300 repetitions of the sample.

**Table 6. Hausman test to evaluate model identification**

| Excluded variable | $H_0$: Difference in coefficients of type equation between base model and alternative specifications not systematic |
|---|---|
| Ln household annual income | 57.55 |
| | (0.00) |
| If shops around | 0.14 |
| | (0.99) |
| If risk averse | 7.05 |
| | (0.22) |
| If head male | 5.97 |
| | (0.31) |
| If head black | 4.66 |
| | (0.46) |

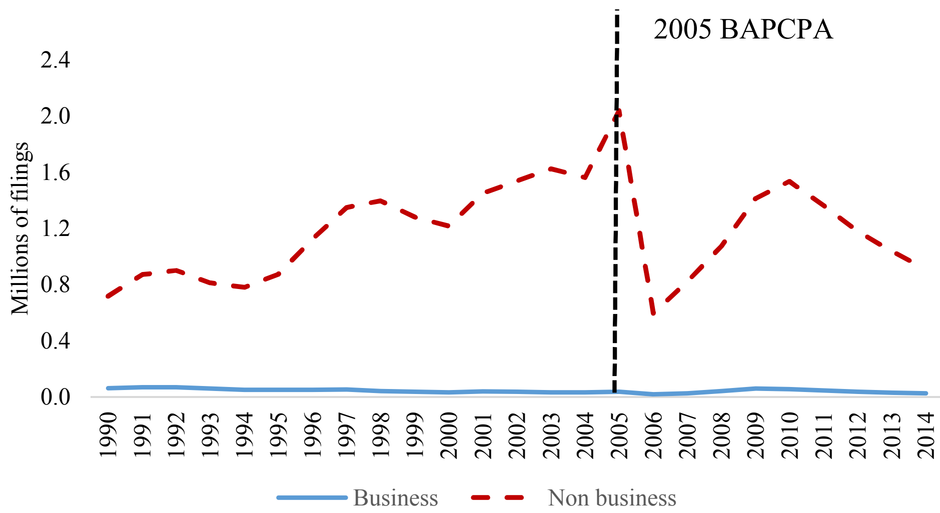
Note: Hausman Chi-squared statistics reported and corresponding p-values in parentheses.

**Table 7. Out-of-sample performance of models**

| Indicator | Probit model | Two-type model | |
|---|---|---|---|
| | | "Naïve" | "Conservative" |
| Mean Square Predicted Error | 0.011 | 0.016 | 0.017 |
| Predictive performance | 73.5% | 78.4% | 78.8% |
| Correct filing/non-filing classification | 78.2% | 81.7% | 82.0% |
| Correct filing classification (sensitivity) | 66.4% | 69.6% | 69.2% |
| Correct non-filing classification (specificity) | 78.3% | 81.8% | 82.1% |

Note: The "naïve" approach is based on the unconditional probability of filing. The "conservative" approach uses both the conditional and unconditional probability of filing based on the likelihood of being of a particular type. The performance and classification rates are based on converting the estimated filing probabilities to the standard 0/1 binary regime prediction. The predictive performance measure is based on McFadden, Puig and Kirschner (1977); the measure is equal to $p_{11} + p_{22} - p_{12}^2 - p_{21}^2$ where $p_{ij}$ is the *ij*th entry in the standard 2x2 confusion matrix of actual versus predicted (0,1) outcomes in which the entries are expressed as a fraction of the sum of all entries. Sensitivity accounts for the percentage of cases in which individuals filing are also predicted to file, while specificity measures the percentage of cases in which individuals not filing are also predicted to not file. The results are based on 200 repeated 80-20% data partitions (averages reported).

**Figure 1. Annual business and non-business filings in the US, 1990-2014**




Note: The number of filings includes all bankruptcy petition filings commenced during each calendar year (12-month period ending December 31) reported by the US Courts (www.uscourts.gov/Statistics.aspx). BAPCPA is the Bankruptcy Abuse Prevention and Consumer Protection Act of 2005.