Emotional Safety Net Against Financial Distress

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December 28, 2022

Abstract

Does emotional support matter for financial outcomes? Using microdata from U.S. and Australian household surveys, I document that individuals who lack emotional support are more likely to experience financial hardship. This relationship is not confounded by other forms of support—such as financial assistance, care giving, and advice provision—and is confirmed by between-siblings and within-individual analyses as well as an instrumental variable strategy. The underlying mechanisms involve emotional support not only improving financial preparedness, but also aiding in coping with adverse shocks after they are realized. Overall, my findings offer a novel psychological perspective on household financial distress.

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1. Introduction

Adverse emotional states such as sadness, frustration, and anxiety are an inevitable part of life. Often times people seek emotional support from their networks of family, friends, and acquaintances. Those who lack such support tend to suffer from physical and mental health problems, poor quality of life, and an increased risk of mortality (e.g., Uchino, Cacioppo, and Kiecolt-Glaser, 1996; Reblin and Uchino, 2008). The importance of emotional support has been further highlighted by the recent coronavirus pandemic due to the disruptive nature of this global crisis.

While the link between emotional support and health outcomes has been relatively well studied in the psychology literature, little is known about whether emotional support matters for financial outcomes, another equally important dimension of family well-being. This paper fills this gap by exploring the role of emotional support in affecting financial distress. My focus on financial distress is motivated by its prevalence and persistence in the U.S. and globally (e.g., Lusardi, Schneider, and Tufano, 2011). To elaborate, four in 10 U.S. adults have difficulty handling an unexpected expense of $400 (Federal Reserve Board, 2020); some have frequent trouble with money and their children face similar prospects (Athreya, Mustre-del-Río, and Sánchez, 2019; Kreiner, Leth-Petersen, and Willerslev-Olsen, 2020). While this phenomenon has attracted considerable attention among policymakers and economists alike, why some households are financially fragile while many others are not is not fully understood.

In this paper, I propose emotional support as an important determinant of household financial fragility. To avoid financial distress, it is important that households not only use financial instruments effectively, but also plan ahead (e.g., Ameriks, Caplin, and Leahy, 2003). While formulating a comprehensive financial plan is a daunting task for many households because of their limited financial knowledge (e.g., Campbell, 2006; Lusardi and Mitchell, 2014; Campbell, 2016), making and carrying out a plan as straightforward as setting up a rainy-day fund can be equally challenging, psychologically. A key insight of this paper is that emotional support can overcome psychological barriers that impede the formulation and execution of financial plans. Emotional support therefore improves financial preparedness for potential adverse shocks and lowers the propensity toward financial hardship. Even after realization of negative shocks, emotional support may continue to play an important role. For instance, in the event of unemployment, emotional support can boost the unemployed job seekers' confidence about their ability to find a job. They may thus exert more job search effort, which leads to a higher probability of job finding and, in turn, a lower likelihood of financial distress.

Building on these ideas, I investigate the relationship between emotional support and financial hardship using microdata from three complementary household surveys: (i) the U.S. National Longitudinal Survey of Youth (NLSY) 1979 Child and Young Adult cohort; (ii) the U.S. Health and Retirement Study (HRS); and (iii) the Household, Income and Labour Dynamics in Australia (HILDA) Survey. Leveraging the unique common feature that respondents in these surveys report their perceived levels of emotional support, I document in all three samples that individuals who lack emotional support are more likely to experience financial hardship, controlling for a standard set of demographic characteristics. This relationship is economically material: a one standard deviation reduction in emotional support increases the likelihood of financial hardship by 18 to 27 percent relative to the sample means.

A natural question is whether the above relationship could reflect financial, rather than emotional, support. This is unlikely because the estimates of the buffering effect of emotional support on financial hardship are, if anything, slightly larger among households that receive little to no financial assistance. The buffering effect of emotional support is also distinct from the effect of practical help such as child care and elderly care. This is because my findings are robust to restricting the sample to either never-married single individuals, or those without any impairments or health problems, two groups of people with less need for practical help. Another possibility is that the buffering effect may in fact reflect informational support such as information sharing and advice provision. If this is the case, one would expect the buffering effect to be mitigated among individuals who are less receptive to information and advice. The buffering effect, however, remains largely the same among narrow-minded individuals and those who do not seek information or advice from family and friends when it comes to retirement planning. Moreover, I perform a heterogeneity analysis by one of the Big Five personality traits—emotional instability. A more pronounced buffering effect is observed for individuals with higher levels of emotional instability, which offers more direct evidence that points to the emotional aspect of social support.

A potential concern with my findings is omitted variable bias—that is, there may be unobserved characteristics that affect both emotional support and the likelihood of financial hardship. I perform a number of analyses to alleviate this concern. Starting with a bounding exercise following Oster (2019), I find that selection on unobservables is unlikely to explain the observed negative relationship between emotional support and financial hardship. The negative relationship is further confirmed by between-siblings and within-individual analyses. Specifically, many respondents in the NLSY sample have siblings and their siblings are also in the sample. I leverage this feature to exploit between-siblings variation in emotional support using sibling fixed effects, which difference out confounding factors that are fixed within the family the siblings grew up in, such as parental socioeconomic status and parenting style. I show that individuals with weaker emotional support in adulthood than their siblings have a higher propensity toward financial hardship. Another key feature of the microdata used in this paper is that a majority of the respondents in all three samples report their perceived levels of emotional support in multiple waves. I am thus able to exploit within-individual variation in emotional support using individual fixed effects, which eliminate persistent confounding individual heterogeneity such as time and risk preferences, cognitive abilities, financial literacy, and noncognitive skills. I find that individuals are more likely to experience financial hardship as emotional support dwindles over time.

Another potential concern is reverse causality, as individuals in better financial situations may spend more time with their family and friends and therefore enjoy stronger emotional support from them. To address this concern, I exploit the long panel feature of the HILDA sample and show that my findings are robust to measuring emotional support even a decade before household financial outcomes are realized. To further mitigate both the reverse causality and the omitted variable bias concerns, I leverage the fact that the HILDA sample contains information on respondents' socialization patterns and perform an instrumental variable (IV) analysis. Specifically, I use frequency of socialization as an instrument for emotional support based on the simple idea that people are more likely to receive effective emotional support if they socialize with their potential support providers more frequently (e.g., Burleson, 2003). The IV regressions confirm the existence of a strong, negative relationship between emotional support and financial hardship, conditional on the size of friendship network as well as all the demographic controls. To further strengthen the causal interpretation, I employ the methodology developed by Conley, Hansen, and Rossi (2012) and show that the my findings are robust even under substantial violations of the exclusion restriction.

In the final part of my analysis, I explore potential mechanisms underlying the buffering effect of emotional support on financial hardship. I find that individuals who lack emotional support are less likely to set aside emergency funds, or to save regularly. This suggests that individuals who lack emotional support are more likely to experience financial hardship in part because they are less likely to take precautions to mitigate potential adverse shocks. I present further evidence that the lack of emotional support limits these individuals' financial planning horizons. This evidence is consistent with the interpretation that individuals who lack emotional support are more likely to lack the bandwidth to formulate as well as to execute long-term financial plans (Schilbach, Schofield, and Mullainathan, 2016). To assess the role of emotional support after negative shocks are realized, I leverage the large sample size of the HILDA sample and focus on unemployed job seekers. Those who lack emotional support are more pessimistic about their employment prospects and thus less likely to submit job applications. They are consequently less likely to end their unemployment spell and, in turn, more likely to experience financial distress.

Psychologists have long studied the link between emotional support and health outcomes (e.g., Uchino, Cacioppo, and Kiecolt-Glaser, 1996; Reblin and Uchino, 2008). Economists on the other hand have paid little attention to the psychological dimension of social support. To my best knowledge, the only rare exception is the excellent recent work by Bergman, Chetty, DeLuca, Hendren, Katz, and Palmer (2020). These authors study barriers to neighborhood choice and highlight that providing emotional support is critical to the success of affordable housing policies. My paper joins this nascent literature and provides the first evidence that the consequences of a lack of emotional support extend beyond negative health impacts—it has financial consequences as well.

This paper also builds on the literature that studies determinants of household financial distress (Dynan, 2009). A non-exhaustive list of important determinants includes job displacement (e.g., Keys, 2018), medical costs (e.g., Gross and Notowidigdo, 2011), credit market environment (e.g., Livshits, MacGee, and Tertilt, 2010), educational attainment (e.g., Cole, Paulson, and Shastry, 2014), cognitive abilities and financial literacy (e.g., Gerardi, Goette, and Meier, 2013), noncognitive skills (e.g., Xu, Beller, Roberts, and Brown, 2015; Kuhnen and Melzer, 2018; Parise and Peijnenburg, 2019), and early life exposure to finance (e.g., Brown, Cookson, and Heimer, 2019). I contribute to this literature by proposing emotional support as another important determinant and offering a novel psychological perspective on household financial distress.

This paper further relates to the emerging literature that studies the effects of interactions through social networks on household financial behavior (Hirshleifer, 2015; Kuchler and Stroebel, 2021). This literature has documented peer effects on active trading (e.g., Hong, Kubik, and Stein, 2004; Kaustia and Knüpfer, 2012; Heimer, 2016), retirement savings (e.g., Duflo and Saez, 2003; Beshears, Choi, Laibson, Madrian, and Milkman, 2015), insurance decisions (e.g., Hu, 2022), home ownership (e.g., Bailey, Cao, Kuchler, and Stroebel, 2018), mortgage refinancings and defaults (e.g., Guiso, Sapienza, and Zingales, 2013; Gupta, 2019; Maturana and Nickerson, 2019), household debt (e.g., Georgarakos, Haliassos, and Pasini, 2014; Kalda, 2020), and consumer bankruptcy (e.g., Kleiner, Stoffman, and Yonker, 2021), among others. A common thread through these studies is that peer effects predominantly operate through an information channel that involves changes in beliefs and sometimes preferences. This paper, by sharp contrast, highlights the role of the psychological dimension of social interactions in shaping household financial outcomes.

The remainder of this paper proceeds as follows. Section 2 describes the data, Section 3 presents the results, and Section 4 concludes.

2. Data

To investigate the relationship between emotional support and financial hardship, I draw on microdata from three complementary household surveys: (i) the National Longitudinal Survey of Youth (NLSY) 1979 Child and Young Adult cohort; (ii) the Health and Retirement Study (HRS); and (iii) the Household, Income and Labour Dynamics in Australia (HILDA) Survey. A unique common feature of these surveys is that respondents report their perceived levels of emotional support, which refers to having someone available to listen, care, sympathize, provide reassurance, and make one feel valued, loved and cared for (Helgeson, 2003). Meanwhile, all these surveys collect information on the dependent variable of interest, financial hardship, in addition to a standard set of demographic characteristics.

2.1 The NLSY Sample

The NLSY79 Child and Young Adult cohort is a panel of biological children of the female respondents in the NLSY79, which itself is a nationally representative panel survey of 12,686 U.S. individuals aged between 14 and 22 in 1979. I focus on respondents aged 18 or older and the sample period starts in 2008, when information on emotional support was collected for the first time. Despite the "child and young adult" label, respondents in this survey are interviewed throughout adulthood and by 2018, the most recent survey year, many are in their late 30s or early 40s.

I use four questions to characterize emotional support: (i) "How much do you feel loved and cared for by your relatives?" (ii) "How much can you open up to your relatives if you need to talk about your worries?" (iii) "How much do you feel loved and cared for by your friends?" and (iv) "How much can you open up to your friends if you need to talk about your worries?" For each question, a respondent's rating ranges from one to five, where one means "not at all" and five means "a great deal." I first sum all four ratings to get a total raw rating ranging between four and 20. To ease comparisons across samples, I then convert respondents' total raw ratings to percentile ranks.

To capture financial hardship, I construct an indicator indicating whether the household had either "quite a bit" or "a great deal" of difficulty in paying bills over the past year. I focus on this aspect of financial hardship primarily because information about payment difficulties is also available in the other two household surveys, which enables me to examine the relationship between emotional support and financial hardship in a unified framework. Moreover, I show in Section 3.2 that my findings are robust to multiple alternative financial hardship indicators across samples.

2.2 The HRS Sample

The HRS is a longitudinal study that surveys a nationally representative sample of U.S. individuals over the age of 50. I focus on financial respondents under the age of 80 and the sample period starts in 2004, when the study began to collect information on emotional support coming from spouse, children, other immediate family members, and friends.[1] Respondents are asked (i) how much they can open up to each source about worries; and (ii) how much each source really understands the way they feel, both on a scale from zero to

[1]In the HRS sample, the household member who answers questions about household finances is designated as the financial respondent.

three, where zero means "not at all" and three means "a lot." A rating of zero is assigned if a respondent does not have anyone for a particular source. To measure emotional support, I sum all eight ratings to get a total raw rating ranging between zero and 24, which is then converted to a percentile rank as is done in the NLSY sample. To capture financial hardship, I construct an indicator similar to that in the NLSY sample, indicating whether it is either "very difficult" or "completely difficult" for the household to meet monthly bill payments.

2.3 The HILDA Sample

The HILDA survey is an annual nationally representative longitudinal study of Australian households. I focus on household heads aged between 18 and 80. The sample period ranges from 2001, the inception year of the survey, to 2021, the most recent survey year. Emotional support is measured based on the statements (i) "there is someone who can always cheer me up when I am down" and (ii) "I do not have anyone that I can confide in" on a scale from one to seven, where one means "strongly disagree" and seven means "strongly agree." The scoring for (ii) is reversed so that higher scores correspond to higher levels of emotional support. I sum these two scores to get a total raw score ranging between two to 14, which is then converted to a percentile rank. It is worth noting that this emotional support measure, unlike those in the two U.S. samples, does not specify the source of emotional support. This measure can thus potentially capture emotional support from sources other than family and friends, such as that from neighbors, coworkers, and religious communities.

To characterize financial hardship, I focus on both housing and utility payment difficulties. Specifically, I construct two indicators indicating whether the household could not pay (i) mortgage or rent and (ii) electricity, gas or telephone bills on time in the past year because of a shortage of money, complementing the more subjective measurements of household payment difficulties in the two U.S. samples.

The HILDA sample offers a number of additional advantages. First, it provides non-U.S. evidence of the buffering effect of emotional support on financial hardship, suggesting that this effect generalizes to other countries. Second, while the NLSY and the HRS samples focus on young adults and individuals in their middle to late adulthood, respectively, the HILDA sample covers the entire age distribution. Thus the fact that the buffering effect of emotional support is robust to using the HILDA sample suggests that this effect is not limited to any particular age profiles. Third, the large sample size of the HILDA survey allows me to obtain a sufficiently large sample of unemployed job seekers. By focusing on this subsample, I am able to investigate the role of emotional support after realization of negative shocks. Finally, the HILDA survey collects information on a wide array of individual and household characteristics including, among others, size of friendship network, frequency of socialization, household saving habits, financial planning horizons, subjective beliefs about employment prospects, and job search activities, which is crucial for a comprehensive analysis of the relationship between emotional support and financial hardship.

2.4 Summary Statistics

Table 1 reports summary statistics for each of the three samples. In the NLSY sample, 9.3 percent of the households had great difficulty in paying bills over the past year. In the HRS sample, 9.8 percent of the households report substantial difficulty in meeting monthly bill payments. In the HILDA sample, 7.1 percent and 14.2 percent of the households were late on housing and utility payments, respectively, because of a shortage of money. These statistics reflect the prevalence of financial hardship in both the U.S. and Australia.

Turning to demographic characteristics, 48 percent of the respondents in the NLSY sample are men and the average age is 27. Sixty-two percent receive college education, 22 percent are married, and 56 percent are in great health. The average family income is about $33,300 and home ownership rate is 19 percent. In the HRS sample, 44 percent of the respondents are men and the average age is 65. Fifty-one percent of the respondents are college-educated, the same proportion are married, and 41 percent are in great health. The average family income is close to $68,000 and home ownership rate is 76 percent. The differences in demographic profiles between the two U.S. samples capture the fact that the respondents in these samples are in fairly different phases of their life cycles. In the HILDA sample, 76 percent of the household heads are men and the average age is 48. Sixty-three percent receive college education, 48 percent are married, and 44 percent are in great health. The average family income is $96,500 AUD and home ownership rate is 66 percent.

3. Results

3.1 Baseline

To investigate the relationship between emotional support and financial hardship, I estimate

$$y_{it} = \alpha + \beta \cdot \textit{Emotional support}_{it} + \gamma' \mathbf{X}_{it} + \varepsilon_{it}, \tag{1}$$

where y indicates financial hardship and *Emotional support* is the key explanatory variable constructed in Section 2. The vector $\mathbf{X}$ contains a standard set of control variables that are important for household financial decisions (Guiso and Sodini, 2013; Gomes, Haliassos, and Ramadorai, 2021), including the gender, race, age, educational attainment, marital status, and health status of the respondent, as well as family income and home ownership. Given the persistent disparities in financial distress across regions (Keys, Mahoney, and Yang, 2022), I include region by survey wave fixed effects to absorb all sources of variation across regions over the years. The coefficient of interest, β, captures the relationship between emotional support and financial hardship, conditional on all of the aforementioned controls. I run ordinary least square regressions and cluster standard errors at the household level.[2]

Before examining the regression estimates, I plot in Figure 1 for each sample the financial hardship rates for individuals in each tercile of emotional support. The first panel shows that 14.2 percent of the respondents with low levels of emotional support in the NLSY sample

[2] My findings are robust to using a probit model. They are also robust to clustering standard errors at the region level, year level, or both.

had great difficulty in paying bills over the past year, compared with 8.8 percent and 6.1 percent for those with medium and high levels of emotional support, respectively. This clear monotonic pattern also emerges in the HRS and the HILDA samples, as shown in the next three panels. Figure 1 thus provides initial support for a buffering effect of emotional support on financial hardship.

I further examine the relationship between emotional support and financial hardship by estimating equation (1) and Table 2 reports the regression results. The first column shows that controlling for a standard set of demographic characteristics, the likelihood of a household in the NLSY sample having great difficulty in paying bills over the past year increases by 8.6 percentage points when moving from the top of the emotional support distribution to the bottom (i.e., from the 100^{th} to the 0^{th} percentile). This estimate implies that a one standard deviation reduction in emotional support leads to a 2.5 percentage point increase in the probability of a household having great difficulty in paying bills. Since 9.2 percent of the households had great difficulty in paying bills, this represents an increase of 27 percent, which is economically material. To put this buffering effect of emotional support on financial hardship into perspective, I compare it with the effect of socioeconomic status measured by educational attainment and family income. Column (1) suggests that a lack of college education and a one standard deviation decline in family income correspond to a 3.0 percentage point increase and a 2.0 percentage point increase, respectively, in the probability of a household having great difficulty in paying bills. Hence, the effect of emotional support and that of socioeconomic status are comparable in economic magnitude.

Estimates for the HRS sample are presented in the next column. A one standard deviation decrease in emotional support leads to a 2.2 percentage point increase in the probability of a household reporting substantial difficulty in meeting monthly bill payments. Given that 9.8 percent of the households face significant bill payment difficulties, this represents an economically significant increase of 23 percent.

Turning to the next two columns in which the baseline results for the HILDA sample are reported, column (3) shows that a one standard deviation reduction in emotional support is associated with a 1.3 percentage point increase in the probability of a household being late on housing payments because of a shortage of money. Since 7.1 percent of the households were late on housing payments, this represents an economically significant increase of 19 percent. Column (4) shows that a one standard deviation decline in emotional support leads to a 2.5 percentage point rise in the likelihood of a household being late on utility payments due to lack of money. Given that 14.2 percent of the households were late on utility payments, this implies an increase of 18 percent, which is again economically material.

In short, I document in all three samples a substantial buffering effect of emotional support on financial hardship: a one standard deviation decrease in emotional support increases the likelihood of a household experiencing financial hardship by 18 to 27 percent relative to the sample means.

3.2 Robustness

I conduct three tests in the Internet Appendix to assess the robustness of the buffering effect of emotional support. First, household wealth is not included as one of the common set of controls in the baseline specification. This is because household wealth is not measured in the NLSY sample and only measured in five out of the 20 waves of the HILDA survey. Given the importance of wealth for household financial decision-making (e.g., Calvet, Campbell, and Sodini, 2007), a potential concern is that the buffering effect could be driven by household wealth, which is not controlled for in the baseline regressions. To explicitly address this concern, I restrict the HRS and the HILDA samples to households with non-missing values on household wealth and rerun the baseline regressions with and without the wealth control. Table IA1 presents the results. After controlling for household wealth, the buffering effect of emotional support decreases by only 5 percent in the HRS sample and by 8 to 10 percent in the HILDA sample. These results suggest that the buffering effect of emotional support is unlikely to be confounded by household wealth.

Second, to ensure that my findings are robust in a purely cross-sectional analysis, I leverage the longitudinal features of all three household surveys and use the average value of emotional support over the years as the key explanatory variable. Specifically, I collapse individual-year observations to the individual level and code the financial hardship indicators as their maximums over the sample period (i.e., whether the respondent experiences financial hardship at least once over the years). Meanwhile, the time-varying control variables are averaged over the sample period. Table IA2 reports the results and shows that a one standard deviation reduction in emotional support increases the likelihood of a household experiencing financial hardship by 14 to 24 percent relative to the sample means. These estimates are comparable in magnitude to those in the baseline regressions.

Third, I focus on payment difficulties as the primary aspect of household financial hardship in this paper. Here I take advantage of the rich information available in all three samples and construct four alternative financial hardship indicators. The first one captures whether a household cuts back on necessities. In the NLSY sample, the indicator indicates whether the household has to put off buying necessities such as food, clothing, medical care, and housing either "frequently" or "all the time." In the HRS sample, the indicator indicates whether the respondent either ate less than they should over the past year because there was insufficient money to buy food, or ended up taking less medication than was prescribed over the past two years due to cost. In the HILDA sample, the indicator indicates whether the household was either unable to heat home or went without meals because of a shortage of money in the past year. The other three alternative financial indicators are constructed using the NLSY sample, indicating (i) whether the household ended up with insufficient money to make ends meet at the end of each month over the past year; (ii) whether the household has been more than 60 days late on required debt payments such as mortgage, credit card debt, and auto loan payments over the last 12 months; and (iii) whether the household has been more than 60 days late on utilities, medical, or other bills over the last 12 months. I rerun the baseline regressions with all these alternative financial hardship indicators as the dependent variable and Table IA3 reports the results. The first three columns show that a one standard deviation decline in emotional support increases the probability of a household cutting back on necessities by 2.6 percentage points (or 27 percent) in the NLSY sample, by 2.0 percentage points (or 13 percent) in the HRS sample, and by 2.8 percentage points (or 42 percent) in the HILDA sample. The next three columns show that a one standard deviation decrease in emotional support leads to a 1.9 percentage point (or 30 percent) increase, a 1.8 percentage point (or 18 percent) increase, and a 2.7 percentage point (or 22 percent) increase in the probabilities of a household ending up with insufficient money to make ends meet, being late on required debt payments, and reporting late bill payments, respectively. These results suggest that my findings generalize to aspects of financial hardship beyond payment difficulties.

3.3 Emotional vs. Non-Emotional Support

A natural question arises: can the buffering effect of emotional support on financial hardship in fact reflect non-emotional aspects of social support? To answer this question, I first examine the role of financial support by performing a subsample analysis on households that receive little to no financial assistance. Specifically, I rerun the baseline regressions limiting the NLSY sample to households that did not receive financial support from anyone in the past year, the HRS sample to those that did not receive financial help totaling $500 or more from children, other immediate family members, or friends in the past two years, and the HILDA sample to those that did not ask for financial help from family or friends in the past year.

Table 3 reports the results and shows that a one standard deviation reduction in emotional support increases the probability of a household experiencing financial hardship by 2.4 percentage points (or 27 percent) in the NLSY sample, by 2.2 percentage points (or 25 percent) in the HRS sample, and by 0.6 to 1.5 percentage points (or 20 percent) in the HILDA sample. These estimates are slightly larger than those in the baseline regressions, indicating that the buffering effect of emotional support is not driven by financial assistance.

Another possibility is that the constructed measures of emotional support capture practical help such as child care and elderly care. To assess this possibility, I perform a subsample analysis focusing on two groups of people with less need for practical help—never-married single individuals and those without any impairments or health problems. Table 4 presents the regression results. Columns (1), (3), and (4) show that a one standard deviation decline in emotional support increases the probability of a never-married single individual experiencing financial hardship by 2.6 percentage points (or 28 percent) in the NLSY sample, and by 1.8 to 3.8 percentage points (or 17 percent) in the HILDA sample. The remaining columns show that a one standard deviation decrease in emotional support is associated with a 1.4 percentage point (or 22 percent) increase, and a 1.1 to 2.1 percentage point (or 16 to 17 percent) increase in the probabilities of an individual with no work-limiting conditions experiencing financial hardship in the HRS and the HILDA samples, respectively. These estimates are comparable in magnitude to those in the baseline regressions, suggesting that the buffering effect of emotional support is distinct from the effect of practical help.

Relatedly, one might argue that the emotional support measures could capture informational support such as information sharing and advice provision. If this is the case, one would expect an attenuated buffering effect for individuals who are less receptive to information and advice. Table 5 presents evidence against this interpretation. In column (1), I restrict the HRS sample to narrow-minded individuals—whose self-rating of broad-mindedness is either "a little" or "not at all"—and rerun the baseline regression. A one standard deviation reduction in emotional support leads to a 2.6 percentage point, or 22 percent, increase in the probability of a household reporting payment difficulties. In the next two columns, I rerun the baseline regressions limiting the HILDA sample to individuals who do not seek information or advice from family and friends when it comes to retirement planning. A one standard deviation decline in emotional support increases the probability of a household being late on (i) housing payments by 1.0 percentage points, or 15 percent; and (ii) utility payments by

2.1 percentage points, or 16 percent. Again, these estimates are comparable in magnitude to those in the baseline regressions, indicating that the buffering effect of emotional support is also distinct from the effect of informational support.

To offer more direct evidence that points to the emotional aspect of social support, I perform a heterogeneity analysis along the personality dimension focusing on one of the Big Five personality traits—neuroticism, or emotional instability (Goldberg, 1993). This is a trait characterizing a tendency toward negative feelings such as anxiety and depression. Therefore, if my findings indeed reflect the emotional aspect of social support, one would expect a stronger buffering effect of emotional support on financial hardship for individuals with higher levels of emotional instability. Table 6 reports the interaction effects of emotional support with emotional instability on financial hardship. The first two columns show that for a one standard deviation shift in emotional support, moving from the 25$^{\text{th}}$ to the 75$^{\text{th}}$ percentile of the emotional instability distribution increases the effect of emotional support on the probability of a household reporting great difficulty in paying bills from 1.8 to 2.5 percentage points (or from 19 to 27 percent) in the NLSY sample, and from 0.6 to 2.2 percentage points (or from 6 to 23 percent) in the HRS sample. The next two columns show that for a one standard deviation shift in emotional support, the same rise in the level of emotional instability in the HILDA sample increases the effect of emotional support on the likelihood of a household being late on (i) housing payments from 0.7 to 1.4 percentage points, or from 10 to 21 percent; and (ii) utility payments from 1.8 to 2.6 percentage points, or from 13 to 19 percent. These results further speak to the emotional aspect of social support.

3.4 Additional Analyses

In this subsection, I perform several additional analyses to alleviate potential endogeneity concerns.

3.4.1 A bounding exercise.

A potential concern with identifying the effect of emotional support is unobserved characteristics that affect both emotional support and the likelihood of financial hardship. To alleviate this concern, I start by implementing a bounding exercise first developed by Altonji, Elder, and Taber (2005) and recently extended by Oster (2019). This exercise examines the sensitivity of my baseline results in Table 2 to observable and unobservable selection bias and Table IA4 in the Internet Appendix presents the results. Column (1) shows that in the NLSY sample, the coefficient estimate on emotional support in an uncontrolled regression is -0.115. Column (2) shows that after including all the controls in the baseline regression specification, the coefficient estimate on emotional support becomes -0.088. Following the guidance in Oster (2019), I assume in column (3) that the amount of selection on observables is the same as selection on unobservables and that the maximum R^2 is 1.3 times the R^2 obtained with the full set of controls in Table 2. The adjusted estimate is -0.075, which is slightly lower in magnitude than the baseline estimate. As shown in the last column, selection on unobservables would need to be $4-5$ times as strong as selection on observables to explain away the buffering effect of emotional support. Similar results are obtained in both the HRS and the HILDA samples, suggesting that unobservable omitted variables are unlikely to spuriously drive my results.

3.4.2 A between-siblings analysis.

To further alleviate the omitted variable bias concern, I leverage the unique feature of the NLSY sample that many respondents have siblings and the siblings are also in the sample. In particular, I exploit between-siblings variation in emotional support by including sibling fixed effects in the baseline regression specification. This differences out confounding factors that are fixed within the family the siblings grew up in, such as parental socioeconomic status and parenting style.

The first column of Table 7 reports the result and shows that individuals with weaker emotional support in adulthood than their siblings are more likely to experience financial hardship. A one standard deviation reduction in emotional support leads to a 1.6 percentage point, or 17 percent, rise in the probability of a household having great difficulty in paying bills. This result suggests that the buffering effect of emotional support on financial hardship is unlikely to be driven by persistent family-level confounding factors.

3.4.3 A within-individual analysis. Even for siblings born and raised in the same family, they may differ along a number of dimensions such as time and risk preferences, cognitive abilities, and financial literacy. To ensure that my findings are neither driven by such confounding factors, I perform a within-individual analysis leveraging the fact that a majority of the respondents in all three samples report their perceived levels of emotional support in multiple waves. Specifically, I exploit within-individual variation in emotional support by including in the baseline regression specification individual fixed effects, which eliminate persistent confounding individual heterogeneity.

The remaining columns of Table 7 present the results, showing that individuals are more likely to experience financial hardship as emotional support dwindles over time. Column (2) shows that in the NLSY sample, a one standard deviation decline in emotional support increases the probability of a household having great difficulty in paying bills by 1.2 percentage points, or 13 percent. Column (3) shows that in the HRS sample, a one standard deviation decrease in emotional support is associated with a 1.1 percentage point, or 12 percent, rise in the likelihood of a household reporting substantial difficulty in meeting monthly bill payments. Results for the HILDA sample are reported in the next two columns. Column (4) shows that with a one standard deviation reduction in emotional support, households are 0.5 percentage point, or 7 percent, more likely to be late on housing payments because of a shortage of money. Column (5) shows that a one standard deviation decline in emotional support is associated with a 0.9 percentage point, or 7 percent, rise in the likelihood of a household being late on utility payments due to lack of money. Given that the buffering effect of emotional support on financial hardship remains both statistically and economically significant across samples, it is unlikely that my findings are confounded by persistent individual heterogeneity. In particular, the buffering effect of emotional support is above and beyond the effect of noncognitive abilities such as personality traits and self-efficacy, which have recently been documented in the literature as important predictors of household financial distress (e.g., Xu et al., 2015; Kuhnen and Melzer, 2018; Parise and Peijnenburg, 2019).

The above results also address the concern about the subjective aspect of the emotional support measures as well as that of the financial hardship indicators. To elaborate, one might argue that different individuals can have fairly different interpretations of, for example, whether there is "a great deal" of emotional support or whether it is "completely difficult" to meet monthly bill payments. Such concern is unwarranted because the buffering effect of emotional support on financial hardship continues to hold in this within-individual analysis, where the heterogeneity in interpretation of survey questions across individuals is eliminated.

3.4.4 An instrumental variable approach. Given that emotional support and financial hardship are measured contemporaneously in the baseline regression specification, one might be concerned that individuals in better financial situations tend to spend more time with their family and friends and thus enjoy stronger emotional support from them. To address this reverse causality concern, I leverage the long panel feature of the HILDA sample and rerun the baseline regressions using instead emotional support lagged by five and 10 years as the key explanatory variable. Table IA5 in the Internet Appendix reports the results and shows that the estimates of the buffering effect of emotional support on financial hardship are somewhat attenuated, but remain both statistically and economically significant.

To further alleviate the reverse causality as well as the omitted variable bias concerns, I employ an instrumental variable (IV) approach leveraging the fact that the HILDA survey collects information on respondents' socialization patterns. Specifically, my instrument for emotional support is frequency of socialization. In each wave, respondents are asked how often they get together socially with friends or relatives not living with them on a scale from one to five, where one means "less often than once a month" and five means "multiple times a week." I expect socialization frequency to predict emotional support based on the simple idea that individuals are more likely to receive effective emotional support if they socialize with their potential support providers more frequently (e.g., Burleson, 2003). To provide evidence on the relevance of the instrument, I plot in Figure 2 the average emotional support in percentile rank for individuals in each category of socialization frequency. This figure reveals that emotional support is monotonically increasing in the frequency of socialization, with individuals who socialize with their family and friends less often than once a month reporting an average emotional support of the 34$^{\text{th}}$ percentile and those who socialize multiple times a week reporting an average emotional support of the 56$^{\text{th}}$ percentile.

The first column of Table 8 presents formal first-stage estimates. Consistent with Figure 2, an individual's frequency of socialization is highly predictive of their perceived level of emotional support. A one standard deviation increase in socialization frequency is associated with a 3.0 percentile, or 7 percent, increase in emotional support. The sizable F-statistic indicates that weak instrument bias is unlikely to be a concern. It is important to note that in addition to the standard set of demographic characteristics included in the baseline regression specification, I nonparametrically control for size of friendship network measured based on the statement "I seem to have a lot of friends" on a scale from one to seven, where one means "strongly disagree" and seven means "strongly agree." The inclusion of the size of friendship network fixed effects ensures that I exploit variation in frequency of socialization across individuals with similar size of friendship network.

The next four columns of Table 8 report the results for the OLS and IV estimation of the relationship between emotional support and financial hardship. In all specifications, I include the size of friendship network fixed effects as well as all the controls in the baseline regressions. I start with the OLS specification in column (2), which shows that a one standard deviation reduction in emotional support leads to a 1.3 percentage point, or 19 percent, increase in the probability of a household being late on housing payments because of a shortage of money. Column (3) shows that the IV estimate of the effect of emotional support on the likelihood of late housing payments is -0.185, nearly four times as large as the OLS estimate of -0.047, and it is statistically significant at the one percent level.

The same pattern is observed in the next two columns, where financial hardship is measured as being late on utility payments due to lack of money. Column (4) reports the OLS regression result showing that a one standard deviation decline in emotional support is associated with a 2.4 percentage point, or 17 percent, rise in the likelihood of a household being late on utility payments. The last column shows that the IV estimate is both statistically and economically significant, about 3.5 times as large as the OLS estimate. That the IV estimates are larger in magnitude than the OLS estimates in this table suggests emotional support may be measured with error, which causes attenuation.

I then assess whether the IV results are robust to violations of the exclusion restriction assumption, which requires that after controlling for the size of friendship network as well as a standard set of demographic characteristics, frequency of socialization is unrelated to the likelihood of financial hardship except through its influence on emotional support. Following the methodology in Conley, Hansen, and Rossi (2012), I show in Figure 3 that the buffering effect of emotional support on financial hardship remains significant at the 95 percent level even when about 60 percent of the reduced-form effect of the instrument on financial hardship can be attributed to a direct effect of the instrument itself. This sensitivity analysis suggests that the IV estimates of the buffering effect of emotional support are robust to substantial violations of the exclusion restriction.

In summary, the buffering effect of emotional support on financial hardship continues to hold when I compare between siblings, analyze the same individuals over time, or perform an IV strategy. While each of the three specifications in and of itself may not be definitive, the stability of the results across the different sources of variation in emotional support suggests that my findings are unlikely to be driven by confounding factors.

3.5 Mechanisms

Why would emotional support affect the likelihood of financial hardship? To investigate this question, I evaluate the role played by emotional support both before and after realization of negative shocks. I start by exploring whether emotional support improves financial preparedness. This analysis is motivated by the importance of planning ahead for household financial well-being (e.g., Ameriks, Caplin, and Leahy, 2003). In the NLSY sample, I construct a financial preparedness indicator indicating whether the household sets aside emergency funds that would cover expenses for three months in case of sickness, job loss, economic downturn, or other emergencies. In the HILDA sample, I construct a similar indicator indicating whether the household saves regularly by putting money aside each month.

The first two columns of Table 9 present evidence that individuals who lack emotional support are less likely to take precautions to mitigate potential adverse shocks. Column (1) shows that in the NLSY sample, a one standard deviation reduction in emotional support leads to a 3.6 percentage point decrease in the probability of a household setting aside emergency savings. Since 38 percent of the households have rainy-day funds, this represents an economically significant decrease of 9 percent. The next column shows that in the HILDA sample, a one standard deviation decline in emotional support is associated with a 2.6 percentage point decrease in the likelihood of a household saving regularly by putting money aside each month. Given that 26 percent of the households save regularly, this implies a decrease of 10 percent, which is again economically material.

I provide further evidence on why individuals who lack emotional support are less financially prepared. In particular, I examine whether the lack of emotional support limits these individuals' financial planning horizons. I rely on both the HRS and the HILDA samples, where information on financial planning horizon is collected. Specifically, both surveys ask: "In planning your savings and spending, which of the following time periods is most important to you?" Possible answers are "next week," "next few months," "next year," "next 2 to

4 years," "next 5 to 10 years," and "more than 10 years ahead." A short financial planning horizon is defined if the most important time period is no more than one year.

The remaining two columns of Table 9 report the regression results showing that a lack of emotional support limits household financial planning horizon. Column (3) shows that in the HRS sample, a one standard deviation reduction in emotional support increases the probability of a household having a short financial planning horizon by 1.7 percentage points, or 6 percent. The last column shows that in the HILDA sample, a one standard deviation decline in emotional support is associated with a 1.5 percentage point, or 2 percent, rise in the likelihood of a household having a short financial planning horizon. These results are consistent with the interpretation that individuals who lack emotional support are less likely to have the bandwidth to formulate as well as to execute long-term financial plans (Schilbach, Schofield, and Mullainathan, 2016). They are therefore less financially prepared for potential adverse shocks and, in turn, more likely to experience financial hardship.

Next, I investigate the role of emotional support after negative shocks are realized. I focus on unemployment events leveraging the large sample size of the HILDA sample, which allows me to obtain a sufficiently large sample of unemployed job seekers. As shown in the first column of Table 10, unemployed job seekers who lack emotional support are less likely to find a job. Specifically, a one standard deviation reduction in emotional support decreases the probability of an unemployed job seeker finding a job within a year by 3.7 percentage points, or 8 percent.

To better understand this finding, I examine the possibility that the unemployed job seekers with strong emotional support are more likely to find a job because they have lower reservation wages. Column (2) of Table 10 provides evidence against this possibility. A one standard deviation rise in emotional support leads to a \$0.40 AUD increase in the lowest before-tax wage per hour that an unemployed job seeker would accept.

Building on recent work that uses job seekers' subjective beliefs to study their job search behaviors (e.g., Mueller, Spinnewijn, and Topa, 2021), I investigate whether emotional support boosts unemployed job seekers' confidence about their ability to find a job. Column (3) of Table 10 shows that a one standard deviation increase in emotional support is associated with a 2.9 percentage point, or 4 percent, rise in an unemployed individual's belief about the probability of finding a suitable job in the next 12 months. The last column shows that with a boost in confidence about their employment prospects, the unemployed job seekers with strong emotional support are more likely to have written, phoned, or applied in person to an employer for work in the past four weeks. Such an increase in job search effort by the unemployed individuals with strong emotional support lines up well with their higher propensity to end their unemployment spell and, in turn, their lower likelihood of experiencing financial hardship.

4. Conclusion

This paper provides the first evidence that emotional support matters for financial outcomes. Drawing on microdata from three complementary household surveys, I document that individuals who lack emotional support are more likely to experience financial hardship. This relationship does not reflect non-emotional aspects of social support and is confirmed by between-siblings and within-individual analyses as well as an IV approach. Further investigation reveals the important roles played by emotional support—both before and after realization of negative shocks—in avoiding financial distress. Specifically, emotional support has a *preventive* effect because it improves financial preparedness for potential adverse shocks. Emotional support also has a *restorative* effect because it boosts individuals' confidence in overcoming the shock after its realization.

These findings raise several important open questions for future research. First, in the two U.S. samples, I focus on family and friends as emotional support providers. Despite this focus, other sources of emotional support such as neighbors, coworkers, and religious communities might as well be relevant. Evaluating the relative importance of various sources will provide a more comprehensive view of how emotional support affects financial distress. Second, emotional support may play important roles in shaping aspects of household financial behavior and outcomes beyond financial distress. Examples include entry into entrepreneurship and stock market participation, both of which bear important implications for wealth distribution in the economy (Quadrini, 2000; Cagetti and De Nardi, 2006; Guvenen, 2009; Favilukis, 2013). Finally, while this paper does not focus on how emotional support arises and evolves over time, thoroughly examining this process within a network framework would be a promising avenue to advance our understanding of how emotional support shapes household economic and financial decision-making.

References

Altonji, Joseph G., Todd E. Elder, and Christopher R. Taber, 2005, Selection on observed and unobserved variables: assessing the effectiveness of Catholic schools, *Journal of Political Economy* 113, 151–184.

Ameriks, John, Andrew Caplin, and John Leahy, 2003, Wealth accumulation and the propensity to plan, *Quarterly Journal of Economics* 118, 1007–1047.

Athreya, Kartik, José Mustre-del-Río, and Juan M. Sánchez, 2019, The persistence of financial distress, *Review of Financial Studies* 32, 3851–3883.

Bailey, Michael, Ruiqing Cao, Theresa Kuchler, and Johannes Stroebel, 2018, The economic effects of social networks: evidence from the housing market, *Journal of Political Economy* 126, 2224–2276.

Bergman, Peter, Raj Chetty, Stefanie DeLuca, Nathaniel Hendren, Lawrence F. Katz, and Christopher Palmer, 2020, Creating moves to opportunity: experimental evidence on barriers to neighborhood choice, NBER Working Paper No. 26164.

Beshears, John, James J. Choi, David Laibson, Brigitte C. Madrian, and Katherine L. Milkman, 2015, The effect of providing peer information on retirement savings decisions, *Journal of Finance* 70, 1161–1201.

Brown, James R., J. Anthony Cookson, and Rawley Z. Heimer, 2019, Growing up without finance, *Journal of Financial Economics* 134, 591–616.

Burleson, Brant R., 2003, Emotional support skills, in Brant R. Burleson John O. Greene, ed., *Handbook of Communication and Social Interaction Skills* (Routledge, Oxfordshire).

Cagetti, Marco, and Mariacristina De Nardi, 2006, Entrepreneurship, frictions, and wealth, *Journal of Political Economy* 114, 835–870.

Calvet, Laurent E., John Y. Campbell, and Paolo Sodini, 2007, Down or out: assessing the welfare costs of household investment mistakes, *Journal of Political Economy* 115, 707–747.

Campbell, John, 2006, Household finance, *Journal of Finance* 61, 1553–1604.

Campbell, John, 2016, Restoring rational choice: the challenge of consumer financial regulation, *American Economic Review* 106, 1–30.

Cole, Shawn, Anna Paulson, and Gauri Kartini Shastry, 2014, Smart money? The effect of education on financial outcomes, *Review of Financial Studies* 27, 2022–2051.

Conley, Timothy G., Christian B. Hansen, and Peter E. Rossi, 2012, Plausibly exogenous, *Review of Economics and Statistics* 94, 260–272.

Duflo, Esther, and Emmanuel Saez, 2003, The role of information and social interactions in retirement plan decisions: evidence from a randomized experiment, *Quarterly Journal of Economics* 118, 815–842.

Dynan, Karen E., 2009, Changing household financial opportunities and economic security, *Journal of Economic Perspectives* 23, 49–68.

Favilukis, Jack, 2013, Inequality, stock market participation, and the equity premium, *Journal of Financial Economics* 107, 740–759.

Federal Reserve Board, 2020, Report on the economic well-being of U.S. households in 2019, Technical Report.

Georgarakos, Dimitris, Michael Haliassos, and Giacomo Pasini, 2014, Household debt and social interactions, *Review of Financial Studies* 27, 1404–1433.

Gerardi, Kristopher, Lorenz Goette, and Stephan Meier, 2013, Numerical ability predicts mortgage default, *Proceedings of the National Academy of Sciences* 110, 11267–11271.

Goldberg, Lewis R., 1993, The structure of phenotypic personality traits, *American Psychologist* 48, 26–34.

Gomes, Francisco, Michael Haliassos, and Tarun Ramadorai, 2021, Household finance, *Journal of Economic Literature* 59, 919–1000.

Gross, Tal, and Matthew J. Notowidigdo, 2011, Health insurance and the consumer bankruptcy decision: evidence from expansions of Medicaid, *Journal of Public Economics* 95, 767–778.

Guiso, Luigi, Paola Sapienza, and Luigi Zingales, 2013, The determinants of attitudes toward strategic default on mortgages, *Journal of Finance* 68, 1473–1515.

Guiso, Luigi, and Paolo Sodini, 2013, Household finance: an emerging field, in George M. Constantinides, Milton Harris, and Rene M. Stulz, eds., *Handbook of the Economics of Finance* (Elsevier, Amsterdam).

Gupta, Arpit, 2019, Foreclosure contagion and the neighborhood spillover effects of mortgage defaults, *Journal of Finance* 74, 2249–2301.

Guvenen, Fatih, 2009, A parsimonious macroeconomic model for asset pricing, *Econometrica* 77, 1711–1750.

Heimer, Rawley Z., 2016, Peer pressure: social interaction and the disposition effect, *Review of Financial Studies* 29, 3177–3209.

Helgeson, Vicki S., 2003, Social support and quality of life, *Quality of Life Research* 12, 25–31.

Hirshleifer, David, 2015, Behavioral finance, *Annual Review of Financial Economics* 7, 133–159.

Hong, Harrison, Jeffrey D. Kubik, and Jeremy C. Stein, 2004, Social interaction and stock-market participation, *Journal of Finance* 59, 137–163.

Hu, Zhongchen, 2022, Social interactions and households flood insurance decisions, *Journal of Financial Economics* 144, 414–432.

Kalda, Ankit, 2020, Peer financial distress and individual leverage, *Review of Financial Studies* 33, 3348–3390.

Kaustia, Markku, and Samuli Knüpfer, 2012, Peer performance and stock market entry, *Journal of Financial Economics* 104, 321–338.

Keys, Benjamin J., 2018, The credit market consequences of job displacement, *Review of Economics and Statistics* 100, 405–415.

Keys, Benjamin J, Neale Mahoney, and Hanbin Yang, 2022, What determines consumer financial distress? Place- and person-based factors, *Review of Financial Studies,* forthcoming.

Kleiner, Kristoph, Noah Stoffman, and Scott E. Yonker, 2021, Friends with bankruptcy protection benefits, *Journal of Financial Economics* 139, 578–605.

Kreiner, Claus Thustrup, Søren Leth-Petersen, and Louise Charlotte Willerslev-Olsen, 2020, Financial trouble across generations: evidence from the universe of personal loans in Denmark, *Economic Journal* 130, 233–262.

Kuchler, Theresa, and Johannes Stroebel, 2021, Social finance, *Annual Review of Financial Economics,* 13, 37–55.

Kuhnen, Camelia M., and Brian T. Melzer, 2018, Noncognitive abilities and financial delinquency: the role of self-efficacy in avoiding financial distress, *Journal of Finance* 73, 2837–2869.

Livshits, Igor, James MacGee, and Michèle Tertilt, 2010, Accounting for the rise in consumer bankruptcies, *American Economic Journal: Macroeconomics* 2, 165–193.

Lusardi, Annamaria, and Olivia S. Mitchell, 2014, The economic importance of financial literacy: theory and evidence, *Journal of Economic Literature* 52, 5–44.

Lusardi, Annamaria, Daniel Schneider, and Peter Tufano, 2011, Financially fragile households: evidence and implications, *Brookings Papers on Economic Activity* 83–134.

Maturana, Gonzalo, and Jordan Nickerson, 2019, Teachers teaching teachers: the role of workplace peer effects in financial decisions, *Review of Financial Studies* 32, 3920–3957.

Mueller, Andreas I., Johannes Spinnewijn, and Giorgio Topa, 2021, Job seekers' perceptions and employment prospects: heterogeneity, duration dependence, and bias, *American Economic Review* 111, 324–363.

Oster, Emily, 2019, Unobservable selection and coefficient stability: theory and evidence, *Journal of Business & Economic Statistics* 37, 187–204.

Parise, Gianpaolo, and Kim Peijnenburg, 2019, Noncognitive abilities and financial distress: evidence from a representative household panel, *Review of Financial Studies* 32, 3884–3919.

Quadrini, Vincenzo, 2000, Entrepreneurship, saving, and social mobility, *Review of Economic Dynamics* 3, 1–40.

Reblin, Maija, and Bert N. Uchino, 2008, Social and emotional support and its implication for health, *Current Opinion in Psychiatry* 21, 201–205.

Schilbach, Frank, Heather Schofield, and Sendhil Mullainathan, 2016, The psychological lives of the poor, *American Economic Review* 106, 435–440.

Uchino, Bert N, John T Cacioppo, and Janice K Kiecolt-Glaser, 1996, The relationship between social support and physiological processes: a review with emphasis on underlying mechanisms and implications for health, *Psychological Bulletin* 119, 488–531.

Xu, Yilan, Andrea H. Beller, Brent W. Roberts, and Jeffrey R. Brown, 2015, Personality and young adult financial distress, *Journal of Economic Psychology* 51, 90–100.

Table 1. Summary Statistics

This table reports summary statistics for the three samples in this paper: (i) the National Longitudinal Survey of Youth (NLSY) 1979 Child and Young Adult cohort; (ii) the Health and Retirement Study (HRS); and (iii) the Household, Income and Labour Dynamics in Australia (HILDA) Survey. Emotional support in the NLSY sample is a composite of four variables rating (i) how much the respondent feels loved and cared for by relatives; (ii) how much the respondent can open up to relatives about worries; (iii) how much the respondent feels loved and cared for by friends; and (iv) how much the respondent can open up to friends about worries. The ratings range from one to five, where one means "not at all" and five means "a great deal." Emotional support in the HRS sample is a composite of eight variables rating how much the respondent can open up to (i) spouse, (ii) children, (iii) other immediate family members, and (iv) friends about worries; and how much each source really understands the way the respondent feels. The ratings range from zero to three, where zero means "not at all" and three means "a lot." A rating of zero is assigned if a respondent does not have anyone for a particular source. Emotional support in the HILDA sample is based on the statements (i) "there is someone who can always cheer me up when I am down" and (ii) "I do not have anyone that I can confide in" on a scale from one to seven, where one means "strongly disagree" and seven means "strongly agree." The scoring for (ii) is reversed so that higher scores correspond to higher levels of emotional support. To ease comparisons across samples, all emotional support measures are in percentile ranks. Payment difficulties (PD) in the NLSY sample is a dummy equal to one if the household had "quite a bit" or "a great deal of" difficulty paying bills over the past 12 months. PD in the HRS sample is a dummy equal to one if it is "very difficult" or "completely difficult" for the household to meet monthly bill payments. Housing PD is a dummy equal to one if the household could not pay mortgage or rent on time in the past year because of a shortage of money. Utility PD is a dummy equal to one if the household could not pay electricity, gas or telephone bills on time in the past year because of a shortage of money. Male is a dummy equal to one if the respondent is male. In the NLSY sample, children of the female respondents in the original NLSY79 sample are the survey respondents. In the HRS sample, the family member who answers questions about household finances is designated as the respondent. In the HILDA sample, the head of the household is the survey respondent. Age denotes age in years. College is a dummy if the respondent is college-educated. Married is a dummy equal to one if the respondent is married. Healthy is a dummy equal to one if the respondent's self-reported health is either "very good" or "excellent." Log family income denotes the logarithm of family income in the previous year. Own home is a dummy equal to one if the household owns the home.

	NLSY ($N = 29,076$)		HRS ($N = 27,917$)		HILDA ($N = 119,199$)	
	Mean	SD	Mean	SD	Mean	SD
Emotional support	0.50	0.29	0.46	0.29	0.47	0.28
Payment difficulties (PD)	0.09	0.29	0.10	0.30		
Housing PD					0.07	0.26
Utility PD					0.14	0.35
Male	0.48	0.50	0.44	0.50	0.76	0.43
Age	26.50	5.37	65.16	8.56	48.27	15.95
College	0.62	0.49	0.51	0.50	0.63	0.48
Married	0.22	0.41	0.51	0.50	0.48	0.50
Healthy	0.56	0.50	0.41	0.49	0.44	0.50
Log family income	8.76	3.39	10.47	1.53	11.09	1.05
Own home	0.19	0.39	0.76	0.43	0.66	0.47

Table 2. Emotional Support and Financial Hardship: Baseline Regressions

This table reports the baseline OLS estimates of the effect of emotional support on financial hardship. Variables are defined in Table 1. Standard errors in parentheses are clustered at the household level and levels of significance are denoted as follows: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

	NLSY	HRS	HILDA	
	Payment difficulties	Payment difficulties	Housing PD	Utility PD
	(1)	(2)	(3)	(4)
Emotional support	−0.088***	−0.077***	−0.047***	−0.090***
	(0.007)	(0.008)	(0.004)	(0.006)
College	−0.030***	−0.012***	−0.008***	−0.024***
	(0.005)	(0.004)	(0.003)	(0.004)
Married	−0.007	0.003	−0.018***	−0.018***
	(0.005)	(0.005)	(0.003)	(0.005)
Healthy	−0.034***	−0.052***	−0.029***	−0.066***
	(0.004)	(0.004)	(0.002)	(0.003)
Log family income	−0.006***	−0.023***	−0.016***	−0.027***
	(0.001)	(0.002)	(0.001)	(0.002)
Own home	−0.028***	−0.059***	−0.059***	−0.102***
	(0.005)	(0.006)	(0.003)	(0.005)
Gender FE	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes
Region × Wave FE	Yes	Yes	Yes	Yes
Observations	29,076	27,917	119,199	119,199
R^2	0.045	0.084	0.051	0.104

Table 3. Emotional vs. Financial Support

This table reruns the baseline regressions in Table 2 on households that receive little to no financial support. The NLSY sample is limited to households that did not receive financial support in the past year. The HRS sample is limited to households that did not receive financial support totaling $500 or more from children, other immediate family members, or friends in the past two years. The HILDA sample is limited to households that did not ask for financial help from family or friends in the past year. Standard errors are clustered at the household level and levels of significance are denoted as follows: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

	NLSY	HRS	HILDA	
	Payment difficulties	Payment difficulties	Housing PD	Utility PD
	(1)	(2)	(3)	(4)
Emotional support	−0.083***	−0.077***	−0.023***	−0.054***
	(0.008)	(0.008)	(0.003)	(0.004)
Controls	Yes	Yes	Yes	Yes
Observations	21,288	22,815	103,009	103,009
R^2	0.047	0.084	0.018	0.042

Table 4. Emotional vs. Practical Support

This table reruns the baseline regressions in Table 2 on households with less need for practical support. The NLSY sample is limited to never-married single individuals. The HRS sample is limited to individuals with no impairment or health problem that limits the kind or amount of paid work they can do. The HILDA sample is limited to never-married single individuals in columns (3) and (4), and to individuals who are not limited in the kind of work or other activities as a result of their physical health in columns (5) and (6). Standard errors are clustered at the household level and levels of significance are denoted as follows: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

	NLSY	HRS	HILDA			
	Payment difficulties	Payment difficulties	Housing PD	Utility PD	Housing PD	Utility PD
	(1)	(2)	(3)	(4)	(5)	(6)
Emotional support	−0.090***	−0.050***	−0.064***	−0.132***	−0.039***	−0.074***
	(0.008)	(0.008)	(0.012)	(0.016)	(0.004)	(0.006)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,801	18,070	20,071	20,071	92,536	92,536
R^2	0.041	0.060	0.045	0.107	0.047	0.092

Table 5. Emotional vs. Informational Support

This table reruns the baseline regressions in Table 2 on individuals who are less receptive to information and advice. The HRS sample is limited to individuals whose self-rating of broad-mindedness is either "a little" or "not at all." The HILDA sample is limited to individuals who do not seek information or advice from family and friends when it comes to retirement planning. Standard errors are clustered at the household level and levels of significance are denoted as follows: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

	HRS	HILDA	
	Payment difficulties	Housing PD	Utility PD
	(1)	(2)	(3)
Emotional support	−0.091***	−0.035***	−0.076***
	(0.015)	(0.007)	(0.009)
Controls	Yes	Yes	Yes
Observations	8,132	49,827	49,827
R^2	0.080	0.056	0.112

Table 6. Heterogeneity by Emotional Instability

This table reports the interaction effects of emotional support with emotional instability on financial hardship. Emotional instability in the NLSY sample is the average assessment of the personality trait pair of (i) "anxious, easily upset" and (ii) "calm, emotionally stable" on a scale from one to seven, where one means "strongly disagree" and seven means "strongly agree." The scoring for (ii) is reversed so that higher scores correspond to higher levels of emotional instability. Emotional instability in the HRS sample is the average assessment of the personality traits of (i) moody, (ii) worrying, (iii) nervous, and (iv) calm on a scale from one to four, where one means "a lot" and four means "not at all." The scoring for (i), (ii), and (iii) is reversed so that higher scores correspond to higher levels of emotional instability. Emotional instability in the HILDA sample is the average assessment of the personality traits of (i) calm, (ii) envious, (iii) fretful, (iv) jealous, (v) moody, (vi) temperamental, and (vii) touchy on a scale from one to seven, where one means "does not describe me at all" and seven means "describes me very well." The scoring for (i) is reversed so that higher scores correspond to higher levels of emotional instability. To ease comparisons across samples, all emotional instability measures are linearly rescaled to lie between zero and one. Controls in Table 2 are included and standard errors are clustered at the household level. Levels of significance are denoted as follows: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

	NLSY	HRS	HILDA	
	Payment difficulties	Payment difficulties	Housing PD	Utility PD
	(1)	(2)	(3)	(4)
Emotional support × Emotional instability	−0.108**	−0.239***	−0.127***	−0.136***
	(0.043)	(0.042)	(0.030)	(0.041)
Emotional support	−0.041***	0.028**	0.001	−0.036***
	(0.014)	(0.014)	(0.009)	(0.013)
Emotional instability	0.167***	0.304***	0.122***	0.168***
	(0.028)	(0.025)	(0.020)	(0.027)
Controls	Yes	Yes	Yes	Yes
Observations	28,999	27,572	112,991	112,991
R^2	0.049	0.101	0.051	0.104

Table 7. Between-Siblings and Within-Individual Analyses

This table analyzes the effect of emotional support on financial hardship by including in the baseline regression specification sibling fixed effects in column (1) and individual fixed effects in columns (2) to (5). Standard errors are clustered at the household level and levels of significance are denoted as follows: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

	NLSY		HRS	HILDA	
	Payment difficulties		Payment difficulties	Housing PD	Utility PD
	(1)	(2)	(3)	(4)	(5)
Emotional support	−0.055***	−0.041***	−0.037***	−0.017***	−0.033***
	(0.008)	(0.009)	(0.014)	(0.004)	(0.005)
Controls	Yes	Yes	Yes	Yes	Yes
Sibling FE	Yes	No	No	No	No
Individual FE	No	Yes	Yes	Yes	Yes
Observations	28,939	28,358	21,799	116,256	116,256
R^2	0.239	0.413	0.591	0.393	0.496

Table 8. Emotional Support and Financial Hardship: IV Estimates

This table reports IV estimates of emotional support on financial hardship. The instrumental variable, frequency of socialization, captures how often individuals get socially with friends and relatives not living with them on a scale from one to five, where one means "less often than once a month" and five means "multiple times a week." Included in all regressions are the controls in Table 2 and size of friendship network fixed effects based on the statement "I seem to have a lot of friends" on a scale from one to seven, where one means "strongly disagree" and seven means "strongly agree." Standard errors are clustered at the household level and levels of significance are denoted as follows: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

		Housing PD		Utility PD	
	First Stage	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)
Emotional support		−0.047***	−0.185***	−0.084***	−0.296***
		(0.004)	(0.038)	(0.006)	(0.055)
Frequency of socialization	0.023***				
	(0.001)				
Controls	Yes	Yes	Yes	Yes	Yes
Size of friendship network	Yes	Yes	Yes	Yes	Yes
Observations	117,784	117,784	117,784	117,784	117,784
F-statistics	534				

Table 9. Emotional Support, Financial Preparedness, and Planning Horizon

This table analyzes the effect of emotional support on financial preparedness and planing horizon. Emergency funds is a dummy equal to one if the household sets aside emergency funds that would cover expenses for three months in case of sickness, job loss, economic downturn, or other emergencies. Putting money aside is a dummy equal to one if the household saves regularly by putting money aside each month. Short planning horizon is a dummy equal to one if the most important time period to the household in planning savings and spending is either "next week," "next few months," or "next year." Controls in Table 2 are included and standard errors are clustered at the household level. Levels of significance are denoted as follows: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

	NLSY	HILDA	HRS	HILDA
	Emergency funds	Putting money aside	Short planning horizon	Short planning horizon
	(1)	(2)	(3)	(4)
Emotional support	0.126***	0.092***	−0.059***	−0.053***
	(0.013)	(0.008)	(0.015)	(0.009)
Controls	Yes	Yes	Yes	Yes
Observations	19,206	67,417	13,784	67,198
R^2	0.092	0.041	0.061	0.078

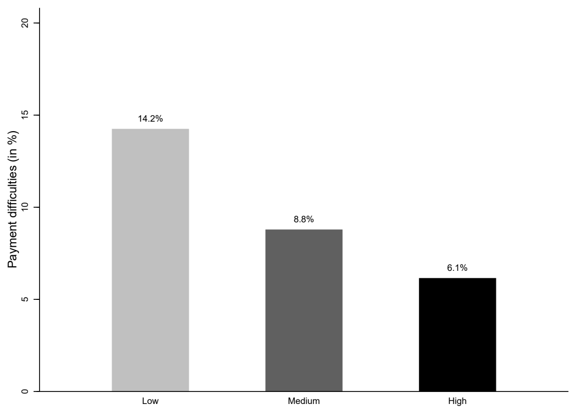
Table 10. Coping with Adverse Shocks: Evidence from Unemployment

This table relies on the HILDA sample limited to unemployed individuals who want to work. Job finding is a dummy equal to one if the unemployed individual finds a job by the next survey wave. Lowest acceptable wage is the lowest before-tax wage per hour that the unemployed individual would accept assuming work is available. Subjective belief is the unemployed individual's belief about the probability of finding a suitable job in the next 12 months. Search effort is a dummy equal to one if the unemployed individual has written, phoned, or applied in person to an employer for work in the past four weeks. Controls in Table 2 are included and standard errors are clustered at the individual level. Levels of significance are denoted as follows: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

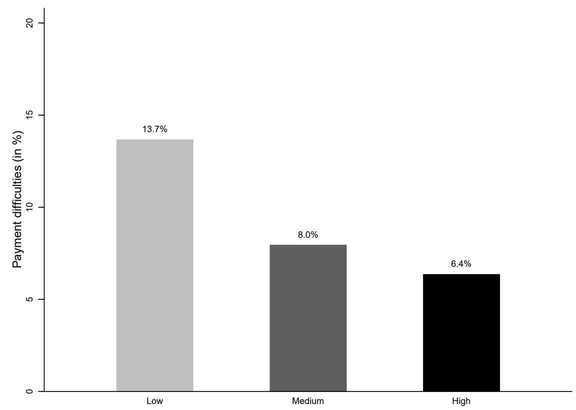
	Job finding	Lowest acceptable wage	Subjective belief	Search effort
	(1)	(2)	(3)	(4)
Emotional support	0.126***	1.362***	0.100***	0.032*
	(0.020)	(0.376)	(0.011)	(0.017)
Controls	Yes	Yes	Yes	Yes
Observations	8,212	9,491	9,787	9,903
R^2	0.102	0.317	0.154	0.039

Figure 1. Emotional Support and Financial Hardship

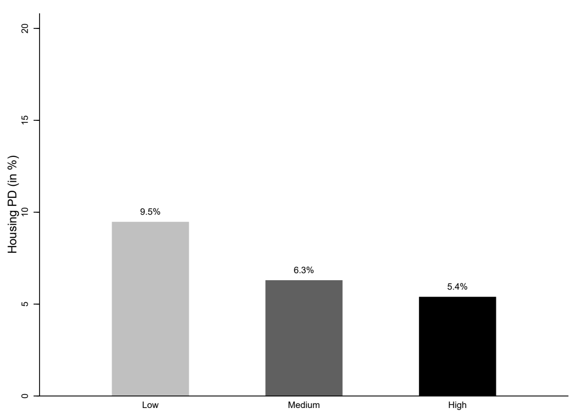
This figure plots for each sample the financial hardship rates for individuals in each tercile of emotional support. Emotional support and financial hardship indicators are defined in Table 1.



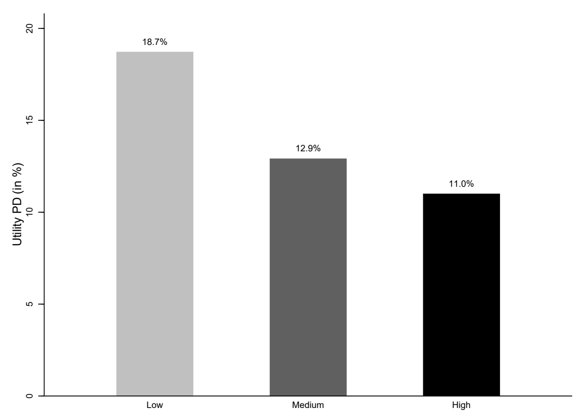
Panel A. NLSY (payment difficulties)



Panel B. HRS (payment difficulties)



Panel C. HILDA (housing PD)



Panel D. HILDA (utility PD)

Figure 2. Frequency of Socialization and Emotional Support

This figure plots the average emotional support in percentile rank for individuals in each category of socialization frequency, which captures how often individuals get together socially with friends and relatives not living with them. Emotional support is defined in Table 1.

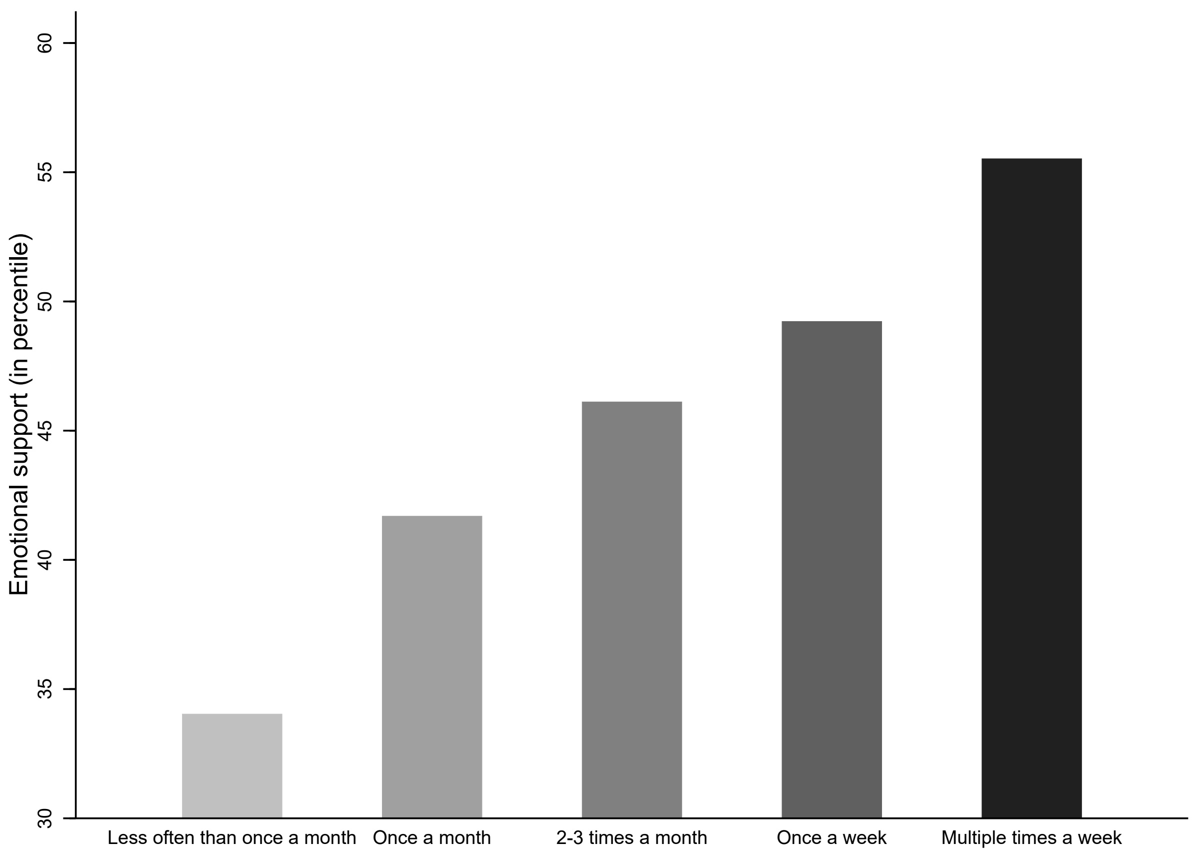
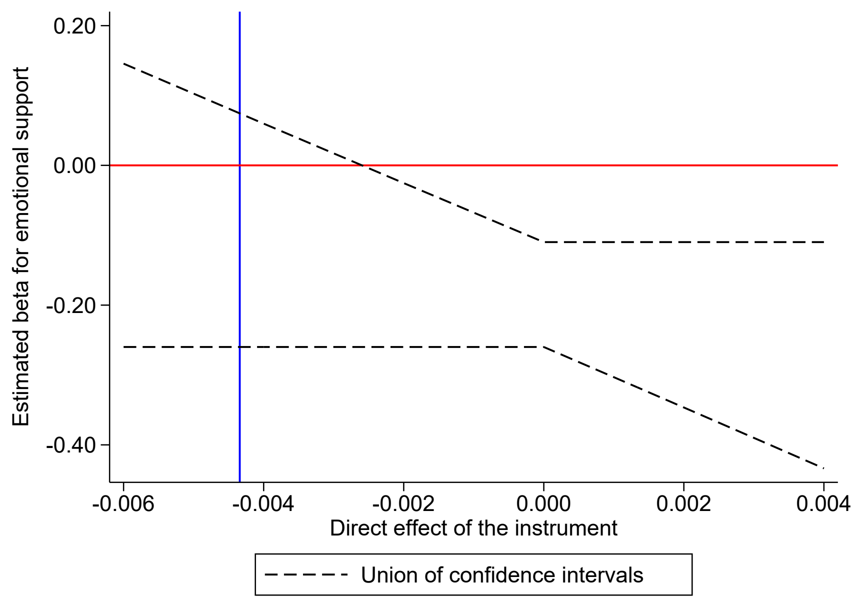
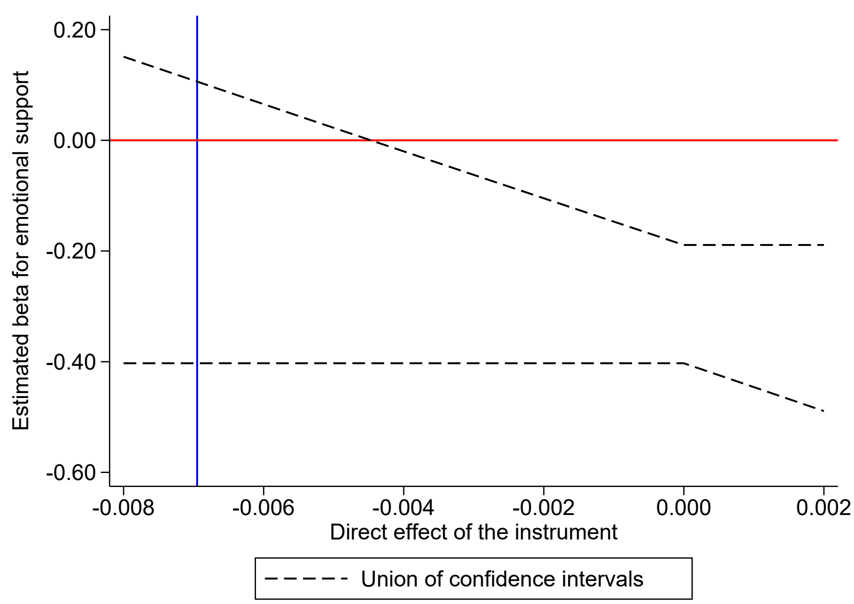


Figure 3. Plausible Exogeneity Test

This figure allows the instrument—frequency of socialization—to have a direct effect on the likelihood of financial hardship and plots union of 95% confidence intervals of the IV estimates when the exclusion restriction assumption is violated (Conley, Hansen, and Rossi, 2012). The blue vertical lines flag the overall reduced-form estimates.



Panel A. Housing PD



Panel B. Utility PD

Table IA1. Robustness: Controlling for Household Wealth

This table restricts the HRS and the HILDA samples to households that are asked about their wealth. The baseline regressions in Table 2 are rerun in columns (1), (3), and (5) for comparison. Logarithm of household wealth is additionally controlled for in columns (2), (4), and (6). Standard errors are clustered at the household level and levels of significance are denoted as follows: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

	HRS		HILDA			
	Payment difficulties		Housing PD		Utility PD	
	(1)	(2)	(3)	(4)	(5)	(6)
Emotional support	−0.061***	−0.058***	−0.039***	−0.036***	−0.081***	−0.073***
	(0.007)	(0.007)	(0.006)	(0.006)	(0.009)	(0.009)
Log household wealth		−0.024***		−0.014***		−0.035***
		(0.002)		(0.002)		(0.002)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24,707	24,707	23,639	23,639	23,639	23,639
R^2	0.062	0.079	0.050	0.055	0.098	0.115

Table IA2. Estimations Using Data Collapsed at the Individual Level

This table collapses all three samples at the individual level and estimates the effect of emotional support on financial hardship. The financial hardship indicators take the value of one if the individual experiences financial hardship in any of the survey waves. Emotional support is the average value of emotional support across survey waves. Controls in Table 2 are included. For time-varying variables, their average values across survey waves are used. Gender, race, and average age are also controlled for. Robust standard errors are reported in parentheses and levels of significance are denoted as follows: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

	NLSY	HRS	HILDA	
	Payment difficulties	Payment difficulties	Housing PD	Utility PD
	(1)	(2)	(3)	(4)
Emotional support	−0.241***	−0.109***	−0.191***	−0.210***
	(0.021)	(0.012)	(0.014)	(0.016)
Controls	Yes	Yes	Yes	Yes
Observations	7,870	14,197	16,643	16,643
R^2	0.095	0.095	0.063	0.086

Table IA3. Alternative Financial Hardship Indicators

This table reruns baseline regressions in Table 2 using alternative financial hardship indicators. Cutting necessities in the NLSY sample is a dummy equal to one if the household has to put off buying necessities (e.g., food, clothing, medical care, and housing) either "frequently" or "all the time." In the HRS sample, it is a dummy equal to one if the respondent either ate less than they should over the past year because there was insufficient money to buy food, or ended up taking less medication than was prescribed over the past two years because of cost. In the HILDA sample, it is a dummy equal to one if the household was either unable to heat home or went without meals because of a shortage of money in the past year. Cannot make ends meet is a dummy equal to one if the household ended up with insufficient money to make ends meet at the end of each month over the past year. Late debt is a dummy equal to one if the household has been more than 60 days late on required debt payments (mortgage, credit card debt, auto loan, or other debt) over the last 12 months. Late bills is a dummy equal to one if the household has been more than 60 days late on utilities, medical, or other bills over the last 12 months. Standard errors are clustered at the household level and levels of significance are denoted as follows: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

	Cutting necessities			Cannot make ends meet	Late debt	Late bills
	NLSY	HRS	HILDA	NLSY	NLSY	NLSY
	(1)	(2)	(3)	(4)	(5)	(6)
Emotional support	−0.090***	−0.070***	−0.098***	−0.067***	−0.062***	−0.096***
	(0.007)	(0.009)	(0.004)	(0.006)	(0.009)	(0.011)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	29,161	28,385	119,345	28,915	14,962	14,973
R^2	0.045	0.117	0.089	0.055	0.029	0.053

Table IA4. Assessing Selection on Unobservables

The table assesses selection on unobservables following Oster (2019). Column (1) reports, for each financial hardship indicator used in each sample, the coefficient estimate on emotional support in an uncontrolled regression. Column (2) reports the baseline coefficient estimates on emotional support with all the controls in Table 2 included. Column (3) reports the bound for the coefficient when assuming that (i) the amount of selection on observables is the same as selection on unobservables (i.e., $\delta = 1$) and (ii) the maximum R^2 is 1.3 times the R^2 obtained with the full set of controls in Table 2. Column 4 reports the amount of selection on unobservables relative to observables, δ, required to explain away the influence of emotional support on the likelihood of financial hardship.

	Uncontrolled	Controlled	$\delta = 1$	δ for $\beta = 0$
	(1)	(2)	(3)	(4)
NLSY: Payment difficulties	−0.115	−0.088	−0.075	4.40
HRS: Payment difficulties	−0.123	−0.077	−0.056	2.85
HILDA: Housing PD	−0.062	−0.047	−0.041	6.51
HILDA: Utility PD	−0.119	−0.090	−0.080	6.78

Table IA5. Lagged Emotional Support and Financial Hardship

This table relies on the HILDA sample and replaces contemporaneous emotional support in the baseline regressions in Table 2 with emotional support measured five and 10 years ago. Standard errors are clustered at the household level and levels of significance are denoted as follows: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

	Housing PD		Utility PD	
	5-year lag	10-year lag	5-year lag	10-year lag
	(1)	(2)	(3)	(4)
Lagged emotional support	−0.022***	−0.014**	−0.061***	−0.048***
	(0.005)	(0.006)	(0.007)	(0.009)
Controls	Yes	Yes	Yes	Yes
Observations	52,132	26,778	52,132	26,778
R^2	0.044	0.045	0.091	0.099