The Persistence of Financial Strains among Low-Income Families: An Analysis of Multiple Indicators

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Abstract:

During the late 1990s, employment and incomes improved for many households in the bottom part of the income distribution in the United States. It is unknown, however, whether these improvements markedly reduced households' financial strains. In this study, I examine how changes in resources, needs and other characteristics are associated with self-reports of financial strains using a longitudinal survey of low-income households from three American cities. I develop and estimate longitudinal Multiple Indicator Multiple Cause models of financial strains. The models combine information from several different measures of strains; they also control for unobserved characteristics, like differences in families' permanent incomes and subjective assessments of needs, that might be confounded with the observed explanatory measures. The analyses reveal that there is considerable persistence in households' reports of financial strains. They also indicate that increases in income are associated with reductions in strains but that the relationship is weak. Other characteristics, such as wealth, disability, social networks and marital status, are more strongly associated with financial strains.

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1. Introduction

During the last decade, social policy in the United States has emphasized personal responsibility and self-reliance, especially work and earnings, as ways of improving the well-being of disadvantaged families. By many measures, these policies have been successful—welfare caseloads have fallen, incomes have risen, and poverty rates have declined. It is less clear, however, whether these policies have improved other aspects of well-being.

While many economists and policymakers simply assume that well-being is closely tied to income, empirical studies that have examined this relationship have generated some surprising findings. Cross-section studies conducted within the U.S. and other countries find a positive association between income and different measures of well-being, but the size of the association is generally small. Studies that have examined data across different countries find weaker associations still, and studies that have examined time series data often find no association at all.

Moreover, the evidence specifically relating to disadvantaged families in the U.S. is thin. Many studies on the determinants of well-being have considered the population as a whole. Of the studies that have investigated disadvantaged families, most have focused on select groups, such as welfare leavers. As welfare caseloads shrink and caseload compositions change, these groups are becoming less representative of the broader set of disadvantaged families.

In this study, I examine the determinants of self-reported financial strains using longitudinal data from a survey of low-income families living in three large U.S. cities: Boston, Chicago and San Antonio. The survey asked people about several types of strains; it also gathered data on their incomes, employment, household composition, and many other

circumstances. Because the data contain several related outcome measures describing strains, I estimate Multiple Indicator, Multiple Cause (MIMIC) models that combine the information from the measures and relate them to a single index. I modify the estimation procedure to account for the fact that the financial strain data take the form of ordered, categorical variables. I also modify the procedure to account for time-invariant omitted variables in the longitudinal data that might otherwise bias the estimated associations. My study contributes to and extends the existing research on well-being outcomes in several ways.

First, by analyzing financial well-being in a sample of low-income families, I am investigating a policy-relevant yet under-studied topic. In addition, the study of low-income families may contribute more general insights into the determinants of well-being. For one thing, disadvantaged families are more likely to be on the margin of reporting financial problems than advantaged families. Thus, disadvantaged families are a group for whom changes in income and other circumstances should matter more. Standard assumptions in economics regarding the declining marginal utility of consumption provide another reason to believe that differences in income may matter more to this group.

Second, the availability of longitudinal data lets me examine a critical substantive question—whether low-income families' reports of financial strains vary much over time. This provides another indication of the sensitivity of well-being to changes in circumstances. The use of longitudinal data also allows me to employ fixed effect controls for omitted variables. This, in turn, helps me to address some qualms that economists have regarding self-reported well-being data. Hamermesh (2004) and others have pointed out that these self-reports are likely to be flavored by people's subjective beliefs and standards, making it difficult to disentangle the objective and subjective elements of the responses. If we believe that people's subjective

standards are stable over short periods of time, longitudinal controls may help to isolate the objective components of the responses.

Third, there is a methodological contribution in the application and extension of the MIMIC framework. The framework provides a formal and data-driven means of combining information from several outcome measures. There is an efficiency gain associated with combining measures. The framework is also an improvement over the informal approaches that many researchers have used to combine data. The extensions of the framework that account for ordered, categorical outcome variables and longitudinal data are additional contributions.

The rest of this report is organized as follows. Section 2 discusses theories regarding the conditions that lead people to experience and report financial strains. Section 2 also reviews the methodologies and results from previous empirical studies. Section 3 describes the Three-City Study and the methods that are used to construct measures and select observations for my analyses. Section 4 describes the longitudinal MIMIC model that is used in the multivariate analyses. Estimation and specification test results from the model follow in Section 5. Conclusions are offered in the final section of the report.

2. Background

I begin by providing a conceptual model of people's perceptions of financial strains that relates these perceptions to more fundamental economic constructs. In neoclassical consumer theory, people choose bundles of goods that maximize their utility subject to the resources that they have, m, and the prices, $\boldsymbol{p}$, and other constraints that they face. People's optimal bundles, or demands, of goods are functions of resources and prices, and their realized expenditures—which equal the sum of each of these goods times their respective prices—are functions of the same things. We can write the expression for realized expenditures as $e(m, \boldsymbol{p})$.

From the same theory, people have "cost functions" that come from the dual of the utility maximization problem. In the dual problem, people find the least expensive bundle of goods that satisfies a particular level of utility. The level of expenditures that does this for a given level of utility, u, and a given set of prices is called the cost function, which can be written $c(\boldsymbol{p}, u)$.

Following Clark et al. (2004), Clark and Oswald (1996), Ravallion and Lokshin (2001) and Schwartze (2004), assume that each person has a level of utility, u^*, that is associated with a self-defined standard of satisfaction. Given a set of prices and a cost function, this level of utility would translate into a threshold level of expenditures, $n^* = c(\boldsymbol{p}, u^*)$ (see, e.g., Danziger et al. 1984 and Kapteyn et al. 1988). Additionally, assume that when answering questions about financial strains, people compare their realized expenditures with these thresholds and report strains if their realized expenditures fall below these amounts, that is, if $e(m, \boldsymbol{p}) < c(\boldsymbol{p}, u^*)$.[1]

This model is extremely simple. Nevertheless, it predicts that, holding all else constant, strains will be negatively associated with incomes, which increase realized expenditures, and positively associated with real and perceived needs, which raise the expenditure thresholds. The model also illustrates how objective elements, such as incomes, and subjective elements, such as people's preferences and definitions of living standards, figure into these reports. Extensions of the model to consider more realistic features, such as life-cycle effects and household production, are straightforward and lead to similar implications.

There have been numerous empirical analyses of the determinants of well-being, which in turn have examined a variety of self-reported measures. One way to classify the measures is to consider the extent to which they framed in terms of an objectively verifiable condition. At

[1] Clark et al. (2004), Clark and Oswald (1996), Ravallion and Lokshin (2001) and Schwartze (2004), who examine life and financial satisfaction rather than financial strains, use a different aspect of consumer theory. In their framework, a person reports being dissatisfied if the indirect utility associated with a given set of resources and prices, $v(m, \boldsymbol{p})$, is less than the threshold utility level, u^*.

one end of the spectrum are the studies of happiness and satisfaction, outcomes that are highly subjective. Examples include Blanchflower and Oswald (2004), Boes and Winkelmann (2004), Clark et al. (2004), Clark and Oswald (1996), D'Ambrosio and Frick (2004), Easterlin (1974), Headey et al. (2004), Schwarze (2004), Winkelmann (2004), and Winkelmann and Winkelmann (1998). In the middle are studies like this one that examine self-reports of objective conditions but allow people to give answers based on subjective thresholds. For example, Layte et al. (2001), Lerman (2002a, b), Mayer and Jencks (1989), and Ribar et al. (2005) have examined financial deprivations and other adverse events; Ravallion and Lokshin (2001) have studied relative economic standing, and a large literature has developed that investigates food insufficiency and insecurity.[2] At the other end of the spectrum are studies that examine material circumstances, such as the availability of a bathroom, kitchen or air conditioning (see, e.g., Mayer and Jencks 1993).[3]

Consistent with the conceptual model, the studies have generally found that well-being increases with income and decreases with needs. However, the associations, especially between well-being and income, are not all that strong.

Several explanations have been offered for the weak empirical relationship between income and well-being. One explanation is that people may smooth their expenditures by borrowing and saving, reducing the association with immediate income. Clark and Oswald (1996), Headey et al. (2004), Mayer and Jencks (1989) and Ravallion and Lokshin (2001) have found that measures of permanent incomes and wealth are associated with well-being. Easterlin (1974) offered a different explanation for the weak relationship between income and well-being,

[2] Gundersen and Ribar (2005) provide references for many of the recent studies of food hardships.
[3] Whelan et al. (2001) used an alternative approach—factor analysis—to classify well-being measures. They examined 24 measures from the European Community Household Panel and found that they could be classified into five groups corresponding to "basic life-style deprivations," "secondary life-style deprivations," "housing facilities," "housing deterioration," and "environmental problems."

arguing that relative income was crucial. In support of this, Clark and Oswald (1996) have found that job satisfaction is negatively associated with comparison incomes, while D'Ambrosio and Frick (2004) have found that life and financial satisfaction are strongly related to a person's position in the income distribution. A related idea is that people's income standards are affected by their income experiences, perhaps through processes of adaptation. Danziger et al. (1984) and Kapteyn et al. (1988) have found that people's assessments of the minimum amounts of income needed for themselves or others to get by increase with the people's levels of incomes.

The evidence regarding relative incomes and adaptation serves as a reminder that subjectivity is a critical concern in analyses of self-reported well-being. One methodological concern is where to set the average thresholds between different responses to well-being questions—that is, how to scale the responses. In situations where the responses take the form of multiple, categorical outcomes, researchers have usually used ordered logit or probit specifications (see, e.g., Ravallion and Lokshin 2001 and Winkelmann 2004), although more flexible generalized threshold models have also been used (Boes and Winkelmann 2004).

Another concern is that people's unobservable subjective standards may be associated with their incomes and other observable characteristics leading to omitted variables bias. To address this concern, several researchers, including Clark et al. (2004), D'Ambrosio and Frick (2004), Headey et al. (2004), Ravallion and Lokshin (2001), and Winkelmann and Winkelmann (1998), have estimated fixed effects models and other types of longitudinal specifications.

A final methodological concern, especially among the studies of deprivations and material hardships, is that studies sometimes collect data on several closely related outcomes. For instance, Mayer and Jencks (1989) investigated 10 deprivation measures, Layte et al. (2001) examined 13 measures, and the food security studies are based on 6 or 18 measures. In some

cases, such as the food security studies, formal scales have been derived to combine the information from the different measures. In other cases, ad hoc methods, such as simple counts or indicators for experiencing any of a set of hardships, are used to combine measures. In one recent study by Ribar et al. (2005), a MIMIC model was used to combine information.

The empirical analysis in this study addresses many of the issues highlighted in this review. It incorporates measures of wealth to address concerns regarding permanent incomes. It uses longitudinal methods to address omitted variables bias, and it estimates a MIMIC model, modified for categorical outcomes, to address response scaling and data combination issues.

3. Data

My empirical analyses use data from the first two waves of the Welfare, Children, and Families: Three-City Study, a longitudinal survey of families living in low-income neighborhoods in Boston, Chicago and San Antonio. The first wave of the survey in 1999 interviewed just over 2,400 families with children; all of the families had incomes below 200 percent of the U.S. poverty line. The families were reinterviewed in 2000-1; 88 percent of the original families participated in this second round.[4] The unit of observation in the survey is a focal child in each household. In each wave, the child's caregiver is asked questions about the child and about the household's economic circumstances, composition, and other characteristics. These caregiver reports are the basis for my analyses.

For the analyses, I first selected observations in which the household remained in the survey and the same caregiver was available for both interviews. I then dropped a modest number of observations (about five percent of the original sample) because of item non-response. Together, these selection criteria reduced the analysis sample to 2,019 households, with each

[4] A third wave of interviews is being conducted in the spring and summer of 2005.

household contributing two years of data.

Financial strains. In each wave, the survey prompted caregivers to "think about your household's finances." It then asked the following six questions:

ST1: "How often does your household have to borrow money to pay bills?" (responses: "never," "rarely," "occasionally," "frequently," or "all the time")

ST2: "How often does your household put off buying something you need because you don't have the money?" (responses: "never," "rarely," "occasionally," "frequently," or "all the time")

ST3: "How often can your household afford to do things just for fun like going to the movies or eating out?" (responses: "never," "rarely," "occasionally," "frequently," or "all the time")

ST4: "During the past 12 months, how much difficulty did your household have paying bills?" (responses: "no difficulty at all," "a little difficulty," "some difficulty," "quite a bit of difficulty," or "a great deal of difficulty")

ST5: "Does your household have enough money to afford the kind of housing, food and clothing you feel you should have?" (responses: "definitely no," "not quite," "mostly," or "definitely yes")

ST6: "Thinking about the end of each month over the past 12 months, did your household generally end up with…" (responses: "more than enough money left over," "some money left over," "just enough to make ends meet," or "not enough to make ends meet")

As is evident, the number and types of responses differ across the questions. The responses to the first three questions are expressed in terms of frequencies, while the responses to the next three questions are each specific to the questions themselves. Also, the questions differ in terms of asking about negative financial conditions (questions ST1, ST2 and ST4) or positive

conditions (ST3, ST5 and ST6). In forming measures from these questions, I reverse the order of the responses to the three "positive" questions so that larger values indicate higher degrees of financial strain. Finally, the questions ask about conditions with different levels of severity. Questions ST1, ST4 and ST5 are framed in terms of bills and necessities, while question ST3 is expressed in terms of having fun. The range of conditions appears to tap into concepts of both unmet needs and social exclusion.

Financial resources. The conceptual model predicts that greater financial resources will help families to avoid financial strains. My primary indicator of financial resources is the household's total, gross monthly income, which is constructed by summing different sources of earned and unearned income for all household members. The measure does not account for taxes or the Earned Income Tax Credit but does account for transfers from welfare, unemployment insurance, Social Security, food stamps and other programs.

A household's monthly income may be variable, and as a consequence, it may provide an incomplete description of the household's available resources. I include four binary measures to account for differences across households in their opportunities to smooth expenditures. The first measure is an indicator for whether the household owns its home. Homeowners may have equity that they can tap into or borrow against; they may also have credit histories that facilitate other types of borrowing. The second measure is an indicator for whether someone in the household owns a car, which could also reveal access to equity and an ability to borrow. The third measure is an indicator for whether anyone in the household has a bank account or other financial assets. Besides being a direct measure of wealth, holding a bank account may indicate lower costs for bill-paying and other financial transactions and greater knowledge of financial institutions. The fourth measure is an indicator for whether the household has outstanding loans,

including informal loans from friends and relatives. Loans may indicate a negative financial or wealth position; however, they may also reveal an ability to borrow.[5]

As additional measures of financial resources, I also include binary indicators of whether the caregiver usually works part-time or full-time (the omitted category is not working). There are reasons why holding a job may be associated with financial well-being, even after income is accounted for. Jobs may provide a relatively stable source of funds, at least when compared to support from relatives and time-limited welfare or unemployment payments. Jobs may also provide health care and other benefits that are not captured by the total income measure. In addition, jobholders may anticipate that their incomes will grow as they gain experience; thus, their permanent incomes may be higher. A job may also increase the household's security by providing access to social insurance programs or allowing a caregiver to receive welfare payments. To the extent that full-time jobs have higher pay, better benefits and more stability than part-time jobs, I expect them to have stronger associations with financial well-being.

Social resources. Besides their own resources, families may be able to draw on financial help and other kinds of assistance from friends and relatives when times are tough. To measure the extent and usefulness of social networks, I include binary indicators for whether the caregiver feels that she has enough people to listen when she has problems, help with child care, provide small favors, and loan her money.

Needs. I use several measures of household composition as measures of needs: separate indicators for the numbers of adults and children in the household and indicators for the caregiver's marital or cohabitation status. Larger households, especially those with more children, have higher consumption needs than smaller households. While I expect, other things

[5] The survey also asks about amounts of assets and loans. However, I have elected to use the binary indicators for any assets and any loans because these response rates are higher and the conditions may be more reliably reported.

held constant, that larger households will face greater financial hardships, it is possible that the presence of more adults could reduce strains. Contributions of earnings by additional adults should be accounted for by the income measure; however, as I just discussed, jobs may confer advantages that go beyond income. Additional adults could also contribute to the household's time resources and assist in child care or other types of home production.

Similarly, married and cohabiting caregivers may have fewer strains than single caregivers, once the income and family size effects of a spouse or partner are accounted for. These associations could come about because of the increased cooperation and better ability to share resources within a household with married or cohabiting partners. Also, people in romantic unions, especially married couples, may behave more responsibly (Umberson 1987, 1992) and spend their money more carefully than single people (Deleire and Kalil 2002).

My multivariate analyses also include measures of the caregiver's health and disability status. In particular, I use a self-assessed, categorical general health measure, an indicator for whether the caregiver is unable to work because of a disability, and an indicator for whether the caregiver is otherwise limited in work or other activities because of a disability. Health problems or disabilities may require special expenditures, which would increase the financial needs of the household. They may also reduce the opportunities for home production.

Additional measures. I use several other measures describing the caregiver's year of birth, education, race/ethnicity, nativity, and geographic location as general controls for differences in people's opportunities, needs, subjective standards, and preferences.

In several analyses, I also include controls for psychological characteristics. People's perceptions of financial strains may be influenced by their psychological outlooks—people with negative outlooks may perceive more strains than people with positive outlooks. Psychological

health may also affect people's ability to avoid hardships. I use four measures. The first is a general scale of self-esteem, which is summed from the categorical responses to ten questions and constructed so that higher values indicate more esteem. The other three measures are indicators of sleep problems, depression, and anxiety that are constructed from the *Behavioral Symptoms Inventory* (Derogatis 2000). An issue that arises in using these measures is that the causality is unclear—financial strains may be causes rather than consequences of psychological outlook and health. Accordingly, I specify models with and without these measures to see if there are any associations and to see whether including the measures changes my other results.

Table 1 gives short descriptions and sample means of all of the measures used in the analysis. The statistics clearly reflect the low-income nature of the Three-City Study. The average household income in the initial wave was just over $1,200 per month, or about $15,000 per year. Average income grew noticeably, however, across the waves, reaching just over $1,600 per month or $20,000 per year in the second wave. Few of the families owned their own homes, and less than half owned a vehicle. Labor supply and marriage rates were also low. Like income, however, several of these indicators improved from the first to the second wave.

[Table 1 about here.]

The statistics also indicate that sizeable fractions of the households reported different types of financial strains. Consistent with the improvement in the households' economic and other circumstances, average reports of most of the strains declined between the first and second waves. However, the sizes of these changes were relatively small, suggesting that the outcomes were only mildly responsive to the improvement in circumstances.

The sample means do not, of course, tell us how strains changed *within* households over time. For each outcome, the averages could reflect one group of households experiencing strains

at wave 1 and another group experiencing strains at wave 2. Alternatively, the averages could reflect many of the same households experiencing strains in both waves. Figure 1 addresses these longitudinal questions by comparing each household's reports of financial strains in waves 1 and wave 2 and showing bar graphs of the percentages of households for whom strains (a) increased—the dark areas at the bottom of the bars; (b) stayed the same—the lightly shaded areas in the middle of the bars, and (c) decreased—the unshaded areas at the top of the bars. The graphs are constructed so that larger dark areas within the bars indicate greater hardship. To show the association of these changes with changes in economic circumstances, the percentages are calculated separately for households whose monthly incomes decreased by $500 or more, increased or decreased by less than $500, and increased by $500 or more.

[Figure 1 about here.]

The graphs reveal that there is considerable persistence in the reports of financial strains. Depending on the specific outcome and income group being considered, between a third and a half of households reported the same strains from one interview to the next. There is a visible, albeit weak, association with income. Households whose incomes declined by more than $500 were slightly more likely to report that strains increased than decreased, while the opposite pattern appears for households whose incomes increased by more than $500. What is striking about the figure, however, is how small the differences are across income groups and how many households reported that hardships moved in the same direction as their incomes.

4. Econometric Model

For the multivariate analyses, the data on financial strains present us with two statistical challenges: first, how to examine and combine information from multiple, related, categorical outcome measures, and second, how to account for serial correlation and confounding influences

from omitted variables in the longitudinal data. To address the first challenge, I adopt the Multiple Indicator, Multiple Cause (MIMIC) framework (Jöreskog and Goldberger 1975) for my multivariate analyses and modify the framework to consider ordered, categorical outcomes. To address the second challenge I further modify the framework by applying Chamberlain's (1982) quasi-fixed-effects method for non-linear models.

MIMIC framework. The central idea behind the MIMIC approach is that the multiple outcomes that we observe—the reports of different financial strains—all stem from a single, underlying latent variable. To be more concrete, let $h^*(t)$ represent an index of financial hardship for a household at time t with the property that higher values of the index correspond to greater levels of hardship. We do not observe $h^*(t)$ directly. Suppose, however, that we have j continuous indicators, $y_j^*(t)$, that are related to $h^*(t)$ but imperfectly so, in the sense that each of them depends on the index but also on some measurement error or other idiosyncratic random component, $v_j(t)$.

If we stack the indicators $y_j^*(t)$ into a $j \times 1$ matrix, $\mathrm{Y}^*(t)$, stack the random errors $v_j(t)$ into a $j \times 1$ matrix, $\mathrm{V}(t)$, and define and stack a set of coefficients, λ_j, into a $j \times 1$ matrix, Λ, we can write the relationship between the indicators and the underlying latent index as

$$\mathrm{Y}^*(t) = \Lambda h^*(t) + \mathrm{V}(t). \tag{1}$$

Equation (1) describes a factor-analytic relationship, in which the hardship index, $h^*(t)$, takes on the role of the underlying factor and the coefficients in Λ serve as factor loadings. The specification brings with it all of the advantages and disadvantages of a factor analysis. On the one hand, the specification represents a sensible and data-driven approach for summarizing the data by extracting a common variable from the different indicators. The loadings, which are

estimated as part of the MIMIC procedure, effectively weight the different indicators in forming the factor. Thus, instead of imposing an arbitrary weighting on the indicators by summing or averaging them, I allow the data to determine the weights and maximize the amount of common information that is extracted. On the other hand, there is a question regarding how to interpret the specification. The underlying factor is not observed but rather is constructed as part of (is an artifact of) the statistical procedure. While I interpret the factor as an index of hardship, it is formally just a measure of the common element of the indicators, $y_j^*(t)$. The common element may be hardship, but it could also be or include something else.

Modification for categorical indicators. The discussion so far has proceeded as if we have a set of continuous indicators of financial strains; however, recall that the actual measures are ordered categorical variables. The conventional approach to working with discrete measures in the MIMIC framework is to make a somewhat ad hoc transformation of the measures (re-expressing the relationships among the measures in terms of polychoric correlations) and then analyzing them as if they were continuous. Instead of this approximate technique, I take the more exact but computationally intensive step of modeling the categorical outcomes.

I continue to allow $y_j^*(t)$ to be a continuous indicator of the frequency or severity of a given strain. However, as with the general hardship index, $h^*(t)$, I recognize that the continuous indicator is not directly observed. Instead, the household gives a categorical response, $y_j(t)$, for a financial strain. For a five-category question, the response is assumed to follow

$$\begin{aligned}
y_j(t) &= 0 \quad \text{if } y_j^*(t) \le \delta_{0j} \\
y_j(t) &= 1 \quad \text{if } y_j^*(t) > \delta_{0j} \text{ and } y_j^*(t) \le \delta_{1j} \\
y_j(t) &= 2 \quad \text{if } y_j^*(t) > \delta_{1j} \text{ and } y_j^*(t) \le \delta_{2j} \\
y_j(t) &= 3 \quad \text{if } y_j^*(t) > \delta_{2j} \text{ and } y_j^*(t) \le \delta_{3j}
\end{aligned} \tag{2}$$

$$y_j(t) = 4 \qquad \text{if } y_j^*(t) > \delta_{3j}.$$

The specification of relationship between the latent continuous indicator and the observed categorical response is the same used in ordered probit and logit models; it is also easily modified for outcomes with fewer categories. The thresholds, or δ_{mj} terms, are estimated as part of the multivariate model and can take on different values for each type of strain. Thus, the model allows the data to determine the scale of the responses. By estimating different thresholds for each type of strain, it also implicitly adjusts for differences in their severities.

Specifications (1) and (2) together constitute a *measurement model* and describe how the multiple categorical indicators are related to the underlying index, $h^*(t)$. In estimating the measurement model, I assume that the loadings, λ_j, and response thresholds, δ_{mj} are constant across panels and, thus, that the measurement relationships are stable over time. I also assume that the idiosyncratic random components ($v_j(t)$ terms) of the unobserved continuous indicators are independently distributed across outcomes and time and that each of these components follows a standard normal distribution.

Behavioral model. The MIMIC approach combines a measurement model with a *behavioral model* that describes how other explanatory variables influence the general underlying index. I specify the hardship indicator as a linear function of observed time-varying measures $X(t)$, time-invariant measures, Z, and an unobserved variable $\varepsilon(t)$ such that

$$h^*(t) = B_X'X(t) + B_Z'Z + \varepsilon(t) \qquad (3)$$

where B_X and B_Z are matrices of coefficients. In the MIMIC framework, the measurement specifications (1) and (2), the "multiple indicator" part of the model, and the behavioral specification (3), the "multiple cause" part, are estimated together. Conditional on the validity of

the specification's restrictions, the MIMIC approach is more efficient than an alternative strategy of estimating separate models for each of the financial strains. It is also more efficient than a two-stage strategy of first conducting a factor analysis of the different strains and then using the results from that analysis as the dependent variable in a regression model. Despite its economic pedigree, the MIMIC approach has not been widely used by economic researchers; however, there have been some recent applications, including analyses of permanent incomes (Naga and Burgess 2001), food security (Ribar et al. 2005), and institutional reform in transitional economies (Di Tommaso et al. 2003).

Modification for longitudinal data. As I mentioned, there is a second complication involving possible serial correlation in the unobserved determinants of hardship and potential biases from the sources of this correlation. Assume that the error term in equation (3) can be decomposed into a time-invariant component, μ, and a transitory component $e(t)$, such that $\varepsilon(t) = \mu + e(t)$. The presence of the time-invariant component generates serial correlation in the errors for each household. Just as in a least squares regression, this can lead to incorrect standard errors and inefficient estimation. It can also lead to biased estimates of the coefficients in B_X and B_Z if μ is correlated with the explanatory variables in $X(t)$ and Z (Godwin 1988). The review of empirical studies indicates that μ may include hard-to-measure characteristics like subjective assessments of needs and permanent incomes that could lead to biases.

In a linear regression, we could sweep out μ and obtain unbiased estimates of the coefficients in B_X simply by differencing the outcome and explanatory measures across the two waves. Unfortunately, this is not generally possible in non-linear models like the categorical MIMIC specification. An alternative approach of using dummy variables to control for the household-specific effects is computationally impractical and, with only two longitudinal

observations, inconsistent. Instead, I apply Chamberlain's (1982) quasi-fixed-effects procedure, which specifies the time-variant component to be a function of the explanatory variables for all periods and a random error. For my two-period model, the specification is

$$\mu = \Gamma_1'X(1) + \Gamma_2'X(2) + u \tag{4}$$

where Γ_1 and Γ_2 are vectors of coefficients and u is a random error. The random effect, u, allows for correlation over time in the unobserved determinants of hardship. Through the X(1) and X(2) terms, the specification also allows for correlations with the time-varying observed measures in equation (3), thus addressing the source of bias in the estimates of B_X. In a linear model, Chamberlain's method is equivalent to other fixed effects procedures; in non-linear models, it provides an approximate correction.

The final model for household financial strains is a system of 12 ordered probit specifications: six pairs of specifications representing each of the hardships, measured across two waves. The individual ordered probit models have a number of cross-equation restrictions on their parameters. When we combine specifications (1), (3) and (4), the estimating equations for the latent severity of each hardship j in waves 1 and 2 can be written

$$\begin{aligned} y_j^*(1) &= \lambda_j[B_X + \Gamma_1]'X(1) + \lambda_j\Gamma_2'X(2) + \lambda_jB_Z'Z + \lambda_ju + \lambda_je(1) + v_j(1) \\ y_j^*(2) &= \lambda_j\Gamma_1'X(1) + \lambda_j[B_X + \Gamma_2]'X(2) + \lambda_jB_Z'Z + \lambda_ju + \lambda_je(2) + v_j(2). \end{aligned} \tag{5}$$

Besides the restrictions on the parameters, the expressions reveal that there are two error terms that are common across the estimating equations: u, which appears in all 12 equations for a household, and $e(t)$, which appears in the six equations for a given wave for a household. I assume that these errors are distributed independently of each other and of the response-specific

errors, $v_j(t)$, and that they are normally distributed with means of zero and variances of σ_u^2 and σ_e^2, respectively. I obtain maximum likelihood estimates of the parameters in the system using the aML software package (http://www.applied-ml.com), which employs Gauss-Hermite quadrature to "integrate out" the common errors, u and $e(t)$.

5. Estimation Results

Table 2 lists selected parameter estimates and standard errors for three specifications of the longitudinal MIMIC model of financial strains. From left to right, the specifications are increasing in parameterization. The first specification includes household income as the only measure of resources. The second adds measures of wealth, work effort, and social networks as supplemental controls for resources, while the third specification adds psychological measures. All of the specifications control for fixed effects using Chamberlain's approach. To facilitate specification tests and make the models more comparable, the fixed-effects controls in all three models are based on the third, most-parameterized specification. This has no impact on the coefficient estimates on the time-varying measures, as the "extra" controls are entered as fixed measures and associations between them and the time-varying measures are already accounted for by the minimal set of fixed effect controls (this actually provides a way to test the adequacy of Chamberlain's approach, and I will subsequently examine this property in more detail).

[Table 2 about here.]

For brevity, Table 2 only reports estimates for the coefficients from the behavioral model for latent hardships—the B_X and B_Z coefficients from equation (3)—and the standard deviations for the error components, u and $e(t)$, from that model. Thus, the table omits coefficients associated with the fixed-effects controls from the behavioral model and the factor loadings and thresholds from the measurement model. Complete results for the third specification are shown

in Appendix A, and complete results for the other specifications are available upon request.

In the first specification, changes in household income are estimated to be negatively associated with changes in financial strains, with a coefficient that is statistically different from zero. Although the direction of the relationship is consistent with expectations, the magnitude of the relationship is miniscule. Because of the non-linear model and the use of multiple outcomes, it is hard to judge the magnitude from the coefficient itself. To determine the magnitude, I used the estimates from the model to simulate the effect of a change in income. Specifically, I first simulated the financial strains the households would be expected to report in wave 2 given their actual data. I then simulated the strains giving each household an extra $1,000 in its wave 2 monthly income but holding the fixed effect constant.[6] The difference between the simulations shows the impact associated with the coefficient on the time-varying income measure. The results of the simulations are shown below.

	Borrow money to pay bills	Put off buying things	Cannot do things for fun	Difficulty paying bills	Cannot afford housing, food & clothing	Not enough money to make ends meet
Baseline	0.843	1.608	2.267	1.429	1.614	1.957
Add $1,000	0.793	1.536	2.235	1.352	1.565	1.916
% difference	-5.9	-4.5	-1.4	-5.4	-3.0	-2.1

As the figures indicate, an extra $1,000 in monthly incomes hardly reduces financial strains at all. The average categorical response for borrowing money to pay bills falls 5.9 percent, while the average response for not being able to do things for fun falls 1.4 percent. The percentage changes in the average responses for the other indicators are in between these two figures.

[6] Recall that the wave 2 income enters the model both as a time-varying measure and as a fixed control. In these simulations, I altered the time-varying measure but not the fixed control. This is equivalent to giving each household an extra $1,000 in wave 2 but reducing its income in wave 1 to keep the fixed effect constant.

One way to interpret the simulation is as a change in transitory income holding permanent income and other characteristics constant. Because of this, we might not be surprised at the weak association with financial strains. However, the results are not much different when I account for permanent changes by also allowing for a change in the fixed effect. In simulations where both the transitory income and fixed effect change, the average categorical response for borrowing money falls by 8.7 percent, while the average categorical response for not being able to do things for fun falls by 2.1 percent.

When we look at the measures for household needs in Table 2, the time-varying measures for the caregiver's work-preventing disabilities and general health problems are each associated with greater financial strains. The coefficient on the disability measure is particularly large—it implies that becoming disabled is equivalent to a loss of more than $3,000 per month in income.

Being married and having the spouse present in the household is estimated to decrease financial needs by a moderate amount. Lerman (2002a, b) has reported that married families with children experience fewer material hardships and deprivations than unmarried families, even after differences in income are taken into account. The estimates from Table 2 indicate that his conclusions apply to low-income families and are robust to the use of longitudinal controls.

Several other measures of needs have moderate-to-large coefficients but are imprecisely estimated. For instance, the coefficient on having a disability that limits work or other activities is half the size of the coefficient on having a disability that prevents work, but the standard error is very large. The coefficient on having a college degree is negative and nearly the same absolute size as the coefficient on having a work-preventing disability; again, however, the standard error is large. One reason why these estimates are imprecise is that the measured conditions do not change much across waves, leading to relatively little statistical power.

The coefficients for the number and age composition of people in the household and the caregiver's cohabitation status are all close to zero and statistically insignificant. The coefficient estimates for the numbers of adults and children are reasonably precise, so we can rule out very large associations. The results do not appear to be artifacts of over-controlling for family structure—multicollinearity would inflate the standard errors, and alternative specifications (not shown) that only included subsets of the variables produced similar results.

The estimates from the first column of Table 2 also indicate that blacks and Hispanics are substantially less likely than whites to report financial strains, once differences in other characteristics are taken into account. This could be evidence of cultural differences in the ways that people cope with or perceive financial problems. The results may also reflect the white families in the Three-City Study being particularly disadvantaged. Other estimates in the table indicate that reports of hardships increase with the caregiver's age and that reports decreased from the first wave to the second.

The second and third columns of Table 2 list estimates from specifications with additional sets of controls—measures of wealth, work and social networks in the second column and measures of self-concept and psychological symptoms in the third column. Each set of added controls is jointly significant, and several of the coefficients are individually significant. The inclusion of the resource and psychological controls attenuates some of the coefficients from the first specification. For instance, the coefficients on the time-varying measures of income and work-preventing disabilities are each reduced by about a quarter. However, none of the coefficients from the first specification loses its statistical significance.

Among the added time-varying resource controls, home ownership, financial assets, full-time work, having people that can help with child care, and having people that can lend money

are all negatively associated with financial strains, while outstanding loans are positively associated with strains. These results are all consistent with the resource interpretations for the measures. Because the coefficient on income is only slightly attenuated, these resources appear to complement and be different from income. For example, the estimates imply that obtaining an extra $1,000 per month by starting a full-time job reduces financial strains three times more than receiving the same amount of money some other way, a result that accords well with the intentions of recent welfare reforms.

Turning to the psychological controls, people with positive self-concepts report fewer strains, and people with symptoms of anxiety report more strains than other people. While we must be cautious in interpreting these results because of the possibility of reverse causality, the associations are consistent with people with sunnier and less fearful outlooks defining problems differently than people with other outlooks. The results also suggest that there may be a subjective component to the reports. Interestingly, however, the inclusion of the psychological controls does not substantially alter the coefficients of the other explanatory measures.

Specification tests. Table 3 lists results from four specifications of the MIMIC model with expanded resource and psychological controls that are intended to test first, whether the Chamberlain controls for fixed effects belong in the model and second, whether the controls work as intended. The specifications in Table 3 all have the same time-varying measures as the third (most-parameterized) specification in Table 2. The first two specifications drop the fixed measures of the time-varying explanatory measures from the model—that is, restrict Γ_1 and Γ_2 from expression (4) to be zero. The first and third specifications drop the genuinely fixed explanatory measures—that is, restrict B_Z from expression (3) to be zero. To ease comparisons, the fourth column of Table 3 reproduces the results from the last column of the previous table.

[Table 3 about here.]

A comparison of the results from the first and fourth columns of Table 3 shows the differences associated with controlling for fixed explanatory measures. The model in the first column is a random effects specification with only time-varying explanatory measures and no fixed observed controls whatsoever. Likelihood ratio tests indicate that the fixed controls belong in the model and that the pure random effects specification can be rejected. The coefficient estimates for several of the time-varying measures differ substantially across specifications. The most noticeable change occurs in the coefficient for having a college degree, which is positive and significant in the random effects model but strongly negative yet insignificant in the quasi-fixed-effects model. There are several other coefficients that change by 50 percent or more.

When we compare the results from the first and second columns of Table 3, we see that adding just the genuinely fixed measures (the Z variables) to the random effects model also significantly reduces the log likelihood and leads to small but perceptible changes in the coefficients on the time-varying measures. Contrast this, however, to what happens when the same measures are added to the specification in the third column, which has the minimal set of quasi-fixed-effects controls (the X(1) and X(2) measures). The added measures are jointly significant. However, the quasi-fixed-effects controls have done their job in the sense that the coefficients on the time-varying measures barely change across the two specifications.[7]

Another specification issue is how restrictive the use of a single index for hardship is in explaining the separate hardship outcomes. While the index specification combines information from the different outcome measures, it undoubtedly leads to some loss of detail regarding the determinants of the individual measures.

Recall that the estimating model consists of a series of restricted ordered probit equations.

[7] Although I do not show these results, adding the Z measures does lead to changes in the Γ_1 and Γ_2 coefficients.

A convenient way to test whether the index explains the variation associated with an outcome is to respecify the system so that the relevant ordered probit model includes both the index and a general set of observed and unobserved controls. I re-specified the model this way separately for each of the outcomes and found that there were significant idiosyncratic determinants for every one of the outcomes. Thus, there is a loss of information from the single index restriction.

To show how the model estimates vary across outcomes, I report selected coefficients in Table 4 from separate longitudinal ordered probit models of the six financial strain indicators. Only one measure—the caregiver's general health status—is consistently signed and significant across the separate models. Several other measures, including income, financial assets, full-time work, social supports for listening and child care, disability, sleep problems, anxiety, and race and ethnicity, have the same signs across specifications but differ in their significance. Coefficients for several other measures switch signs across specifications. For a small number of measures, including the wave indicator, the caregiver's year of birth, and the caregiver's nativity, there are significant coefficients in different directions.

[Table 4 about here.]

The estimates from Table 4 confirm the results from the specification tests that there are noticeable differences in which characteristics influence particular outcomes. However, the estimates also indicate that there are many similarities across the outcomes. In interpreting the estimates from the longitudinal MIMIC model it is important to emphasize that the model describes these common features and not all of the features in the data.

At the same time, the results from Table 4 allow demonstrate one of the key advantages of the MIMIC framework—the increased precision that comes from combining information from several outcomes. In the MIMIC estimates, the factor loading on the first financial strain—

having to borrow money to pay bills—is fixed at one. This means that the coefficients for the hardship index in Tables 2 and 3 and the coefficients for the ordered probit model in the first column of Table 4 share the same scaling and can be directly compared. When we compare the results, we see that the standard errors on the MIMIC coefficients are much smaller than the corresponding standard errors on the ordered probit coefficients. Because of the increase in precision, several coefficients from the ordered probit model, including those on income, outstanding loans and working full-time, become statistically different from zero in the MIMIC model, even though the coefficients themselves decrease in magnitude.

Another specification issue is the fit of the models. Although there is no universally accepted fit statistic for ordered categorical models, it is possible to show the relative contributions of the different components that form the latent indices in the MIMIC model. For instance, I can use the estimated coefficients from the hardship index and the observations on the explanatory measures from the analysis sample to calculate the variance associated with the "explained portion" of the index. I can combine this calculation with estimates of the unexplained variance obtained from the estimated standard deviations for u and $e(t)$, to arrive at the total variance in the index. I can then examine how the different components contribute to the total variance. Such an analysis reveals that the explained part of the model accounts for 28.5 percent of the variance in the hardship index. The portion of the model associated with the time-varying measures accounts for 8.0 percent of the variance, while the portion associated with the fixed measures accounts for the rest. A similar calculation reveals that the observed and unobserved components of the fixed effect, μ, account for 58.6 percent of the variance of the index. This final calculation shows that the index is highly correlated over time and persistent.

I use a similar approach to examine the components of the model that contribute to the

variances of each of the latent indicators, $y_j^*(t)$, for financial strains. The percentages of the variances in the latent indicators that are attributable to the hardship index and the explained measures within the hardship index are listed below.

Percent of variance from	Borrow money to pay bills	Put off buying things	Cannot do things for fun	Difficulty paying bills	Cannot afford housing, food & clothing	Not enough money to make ends meet
hardship index	42.2	53.1	15.7	57.5	33.9	47.4
expl. measures	12.0	15.2	4.5	16.4	9.7	13.5

As we might have expected given the results from Table 4, the longitudinal MIMIC model does a much better job fitting some of the outcomes than others. In particular, the hardship index explains more than half the variance for the strains involving putting off purchases and difficulty paying bills and nearly half of the variance for the strain involving not having enough money to make ends meet. However, it explains less than a sixth of the variance of the strain involving not being able to do things for fun. The contributions of just the explained portion of the hardship index are (proportionally) smaller and range from 4.5 percent to 16.4 percent.

6. Conclusion

In this study, I have used longitudinal data collected from low-income households in three American cities to examine how changes in resources, needs and other characteristics are related to self-reports of financial strains. A challenge I faced in analyzing these data was that each household provided categorical information about several different types of problems. To examine the information that was common to these different measures, I employed a Multiple Indicator Multiple Cause framework, which I modified to address ordered, categorical outcomes. Another challenge was that unobserved variables, such as households' permanent incomes and

subjective assessments of needs, were potential sources of bias. To address this issue, I further modified the MIMIC procedure to account for household-specific fixed effects.

The development of this modified statistical procedure, especially the controls for fixed effects, represents an important methodological contribution. Specification tests confirmed that the adjustment for household fixed effects was necessary in my data, and comparisons of models that did and did not include this adjustment showed that the controls for fixed effects changed the estimation results. Another set of analyses indicated that the controls successfully accounted for influences from omitted household-specific variables. By combining information from multiple measures and by jointly estimating the measurement and behavioral components of a model, the MIMIC approach can increase the precision of parameter estimates. As economists increasingly study outcomes characterized by multiple measures, such as financial strains, food security, and material well-being, there will be a need for procedures to summarize these data.

The analyses also produced several substantive findings. One of these was that financial strains were very persistent. In the descriptive analyses, roughly a third to a half of households reported the same financial strains in the one wave of interviews as the next, and in the multivariate MIMIC analyses, just over half of the variance in the estimated hardship index was associated with the permanent component. The findings of persistence are notable in themselves but also have two other implications. First, given that many circumstances of the households changed from the first to the second wave, the persistence in reported financial strains implies that they were relatively insensitive to these changes. Second, the large permanent component in the hardship outcomes means that there is considerable scope for bias from omitted variables, which reinforces the methodological concerns regarding fixed effects.

Another substantive finding is that while increases in household income are associated

with reductions in financial strains, the magnitude of the relationship is small. This result is consistent with findings from other studies of self-reported well-being. One difference between my analysis and some previous studies is that I controlled for fixed effects. This approach has the advantage of addressing some biases from subjectivity and other sources, but it also means that the primary associations that I measure are for transitory rather than permanent income. While we might expect a weak association between financial strains and transitory income, this does not appear to be the whole explanation for what I observe. My method for controlling for fixed effects let me investigate associations from the permanent component of income, and when I allowed for changes in both the transitory and permanent components of income, the associations remained small. The policy implication from this result is that increases in income alone will not appreciably reduce financial strains. Conversely, it also means that families may be more resilient or suffer less than we might otherwise think when incomes fall.

Income, of course, is not the only resource available to households, and results from the analyses indicate that we should take a wider view of resources. Positive and negative measures of wealth, including home ownership, bank accounts and outstanding loan balances, were associated with financial strains. For instance, buying a house had roughly the same association with financial strains as a $3,000 increase in monthly income, and opening a bank account had the same association as a $2,000 increase. It is important to remember that these are associations—a reduction in financial strains could allow households to put aside money to purchase a house or open a bank account. However, the results are consistent with households being able to draw down wealth to avoid financial strains. Having a full-time job was also found to be negatively associated with strains. This result may indicate that people are better able to avoid strains when they have a more secure income or expectations of a future income. It also

supports a central tenet of welfare reform—that work is beneficial for disadvantaged people.

Several non-economic resources were also found to be important. Having a social network that included people who could provide child care or make loans was negatively associated with financial strains. Being married with a spouse present was also negatively associated with strains. Social networks and marriage may serve insurance roles that help households through unexpected losses in other resources and increases in needs. Cooperation within networks and marriage may also allow households to be more productive and make better use of the resources that they have. Measures of physical health, disability, self-esteem, and psychological symptoms were also strongly associated with financial strains.

While this research has controlled for permanent, unobserved variables that may jointly influence other observed measures of resources, needs and financial strains, it has only conjectured and not empirically identified what these unobserved variables are. The findings point to the need for additional research that asks households about their subjective assessments of needs, permanent incomes, expectations of income, and perceptions of risk. Such measures would help us to untangle the objective and subjective components in households' reports of financial strains. They may also help to explain why these strains appear to be so persistent for low-income families.

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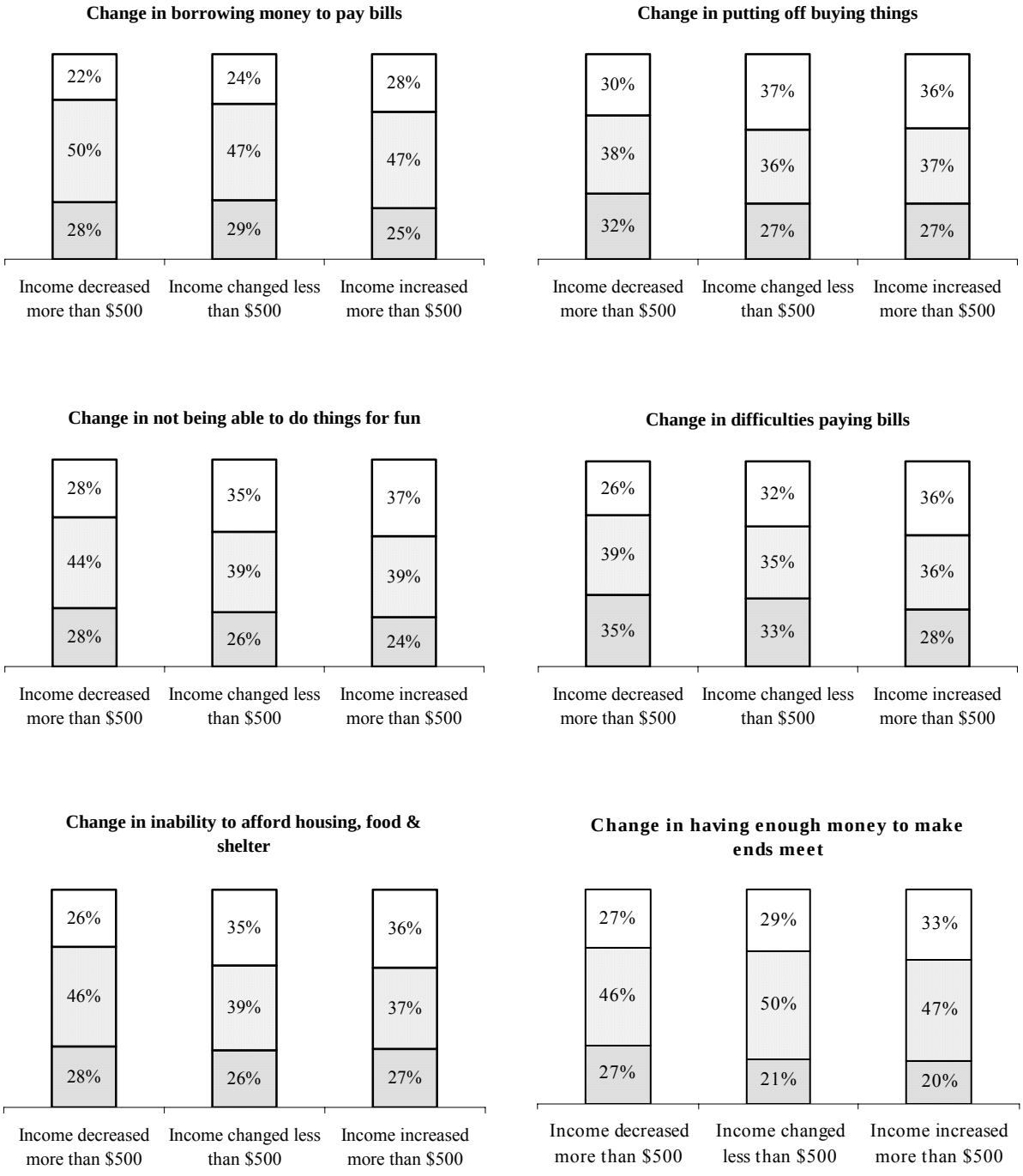
Figure 1. Changes in financial strains associated with changes in monthly incomes



Note: Figures calculated using data from the Three-City Study. In each chart the bottom, darkly shaded portion shows the percentage of households that reported increases in the listed financial strain; the middle, lightly shaded portion shows the percentage that reported no change in the strain, and the top, unshaded portion shows the percentage that reported decreases in the strain.

Table 1. Analysis measures and means across waves

Measures	Wave 1 mean	Wave 2 mean
Outcome measures: financial strains		
Borrow money to pay bills (0 to 4)	0.85	0.89
Put off buying things (0 to 4)	1.74	1.57
Cannot afford to do things for fun (0 to 4)	2.36	2.23
Difficulty paying bills (0 to 4)	1.48	1.45
Cannot afford housing, food & clothing (0 to 3)	1.70	1.60
Not enough money to make ends meet (0 to 3)	2.03	1.93
Time-varying explanatory measures		
Total monthly household income (/$1000)	1.21	1.61
Household owns own home (0, 1)	0.11	0.13
Household owns vehicle (0, 1)	0.39	0.47
Household has bank account or financial assets (0, 1)	0.37	0.40
Household has outstanding loans (0, 1)	0.45	0.49
Caregiver usually works part-time (0, 1)	0.15	0.16
Caregiver usually works full-time (0, 1)	0.24	0.37
Caregiver has enough people to listen (0, 1)	0.49	0.50
Caregiver has enough people to provide child care (0, 1)	0.46	0.46
Caregiver has enough people to provide small favors (0, 1)	0.42	0.42
Caregiver has enough people to loan money (0, 1)	0.33	0.33
Number of adults in household	1.59	1.74
Number of minors in household	2.60	2.64
Caregiver is married with spouse present (0, 1)	0.13	0.17
Caregiver is cohabiting (0, 1)	0.06	0.11
Caregiver's general health status/problems (0, 4)	1.77	1.80
Caregiver has disability that prevents work (0, 1)	0.15	0.17
Caregiver has disability that limits work or other activities (0, 1)	0.06	0.06
Caregiver has HS diploma or GED (0, 1)	0.37	0.39
Caregiver has a college degree (0, 1)	0.19	0.23
Caregiver's general self-concept (10, 50)	42.53	43.43
Caregiver BSI: Sleep problems (0, 24)	2.41	2.43
Caregiver BSI: Depression (0, 24)	3.14	2.94
Caregiver BSI: Anxiety (0, 24)	2.34	2.28
Time-invariant explanatory measures		
Caregiver's year of birth (-1900)	65.73	
Caregiver is non-Hispanic black (0, 1)	0.43	
Caregiver is Hispanic (0, 1)	0.47	
Caregiver was born outside the U.S. (0, 1)	0.19	
Household lives in Boston (0, 1)	0.38	
Household lives in Chicago (0, 1)	0.31	
Number of households	2,019	

Note: Means calculated from the Three-City Study.

Table 2. Selected estimates from longitudinal MIMIC models of financial strains with alternative time-varying controls

	(1)	(2)	(3)
Total monthly household income (/$1000)	-0.0740 *** (0.0216)	-0.0583 ** (0.0228)	-0.0520 ** (0.0226)
Household owns home		-0.1430 * (0.0752)	-0.1510 ** (0.0753)
Household owns vehicle		0.0061 (0.0463)	0.0067 (0.0459)
Household has bank account or financial assets		-0.1115 ** (0.0437)	-0.1071 ** (0.0438)
Household has outstanding loans		0.1018 ** (0.0415)	0.0857 ** (0.0414)
Caregiver usually works part-time		0.0190 (0.0570)	0.0045 (0.0566)
Caregiver usually works full-time		-0.1024 ** (0.0508)	-0.1047 ** (0.0503)
Caregiver has enough people to listen to her		-0.0661 (0.0430)	-0.0509 (0.0430)
Caregiver has enough people to provide child care		-0.1156 *** (0.0434)	-0.1097 ** (0.0436)
Caregiver has enough people to provide small favors		-0.0430 (0.0446)	-0.0293 (0.0448)
Caregiver has enough people to loan money		-0.0842 * (0.0443)	-0.0834 * (0.0445)
Number of adults in household	-0.0191 (0.0276)	-0.0149 (0.0287)	-0.0195 (0.0287)
Number of minors in household	0.0271 (0.0214)	0.0304 (0.0214)	0.0259 (0.0214)
Caregiver is married with spouse present	-0.1314 * (0.0770)	-0.1451 * (0.0769)	-0.1423 * (0.0754)
Caregiver is cohabiting	-0.0449 (0.0652)	-0.0541 (0.0646)	-0.0392 (0.0639)
Caregiver's general health status	0.0876 *** (0.0178)	0.0796 *** (0.0179)	0.0721 *** (0.0182)
Caregiver has disability that prevents work	0.2497 *** (0.0616)	0.2236 *** (0.0628)	0.1904 *** (0.0639)
Caregiver has disability with other limitations	0.1290 (0.0837)	0.1137 (0.0826)	0.1146 (0.0834)
Caregiver has HS diploma or GED	-0.1033 (0.0980)	-0.1052 (0.0966)	-0.1068 (0.0983)

Caregiver has college degree	-0.2280 (0.1479)	-0.2304 (0.1509)	-0.2080 (0.1529)
Caregiver's general self-concept			-0.0082 *** (0.0029)
Caregiver BSI: Sleep problems			-0.0091 (0.0083)
Caregiver BSI: Depression			0.0117 (0.0081)
Caregiver BSI: Anxiety			0.0207 ** (0.0098)
Wave 2	-0.0643 *** (0.0244)	-0.0534 ** (0.0247)	-0.0438 * (0.0246)
Caregiver's year of birth	-0.0071 *** (0.0018)	-0.0071 *** (0.0018)	-0.0071 *** (0.0018)
Caregiver is non-Hispanic black	-0.2028 *** (0.0578)	-0.2022 *** (0.0578)	-0.2017 *** (0.0579)
Caregiver is Hispanic	-0.3102 *** (0.0622)	-0.3090 *** (0.0622)	-0.3083 *** (0.0623)
Caregiver was born outside the U.S.	0.0202 (0.0512)	0.0208 (0.0514)	0.0207 (0.0514)
Household lives in Boston	-0.0337 (0.0460)	-0.0336 (0.0460)	-0.0334 (0.0460)
Household lives in Chicago	-0.0067 (0.0461)	-0.0066 (0.0461)	-0.0066 (0.0460)
σ_e	0.5119 *** (0.0195)	0.4981 *** (0.0194)	0.4913 *** (0.0192)
σ_u	0.5201 *** (0.0218)	0.5258 *** (0.0219)	0.5286 *** (0.0218)
log likelihood	-29747.47	-29718.05	-29703.69

Note: Coefficients are from the behavioral model portions of longitudinal MIMIC specifications estimated using data from the Three-City Study. In addition to the parameters shown, each of the behavioral models includes controls for fixed effects. The MIMIC specifications also include measurement models with loading and threshold parameters relating the behavioral models to categorical reports of financial strains. Details of the estimation procedure are described in the text. Asymptotic standard errors appear in parentheses.
* Significant at .10 level. ** Significant at .05 level. *** Significant at .01 level.

Table 3. Selected estimates from longitudinal MIMIC models of financial strains with alternative controls for fixed effects

	Random effects		Quasi fixed effects	
	w/o fixed observed controls	with fixed observed controls	w/o fixed observed controls	with fixed observed controls
Total monthly household income (/$1000)	-0.0720 *** (0.0168)	-0.0747 *** (0.0167)	-0.0519 ** (0.0227)	-0.0520 ** (0.0226)
Household owns home	-0.1413 *** (0.0487)	-0.1654 *** (0.0488)	-0.1527 ** (0.0755)	-0.1510 ** (0.0753)
Household owns vehicle	-0.0384 (0.0318)	-0.0337 (0.0319)	0.0064 (0.0462)	0.0067 (0.0459)
Household has bank account or financial assets	-0.0989 *** (0.0309)	-0.1083 *** (0.0313)	-0.1080 ** (0.0439)	-0.1071 ** (0.0438)
Household has outstanding loans	0.1972 *** (0.0303)	0.1936 *** (0.0299)	0.0864 ** (0.0416)	0.0857 ** (0.0414)
Caregiver usually works part-time	0.0548 (0.0438)	0.0508 (0.0434)	0.0043 (0.0569)	0.0045 (0.0566)
Caregiver usually works full-time	-0.0249 (0.0370)	-0.0280 (0.0368)	-0.1052 ** (0.0506)	-0.1047 ** (0.0503)
Caregiver has enough people to listen to her	-0.0251 (0.0346)	-0.0311 (0.0346)	-0.0514 (0.0432)	-0.0509 (0.0430)
Caregiver has enough people to provide child care	-0.1158 *** (0.0342)	-0.1247 *** (0.0340)	-0.1102 ** (0.0438)	-0.1097 ** (0.0436)
Caregiver has enough people to provide small favors	-0.0232 (0.0360)	-0.0306 (0.0358)	-0.0290 (0.0450)	-0.0293 (0.0448)
Caregiver has enough people to loan money	-0.1973 *** (0.0364)	-0.2003 *** (0.0363)	-0.0841 * (0.0447)	-0.0834 * (0.0445)
Number of adults in household	-0.0249 (0.0193)	-0.0298 (0.0190)	-0.0194 (0.0288)	-0.0195 (0.0287)
Number of minors in household	0.0259 ** (0.0111)	0.0274 ** (0.0109)	0.0260 (0.0215)	0.0259 (0.0214)
Caregiver is married with spouse present	-0.1497 *** (0.0481)	-0.1376 *** (0.0478)	-0.1435 * (0.0758)	-0.1423 * (0.0754)
Caregiver is cohabiting	-0.0582 (0.0524)	-0.0331 (0.0520)	-0.0396 (0.0641)	-0.0392 (0.0639)
Caregiver's general health status	0.1169 *** (0.0136)	0.1061 *** (0.0136)	0.0726 *** (0.0183)	0.0721 *** (0.0182)
Caregiver has disability that prevents work	0.1125 *** (0.0432)	0.0579 (0.0437)	0.1918 *** (0.0640)	0.1904 *** (0.0639)
Caregiver has disability with other limitations	0.0958 (0.0610)	0.0648 (0.0610)	0.1155 (0.0838)	0.1146 (0.0834)

Caregiver has HS diploma or GED	0.0023	-0.0001	-0.1073	-0.1068
	(0.0373)	(0.0377)	(0.0987)	(0.0983)
Caregiver has college degree	0.1711 ***	0.1492 ***	-0.2081	-0.2080
	(0.0463)	(0.0462)	(0.1536)	(0.1529)
Caregiver's general self-concept	-0.0074 ***	-0.0073 ***	-0.0082 ***	-0.0082 ***
	(0.0021)	(0.0021)	(0.0029)	(0.0029)
Caregiver BSI: Sleep problems	-0.0073	-0.0055	-0.0092	-0.0091
	(0.0057)	(0.0057)	(0.0084)	(0.0083)
Caregiver BSI: Depression	0.0266 ***	0.0291 ***	0.0118	0.0117
	(0.0054)	(0.0054)	(0.0081)	(0.0081)
Caregiver BSI: Anxiety	0.0186 ***	0.0161 **	0.0210 **	0.0207 **
	(0.0068)	(0.0067)	(0.0099)	(0.0098)
Wave 2	-0.0582 **	-0.0543 **	-0.0439 *	-0.0438 *
	(0.0227)	(0.0226)	(0.0247)	(0.0246)
Caregiver's year of birth		-0.0074 ***		-0.0071 ***
		(0.0017)		(0.0018)
Caregiver is non-Hispanic black		-0.1896 ***		-0.2017 ***
		(0.0549)		(0.0579)
Caregiver is Hispanic		-0.3047 ***		-0.3083 ***
		(0.0597)		(0.0623)
Caregiver was born outside the U.S.		0.0545		0.0207
		(0.0502)		(0.0514)
Household lives in Boston		-0.0717 *		-0.0334
		(0.0433)		(0.0460)
Household lives in Chicago		-0.0367		-0.0066
		(0.0437)		(0.0460)
σ_e	0.5039 ***	0.5017 ***	0.4940 ***	0.4913 ***
	(0.0192)	(0.0193)	(0.0192)	(0.0192)
σ_u	0.5577 ***	0.5422 ***	0.5433 ***	0.5286 ***
	(0.0224)	(0.0220)	(0.0222)	(0.0218)
log likelihood	-29788.06	-29763.07	-29727.91	-29703.69

Note: Coefficients are from the behavioral model portions of longitudinal MIMIC specifications estimated using data from the Three-City Study. In addition to the parameters shown, the behavioral models in the last two columns include controls for fixed effects. Each of the specifications also includes measurement models with loading and threshold parameters relating the behavioral models to categorical reports of financial strains. Details of the estimation procedure are described in the text. Asymptotic standard errors appear in parentheses.
* Significant at .10 level. ** Significant at .05 level. *** Significant at .01 level.

Table 4. Selected estimates from longitudinal ordered-probit models of specific financial strains

	Borrow money to pay bills	Put off buying things	Cannot do things for fun	Difficulty paying bills	Cannot afford housing, food & clothing	Not enough money to make ends meet
Total monthly household income (/$1000)	-0.0572	-0.0440	-0.0860 **	-0.0404	-0.0355	-0.0871 **
	(0.0401)	(0.0375)	(0.0368)	(0.0356)	(0.0353)	(0.0401)
Household owns home	-0.1276	-0.1943	0.0522	-0.1149	-0.1371	-0.2160
	(0.1553)	(0.1253)	(0.1237)	(0.1232)	(0.1410)	(0.1381)
Household owns vehicle	-0.0536	0.0902	-0.1791 **	0.0642	-0.0218	0.0194
	(0.0790)	(0.0798)	(0.0794)	(0.0741)	(0.0827)	(0.0828)
Household has bank account or fin. assets	-0.0935	-0.0668	-0.1849 **	-0.1573 **	-0.0420	-0.1456 *
	(0.0772)	(0.0705)	(0.0740)	(0.0730)	(0.0720)	(0.0779)
Household has outstanding loans	0.1090	0.1184 *	0.0404	0.1244 *	-0.0108	0.0706
	(0.0682)	(0.0657)	(0.0668)	(0.0659)	(0.0673)	(0.0716)
Caregiver usually works part-time	0.0174	0.0855	-0.0131	-0.0535	-0.0730	0.0597
	(0.1003)	(0.0873)	(0.0852)	(0.0901)	(0.0910)	(0.0917)
Caregiver usually works full-time	-0.1496	-0.0055	-0.0621	-0.1265	-0.1156	-0.1433 *
	(0.0917)	(0.0794)	(0.0770)	(0.0832)	(0.0827)	(0.0870)
CG has enough people to listen to her	-0.1074	-0.0118	-0.1237 *	-0.0182	-0.1165 *	-0.0199
	(0.0745)	(0.0680)	(0.0685)	(0.0729)	(0.0700)	(0.0714)
CG has enough people to provide child care	-0.0527	-0.0598	-0.0568	-0.1689 **	-0.0648	-0.2002 ***
	(0.0768)	(0.0727)	(0.0717)	(0.0697)	(0.0730)	(0.0757)
CG has enough people to provide small favors	-0.1060	-0.0504	-0.0399	-0.0522	-0.0544	0.1062
	(0.0830)	(0.0752)	(0.0725)	(0.0764)	(0.0780)	(0.0786)
CG has enough people to loan money	0.0097	-0.1349 *	0.0200	-0.1307 *	-0.0759	-0.1170
	(0.0810)	(0.0718)	(0.0749)	(0.0742)	(0.0730)	(0.0767)
Number of adults in household	0.0340	-0.0632	0.0320	-0.0280	-0.0471	-0.0214
	(0.0484)	(0.0463)	(0.0446)	(0.0476)	(0.0469)	(0.0491)
Number of minors in household	0.0563	0.0222	0.0466	0.0186	-0.0199	0.0275
	(0.0381)	(0.0368)	(0.0379)	(0.0367)	(0.0420)	(0.0402)
Caregiver is married with spouse present	-0.2427 *	-0.1236	0.0225	-0.1939	-0.1733	-0.1111
	(0.1291)	(0.1209)	(0.1045)	(0.1217)	(0.1251)	(0.1284)
Caregiver is cohabiting	-0.1237	-0.0394	-0.1149	0.0993	-0.1594	-0.0568
	(0.1146)	(0.1096)	(0.1104)	(0.1108)	(0.1084)	(0.1113)
Caregiver's general health status	0.1036 ***	0.0665 **	0.0486 *	0.0684 **	0.0944 ***	0.0628 **
	(0.0345)	(0.0294)	(0.0292)	(0.0294)	(0.0304)	(0.0317)
CG has disability that prevents work	0.1086	0.2895 ***	0.0349	0.1205	0.1860	0.3059 ***
	(0.1176)	(0.1098)	(0.1124)	(0.1030)	(0.1141)	(0.1096)
CG has disability with other limitations	0.1513	0.1549	-0.0639	0.1703	0.0841	0.1010
	(0.1534)	(0.1348)	(0.1229)	(0.1235)	(0.1213)	(0.1344)
Caregiver has HS diploma or GED	-0.2815	0.1144	0.1649	-0.3427 **	0.0041	-0.1301
	(0.1712)	(0.1579)	(0.1626)	(0.1595)	(0.1481)	(0.1571)

Caregiver has college degree	-0.4513 *	-0.2377	0.2781	-0.4390	0.0830	-0.1419
	(0.2650)	(0.2565)	(0.2445)	(0.2703)	(0.2283)	(0.2293)
Caregiver's general self-concept	-0.0060	-0.0134 ***	0.0019	-0.0060	-0.0047	-0.0153 ***
	(0.0053)	(0.0051)	(0.0050)	(0.0047)	(0.0053)	(0.0052)
Caregiver BSI: Sleep problems	-0.0284 **	-0.0067	-0.0038	-0.0017	-0.0008	-0.0173
	(0.0145)	(0.0135)	(0.0132)	(0.0133)	(0.0146)	(0.0134)
Caregiver BSI: Depression	0.0220	0.0170	0.0021	0.0185	0.0087	-0.0067
	(0.0142)	(0.0134)	(0.0131)	(0.0133)	(0.0137)	(0.0132)
Caregiver BSI: Anxiety	0.0180	0.0017	0.0320 **	0.0235	0.0203	0.0406 **
	(0.0174)	(0.0164)	(0.0148)	(0.0158)	(0.0156)	(0.0162)
Wave 2	0.1217 ***	-0.1447 ***	-0.1213 ***	0.0324	-0.0929 **	-0.0884 **
	(0.0454)	(0.0399)	(0.0404)	(0.0400)	(0.0417)	(0.0418)
Caregiver's year of birth	0.0059 **	-0.0086 ***	-0.0103 ***	-0.0067 **	-0.0170 ***	-0.0082 ***
	(0.0029)	(0.0025)	(0.0025)	(0.0027)	(0.0027)	(0.0027)
Caregiver is non-Hispanic black	-0.2864 ***	-0.3080 ***	-0.2730 ***	-0.1998 **	-0.0359	-0.1191
	(0.0887)	(0.0789)	(0.0866)	(0.0889)	(0.0843)	(0.0841)
Caregiver is Hispanic	-0.3850 ***	-0.5321 ***	-0.0051	-0.3733 ***	-0.1276	-0.1960 **
	(0.0932)	(0.0824)	(0.0875)	(0.0925)	(0.0877)	(0.0882)
Caregiver was born outside the U.S.	-0.0562	0.0620	0.1890 ***	-0.1702 **	0.1112	0.1318 *
	(0.0773)	(0.0710)	(0.0651)	(0.0711)	(0.0729)	(0.0716)
Household lives in Boston	-0.1942 ***	-0.0473	-0.0623	0.0474	-0.1386 **	0.0600
	(0.0712)	(0.0658)	(0.0605)	(0.0654)	(0.0642)	(0.0650)
Household lives in Chicago	-0.1025	-0.0458	0.1361 **	-0.0430	0.0925	-0.0091
	(0.0717)	(0.0642)	(0.0586)	(0.0670)	(0.0636)	(0.0638)
σ_u	0.7079 ***	0.6449 ***	0.5326 ***	0.6705 ***	0.6156 ***	0.5822 ***
	(0.0414)	(0.0342)	(0.0355)	(0.0367)	(0.0367)	(0.0385)
log likelihood	-4698.95	-5808.17	-5261.06	-5659.21	-5178.78	-4148.08

Note: Coefficients are from longitudinal ordered probit models estimated using data from the Three-City Study. In addition to the parameters shown, each of the models includes controls for fixed effects and for response thresholds. Asymptotic standard errors appear in parentheses.
* Significant at .10 level. ** Significant at .05 level. *** Significant at .01 level.

Appendix A. Complete results from longitudinal MIMIC model of financial strains

	Behavioral model parameters		
	B_X coefficients	Γ_1 coefficients	Γ_2 coefficients
Total monthly household income (/$1000)	-0.0520 ** (0.0226)	-0.0092 (0.0298)	-0.0466 ** (0.0236)
Household owns home	-0.1510 ** (0.0753)	-0.0645 (0.0809)	0.0332 (0.0827)
Household owns vehicle	0.0067 (0.0459)	0.0548 (0.0504)	-0.1342 *** (0.0501)
Household has bank account or financial assets	-0.1071 ** (0.0438)	0.0709 (0.0485)	-0.0731 (0.0457)
Household has outstanding loans	0.0857 ** (0.0414)	0.1235 *** (0.0456)	0.0992 ** (0.0437)
Caregiver usually works part-time	0.0045 (0.0566)	0.0544 (0.0613)	0.0542 (0.0596)
Caregiver usually works full-time	-0.1047 ** (0.0503)	0.0729 (0.0553)	0.0728 (0.0520)
Caregiver has enough people to listen to her	-0.0509 (0.0430)	-0.0109 (0.0483)	0.0715 (0.0488)
Caregiver has enough people to provide child care	-0.1097 ** (0.0436)	-0.0125 (0.0489)	-0.0173 (0.0491)
Caregiver has enough people to provide small favors	-0.0293 (0.0448)	0.0407 (0.0552)	0.0109 (0.0546)
Caregiver has enough people to loan money	-0.0834 * (0.0445)	-0.1310 *** (0.0502)	-0.1470 *** (0.0508)
Number of adults in household	-0.0195 (0.0287)	-0.0420 (0.0295)	0.0322 (0.0290)
Number of minors in household	0.0259 (0.0214)	0.0251 (0.0229)	-0.0242 (0.0235)
Caregiver is married with spouse present	-0.1423 * (0.0754)	-0.0129 (0.0816)	0.0597 (0.0740)
Caregiver is cohabiting	-0.0392 (0.0639)	0.0214 (0.0834)	-0.0265 (0.0698)
Caregiver's general health status	0.0721 *** (0.0182)	0.0298 (0.0200)	0.0401 * (0.0205)
Caregiver has disability that prevents work	0.1904 *** (0.0639)	-0.0067 (0.0690)	-0.2122 *** (0.0663)
Caregiver has disability with other limitations	0.1146 (0.0834)	-0.0270 (0.0864)	-0.0838 (0.0786)

Caregiver has HS diploma or GED	-0.1068	0.0390	0.0511
	(0.0983)	(0.0941)	(0.0937)
Caregiver has college degree	-0.2080	0.1586	0.2105
	(0.1529)	(0.1454)	(0.1323)
Caregiver's general self-concept	-0.0082 ***	-0.0007	0.0022
	(0.0029)	(0.0033)	(0.0033)
Caregiver BSI: Sleep problems	-0.0091	-0.0010	0.0087
	(0.0083)	(0.0083)	(0.0090)
Caregiver BSI: Depression	0.0117	0.0082	0.0261 ***
	(0.0081)	(0.0079)	(0.0082)
Caregiver BSI: Anxiety	0.0207 **	0.0129	-0.0304 ***
	(0.0098)	(0.0084)	(0.0099)
Wave 2	-0.0438 *		
	(0.0246)		
		B_Z coefficients	
Caregiver's year of birth		-0.0071 ***	
		(0.0018)	
Caregiver is non-Hispanic black		-0.2017 ***	
		(0.0579)	
Caregiver is Hispanic		-0.3083 ***	
		(0.0623)	
Caregiver was born outside the U.S.		0.0207	
		(0.0514)	
Household lives in Boston		-0.0334	
		(0.0460)	
Household lives in Chicago		-0.0066	
		(0.0460)	
Intercept		0.9426 ***	
		(0.2220)	
		Error components	
σ_e		0.4913 ***	
		(0.0192)	
σ_u		0.5286 ***	
		(0.0218)	

Measurement model parameters

	Borrow money to pay bills	Put off buying things	Cannot do things for fun	Difficulty paying bills	Cannot afford housing, food & clothing	Not enough money to make ends meet
λ_j	*1.0000*	1.2469 ***	0.5050 ***	1.3626 ***	0.8397 ***	1.1120 ***
		(0.0510)	(0.0266)	(0.0555)	(0.0357)	(0.0477)
δ_{0j}	*0.0000*	-1.1011 ***	-1.8609 ***	-0.8926 ***	-1.0097 ***	-2.6168 ***
		(0.0436)	(0.0403)	(0.0428)	(0.0306)	(0.0650)
δ_{1j}	0.8472 ***	-0.1138 ***	-0.9846 ***	0.1945 ***	-0.1587 ***	-0.8843 ***
	(0.0248)	(0.0345)	(0.0256)	(0.0374)	(0.0265)	(0.0341)
δ_{2j}	2.0382 ***	1.1241 ***	0.3573 ***	1.3888 ***	0.7535 ***	0.9510 ***
	(0.0454)	(0.0403)	(0.0231)	(0.0451)	(0.0282)	(0.0358)
δ_{3j}	2.7411 ***	2.0064 ***	1.2530 ***	2.2410 ***		
	(0.0652)	(0.0478)	(0.0269)	(0.0572)		
log likelihood			-29703.69			

Note: Coefficients are from a longitudinal MIMIC model estimated using data from the Three-City Study. Details of the estimation procedure are described in the text. Asymptotic standard errors appear in parentheses.
* Significant at .10 level. ** Significant at .05 level. *** Significant at .01 level.