Expense shocks matter*

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Abstract

Household liquidity shocks have major implications for many topics in economics. As a result, income shocks have been extensively studied, but expense shocks are usually neglected because they are hard to quantify. We use a survey linked to credit bureau records to measure the frequency, size, and financial implications of expense shocks. Expense shocks are at least as frequent and large as income shocks. Large expense shocks that cost more than 80 percent of income are several times more common than comparably large income drops. Using a simple quantitative model of endogenous expense shocks, we show that our empirical results have important implications for precautionary saving, consumer loan delinquency and financial distress, and the distribution of the marginal propensity to consume. We find evidence that expense shock spending is often constrained by available liquidity, so the utility costs of spending needs may be high even if spending is low. Our results demonstrate that households are subject to much more liquidity risk than economic models typically account for and that this risk matters. We provide the information necessary for economic models to fully account for expense shocks.

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1 Introduction

> [Ms.Audet's] free fall into unsustainable debt began last December when her car made a horrible, sputtering sound, and died... medical bills in the thousands arrived for her Crohn's disease. She missed two rent payments. And then the landlord raised her rent $248 a month.
>
> —Rukmini Callimachi, "I Live in My Car", *New York Times*, October 17, 2023.

The liquidity shocks households experience have major implications for many topics in economics, including consumer financial distress, demand for precautionary saving and credit, loan default and bankruptcy, and the distribution of the marginal propensity to consume across households and over business cycles. The theoretical importance of liquidity shocks is widely acknowledged, so measuring income shocks, and consumers' response to them, has formed a core research agenda in economics for decades. Yet, as in Ms. Audet's case described above, households also face unexpected and critical spending needs or "expense shocks." Copious anecdotal evidence and important previous research suggest that expense shocks are important for households, yet economic models typically neglect most or all of them.[1] One reason for this neglect might be that previous work on expense shocks has tended to focus on specific ones—especially medical expenses—and so has understated the importance of expense shocks overall. Another reason is that expense shocks are hard to quantify; even if a researcher did want to account for all expense shocks, it would not be clear how to do so.

In this paper, we use thousands of survey responses linked to credit bureau records to measure the frequency, size, persistence, and financial implications of many different kinds of expense shocks, including medical expenses, auto repair, home repair, legal expenses, unexpected childcare expenses, and other expenses. These unique data allow us to provide the first empirical estimates of the size and frequency of all expense shocks combined. We find that many individual expense shock categories—including but not limited to medical expense shocks—are important, and together expense shocks are at least as common and large as income shocks. Hence, economic

[1]See Kaplan and Violante (2022) or Cherrier, Duarte, and Saidi (2023) for recent reviews of macroeconomic models. We review the literature in Section 2.

research that neglects expense shocks underestimates the magnitude of liquidity shocks by at least half and their welfare costs by potentially much more (Miranda-Pinto et al., 2023), since utility is concave and income and expense shocks often occur at the same time. Moreover, we find that especially large expense shocks costing more than 80 percent of income are far more common than comparably-sized income drops. Hence, extreme liquidity shocks are mostly expense shocks. We provide quantitative estimates of the expense shock distribution to allow economic models to fully account for expense shocks.

The "Making Ends Meet" ("MEM") survey that we use is explicitly designed to study the causes and consequences of consumer financial distress. Importantly for this paper, the MEM survey asked both whether the household experienced a variety of "significant unexpected expenses" and the amount of each expense. The question wording allows us to distinguish between planned and unplanned expenses. For example, buying a new car could be a planned upgrade or an unexpected shock following an accident. While it is impossible to distinguish between these possibilities in typical data, our survey data allow us to measure only unexpected expenses. Similar questions on income drops allow us to compare expense shocks with income shocks, which have been widely studied and so provide a useful benchmark.

Unexpected expenses are about twice as common as income drops: 75 percent of households experience a significant expense shock, while only 38 percent experience a significant income drop. When they do occur, the average share of income lost to unexpected expenses (15 percent) is similar to the average share (17 percent) lost to income drops. As a result, in our MEM data the average household spends about twice as much on expense shocks (10 percent of income) than it loses to income shocks (5 percent of income). Our data come from a period when the labor market was tight and so income drops may have been unusually rare, but even measuring income shocks using Panel Survey of Income Dynamics (PSID) data spanning multiple business cycles, we still find that expense shocks are on average larger than income shocks.

Especially large expense shocks costing 80 percent or more of income are five times more likely than similarly-sized income drops. Such extreme shocks may be particularly important for household welfare and behavior, which is why early researchers such as Carroll (1992) devoted considerable effort to precisely estimating the small probability of extreme income shocks. We find that expense shocks are particularly likely to be extreme for two reasons: (1) because income can fall at most 100 percent while expense shocks are potentially unbounded; and (2) because multiple expense shocks can occur at once, as Ms. Audet's experience illustrates. Hence, while typical research accounting only for income shocks understates liquidity shocks by about half on average, it understates the probability of particularly large shocks even more.

To make it easy for future models to account for expense shocks, Section 5 studies the full distribution of expense shocks. We first show that, when they occur, expense shocks are approximately lognormal. Research can therefore account for expense shocks with a simple process governed by three parameters: the probability of an expense shock, and the mean and variance of the log fraction of income lost to expense shocks. There is a small positive correlation between expense and income shocks, which is partly explained by specific shocks that affect both income and expenses such as illness or childcare. Households that experience expense shocks in one year are somewhat more likely to experience them the next year, but expense shocks' size are unrelated from year to year. In practice—and subject to future research—we believe that assuming expense shocks are independent from income shocks and over time is likely approximately correct. While income and expense shocks are approximately independent, they still often occur at about the same time, with potentially major implications for household welfare (Miranda-Pinto et al., 2023).

We also study variation in the expense shock distribution by household demographics such as income, race, and age. Lower-income households are more exposed to expense shocks; we estimate an income elasticity of expense shocks of 0.39, so expense shocks are necessity goods and not luxury goods. Perhaps surprisingly, expense shocks' incidence and severity varies little with race or ethnicity, although their impact may vary because of underlying wealth differences (Ganong et al., 2020). While people over age 61 are less likely to experience an expense shock, when they do experience one it is much more likely to be very expensive, providing some evidence for De Nardi, French, and Jones (2010)'s hypothesis that the possibility of large expense shocks in retirement may help explain slow wealth decumulation. While De Nardi, French, and Jones (2010) focus on medical shocks, we find that even older households are subject to expense shocks well beyond medical shocks, so the precautionary motive in retirement may be even more important than typically modeled.

What are the implications of expense shocks? Just as household income is partly endogenous, households also have some choice about whether, when, and how much to spend in response to exogenous events (such as a car breaking down). These decisions, which may be influenced by available liquidity and other factors, lead to the partly-endogenous spending that we measure (such as the money spent on fixing or replacing the car). As suggested by different papers that model expense shocks in different ways (Livshits, MacGee, and Tertilt, 2007; Chatterjee et al., 2007; Briglia et al., 2022; Miranda-Pinto et al., 2023), there is no consensus for how to model expense shocks, and so their theoretical and practical implications are unclear.

To illustrate several important modeling issues and provides a basis for future research, we extend a simple model of endogenous medical spending shocks (De Nardi, French, and Jones, 2010) to account for all expense shocks. In the model, the marginal utility of a composite "expense shock good" varies exogenously, creating sudden needs to spend more. But a household's ability to spend in response to these needs is limited by its available liquidity, which is endogenously determined by its preferences and history of shocks.

Within the model, the endogeneity of expense shocks has important implications for their interpretation. An endogenous expense shock can be small either because the exogenous spending need shock is small, or because the household is constrained and cannot afford to spend more. For example, damage to a vehicle that a household cannot afford to fix may have large utility consequences but produce little additional spending. Conversely, high expense shock spending only occurs for households with the ability to pay for it.

We use the model to explore the implications of expense shocks for several major topics in economics. A common theme is that, with expense shocks, income shocks are no longer the only reason households may have a high marginal value of liquidity.

In one stylized experiment, we show that accounting for expense shocks leads even some households with stable income to have urgent spending needs, so it increases the number of households willing to default on debt at a high long-run cost in order to increase current liquidity. As a result accounting for expense shocks causes default to be more liquidity driven and less "strategic," and so the optimal policy response is to be more accommodating to defaulters. This result generalizes theoretical arguments about bankruptcy developed by Livshits, MacGee, and Tertilt (2007) to a broad class of topics related to debt or bill payments, a step we think is important given our results that expense shocks are several times more common than the baseline estimates of Livshits, MacGee, and Tertilt (2007). Across a wide range of literatures, ranging from bankruptcy (Exler and Tertilt, 2020) and mortgage default (Foote and Willen, 2018; Ganong and Noel, 2023; Low, 2023b) to housing insecurity (Abramson, 2024) and insurance lapsation (Koijen, Lee, and van Nieuwerburgh, 2024), there has been a long and ongoing debate about the role of liquidity shocks versus long-term financial considerations in causing consumer debt or bill nonpayment. Our results that liquidity shocks are larger and more common than typically modeled implies that they are more important, and other financial considerations less important, in causing debt nonpayment than typically modeled, with important policy implications (Livshits, MacGee, and Tertilt, 2007).

In another stylized experiment, we consider the implications of expense shocks for households' marginal propensities to consume (MPC) out of small one-time transfers, which are a central focus of recent macroeconomics research (Kaplan and Violante, 2022; Crawley and Theloudis, 2024). In our model, even households with stable income may have high MPCs because of urgent spending needs, helping to reconcile theory with evidence that household liquidity is a surprisingly poor predictor of MPCs (Lewis, Melcangi, and Pilossoph, 2024; Boehm, Fize, and Jaravel, 2023; Colarieti, Mei, and Stantcheva, 2024). Miranda-Pinto et al. (2023) use a richer model to explore other implications of expense shocks for MPCs and macroeconomics.

Consistent with our model, we find that spending on expense shocks often appears constrained by available liquidity. For example, while the magnitude of expense shocks (measured as a percent of income) varies little with credit score, lower credit score consumers are far more likely to report difficulty paying bills or expenses. One reason for this apparent discrepancy is that they are much more likely to report simply not paying for bills or expenses they had difficulty with. This provides suggestive evidence that some financially fragile households do not spend on expense shocks because they cannot afford to, and so measuring expense shocks in terms of spending as we do may understate the utility cost of urgent spending needs for constrained households. This interpretation is consistent with previous research (Adams et al., 2022) that some liquidity-constrained households incur substantial utility costs to avoid spending on emergencies.

Moreover, while expense shocks are generally as predictive of financial distress as income shocks, the very largest expense shocks (roughly 60 percent of income or larger) are less statistically predictive of financial distress than comparably large income shocks. Consistent with our model, one potential explanation for this result is that expense shocks of that size are very difficult to pay for, so only households with substantial liquidity can afford them. If correct, this explanation implies that some households experience sudden and large spending needs but cannot afford to accommodate them, and so rather than pay for large expense shocks that we would observe, these households instead incur unobserved utility costs. Moreover, since (observed) large expense shocks are also several times more common than large income shocks, these estimates imply that financial distress is roughly as related to expense shocks as income shocks. This finding is consistent with causal evidence from the mortgage default literature that income and expense shocks play comparable roles causing debt default (Ganong and Noel, 2023; Low, 2023b). Hence, our broad conclusion is that expense shocks are comparable to income shocks in their welfare implications for households. Expense shocks matter.

2 Literature review

Important previous work with experimental data (Sussman and Alter, 2012; Berman, Tran, and Zauberman, 2016; Peetz et al., 2016; Howard et al., 2022), survey data (Livshits, MacGee, and Tertilt, 2007; Pew Charitable Trusts, 2015; Sabat and Gallagher, 2019; Ratcliffe et al., 2020; Fulford and

Rush, 2020; Bufe et al., 2022) and checking account data (Farrell and Greig, 2017; Farrell, Greig, and Yu, 2019) establishes that a wide variety of expense shocks are important for households. Fulford (2015) and Fulford (2020) find that households do not appear to save or want to save because of income shocks, but do seem to save for expense shocks. We build on these papers by providing quantitative estimates of overall expense shocks that can be used broadly in structural models to account for expense shocks, in the same way that other papers (Carroll and Samwick, 1997; Crawley, Holm, and Tretvoll, 2022; Guvenen, McCay, and Ryan, 2023; Ganong et al., 2024) provide estimates of income shocks that are widely used in structural models to account for income shocks.

3 Data

Our primary data sources are a series of surveys mailed in January 2022, January 2023, and January 2024. These surveys constitute a rotating panel; each year, versions of the survey were sent to respondents to the previous wave, as well as to an entirely new sample. Appendix Figure A-1 shows the primary questions we used as they appeared on the 2023 survey. Across all of the surveys we have 9,681 respondents with expense shock information, but some analyses use only a subset as described in table or figure notes.[2] For example, when examining the persistence of shocks we use only respondents that answered both waves of the survey, and for income shocks we exclude the 2022 survey because it structured the income questions differently.

A key advantage of the MEM surveys is that they are sampled from and matched to the CFPB's Consumer Credit Panel (CCP). The CCP is a comprehensive 1-in-48 sample of credit records maintained by one of the three nationwide consumer reporting agencies. Because of this CCP match, we have considerable information on survey non-respondents, allowing us to adjust for survey non-response more comprehensively than is possible in most other surveys. The combined

[2]The January 2022 survey had 2,125 complete responses. In January 2023, we mailed a second shorter follow-up survey to the same respondents and received 1,076 complete responses. At the same time, we also mailed a survey to a new sample of consumers and we received 2,136 complete responses. Finally, in January 2024, we mailed a follow-up survey to the January 2023 respondents and received 1,389 complete responses, and a new survey, receiving 3,113 complete responses.

surveys are weighted to be representative of the CCP and so are representative of consumers with a credit record. Because nearly all U.S. adults have a credit record, our data are very nearly nationally representative. The survey sampling, protocol, response rates, weighting, and results are described in detail in Fulford et al. (2023).

We clean and check the data in several ways. Our qualitative testing of the income and expense questions suggests that people can put values on the shocks they experience. For example, in qualitative testing respondents often describe calculating an income drop by multiplying the weekly loss by the number of weeks. Our testing suggests that expenses are often less cognitively demanding because they have a clear cost. We ask about distinct kinds of expense shocks and income drops and have an "other" category to allow for other types of expenses. In previous surveys, we included a write-in option and modified our categories to include common options, so our options include the most common income drops and expense shocks. Some respondents with more than one of the same unexpected expense (e.g. multiple unexpected vehicle repairs) may report only one or the largest one, so it is possible that our expense estimates are missing some smaller or less salient expenses.

Although income shocks are not our primary focus, we also provide information about them to serve as a comparison for expense shocks. The income shock and expense shock questions on the 2023 and 2024 surveys are structured similarly, making this comparison straightforward. One potential issue with our income drop questions is that one event could be counted multiple times.[3] Appendix A.1 describes how we identify and suppress potential double-counted income drops. We include these potentially double-counted drops separately when comparing different kinds of income drops but exclude the overlapping answers when calculating the total income drop experienced by the household. While the expense questions were the same for all surveys, the income shock questions had a somewhat different structure in 2022. Appendix A.2 discusses our approach to producing estimates from the 2022 survey, but we exclude the 2022 survey when

[3] For example, a respondent who took fewer shifts because his children were sick might reasonably select both "Worked less to care for others who were sick or injured" and "Worked less or stopped working to take care of children."

estimating income shocks.

4 Expense shocks and income shocks

This section begins by quantifying expense shocks. We then compare expense shocks to income drops, which provide a useful benchmark because they have been widely studied by other papers. For comparability, we express both expense and income shocks as the share of “pre-income drop income”, which is reported household income plus reported income drops.

We show that although income drops cost a slightly larger fraction of pre-drop income when they occur on average, unexpected expenses are more common (and extremely large unexpected expenses are much more common) than similarly large income drops. In our data, the average household can expect to lose twice as much to unexpected expenses than to income drops each year.

4.1 Significant unexpected expenses

The surveys asked each respondent: "In the past 12 months, has your household experienced a significant unexpected expense from any of the following?" and listed nine possible expense categories including a catchall “other” option. If the respondent reported experiencing a significant unexpected expense, the survey followed up with: "About how much was the cost?"

These survey questions are important because we derive most of our results from them. We asked respondents only about "significant" expenses to reduce cognitive burden, so it is likely our results exclude unexpected expenses that households regarded, at least individually, as insignificant. We asked households about "unexpected" expenses to correspond most closely to what economists think of as "shocks." Households may plan for many significant expenses, such as vehicle repairs or replacements, other durable good purchases, or medical procedures, and the question wording was designed to exclude these planned expenses. Cognitive testing for this question suggested that survey respondents indeed excluded planned expenses. We discuss the endoge-

Table 1: Frequency and size of significant unexpected expenses

	Experienced (%)	Inc. lost if exper. (%)	Mean cost ($)	Cost percentile ($) 25	50	75	Mean ln(frac. inc. lost)	Variance ln(frac. inc. lost)
(1) A major out-of-pocket medical or dental expense	34.1	7.3	4445	1000	2000	4500	-3.70	1.57
	(0.84)	(0.94)	(307)				(0.040)	(0.080)
(2) An unplanned gift or loan to a family member or friend	17.0	5.3	5773	500	1500	4400	-3.97	1.80
	(0.68)	(0.67)	(1192)				(0.070)	(0.140)
(3) A major vehicle repair or replacement	38.7	9.7	7886	1000	2000	5000	-3.40	1.91
	(0.88)	(0.67)	(512)				(0.040)	(0.080)
(4) A major house or appliance repair	28.4	7.0	6392	900	2000	5800	-3.72	1.92
	(0.81)	(0.67)	(645)				(0.050)	(0.110)
(5) A computer or mobile phone repair or replacement	26.6	1.2	960	300	700	1100	-4.98	1.08
	(0.80)	(0.10)	(100)				(0.040)	(0.070)
(6) Legal expenses, taxes, or fines	16.4	7.0	5484	700	2000	5000	-3.87	1.86
	(0.66)	(1.95)	(829)				(0.070)	(0.140)
(7) Increase in childcare or dependent care expenses	9.2	2.7	3419	400	1000	3000	-4.54	2.17
	(0.52)	(0.32)	(623)				(0.110)	(0.230)
(8) Moving costs	8.8	4.1	2997	600	1500	3000	-3.87	1.29
	(0.48)	(0.34)	(291)				(0.070)	(0.110)
(9) Some other major unexpected expense	15.6	9.1	9057	1000	2500	6000	-3.41	1.90
	(0.66)	(1.08)	(1729)				(0.080)	(0.250)
Any unexpected expense	75.4	15.3	12663	1700	5000	12350	-2.88	2.03
	(0.75)	(0.82)	(649)				(0.030)	(0.080)

Notes: Standard errors in parentheses. Inc. lost is calculated based on pre-income drop income. The first column includes any respondent who selected the event, whether or not they reported a cost. Figure 2 and Table 3 report the share with non-zero expense shocks. Source: Authors' calculations from the 2022, 2023, and 2024 Making Ends Meet surveys.

nous choices, such as durable good maintenance or insurance, that may affect observed shocks in Subsection 7.1.

Table 1 shows the frequency and size of unexpected expenses that households face. Overall, 75 percent of households faced at least one significant unexpected expense in the previous year. Among them, 34 percent faced a significant out-of-pocket medical expense, 39 percent faced a vehicle repair or replacement, 28 percent a house or appliance repair, and 27 percent a computer or mobile phone replacement or repair. We show how these shocks are related to each other in Appendix B.

The mean share of (pre-income drop) income lost for these events varies from 7.3 percent for an out-of-pocket medical expense and 9.7 percent for a vehicle repair or replacement to 1.2 percent for a computer or mobile phone replacement or repair. The dollars costs for computer and mobile phone repairs match closely with the costs of replacing one or two phones or a computer, suggesting that respondents gave reasonable answers to these questions. Cost distributions are typically wide. For most events, the mean dollar cost is often about as large as the 75th percentile, indicating that a few households experience especially large expense shocks.

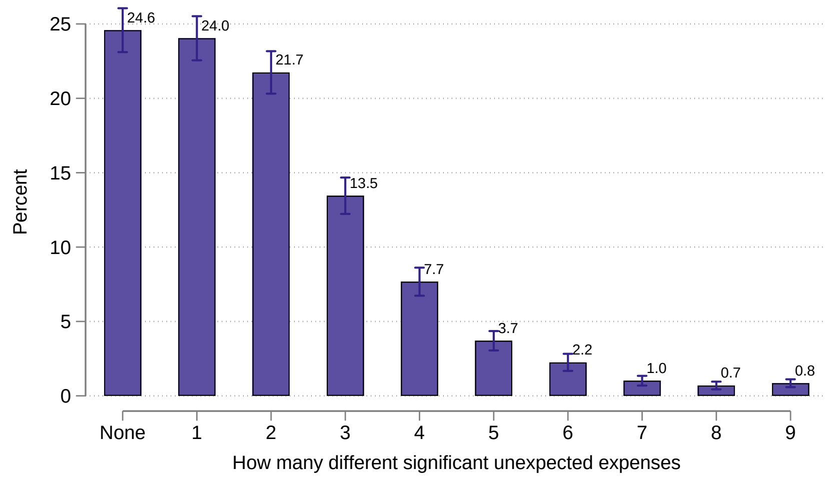
One important lesson from Table 1 is that many different kinds of expense shocks matter. Among unexpected expenses, unexpected medical expenses have received by far the most attention in previous work, but as shown in Table 1 vehicle and home expenses are quantitatively comparable, while several other smaller expense categories are still important. A major reason we obtain total expense shock estimates that are so large, even relative to previous work emphasizing the importance of expense shocks (Livshits, MacGee, and Tertilt, 2007), is that we are able to account for all of these categories.

Importantly, many households experienced more than one significant unexpected expense. Figure 1 shows a histogram of the number of unexpected expenses experienced by households. Roughly a quarter experience only one expense, one-fifth experience two, and one quarter experience more than two. That many household experience multiple shocks highlights the importance of accounting for multiple expense shocks simultaneously and is one reason we find such a thick tail of expense shock severity, discussed more below.

4.2 Income drops

The surveys asked respondents: "In the past 12 months, have you or someone in your household experienced a significant drop in income from any of the following?" and provided a list of 12 possibilities. Note that this question did not ask respondents to distinguish between expected and unexpected income drops. Table 2 shows the frequency with which households experienced different kinds of income drops and their costs. The most common kinds of income loss were a reduction in work hours (reported by 15 percent of respondents) and unemployment (13 percent).

Figure 1: How many different significant unexpected expenses households experience



Notes: A household is counted as experiencing a shock if it indicates it did, even if the household did not report a cost or reported zero cost. Source: Authors' calculations from the 2023 and 2024 Making Ends Meet surveys.

Almost as common, at 11 percent, was working less because of illness or injury. Income drops due to caring for others were also common; 6 percent stopped working or worked less to take care of children and 6.5 percent did the same for others who were sick or injured. While research has sometimes assumed that the main income shock is unemployment, Table 2 shows that many different income shocks matter.

Overall, 38 percent of respondents reported they experienced a significant income drop. Appendix Figure A-2 shows the distribution of distinct shocks and Appendix B shows the relationship between income shocks.

4.3 The relative importance of income and expense shocks

In this section, we quantitatively compare income and expense shocks. We exclude expense shocks larger than ten times income so that extreme tail events do not dominate the results. For maximum power, we pool the 2022, 2023, and 2024 surveys for expense shocks but only use the 2023 and 2024 surveys for income shocks because the 2022 survey structure for income shocks was different.

Comparing Table 1 and Table 2, households with an income drop lost on average 16.7 percent

Table 2: Frequency and size of significant income drops

	Experi-enced (%)	Inc. lost if exper. (%)	Mean cost ($)	Cost percentile ($) 25	50	75
(1) Period of unemployment or furlough	12.7	16.8	19890	3000	8000	20000
	(0.58)	(0.86)	(2300)			
(2) Reduction in work hours	15.1	9.4	8846	1000	3000	10000
	(0.65)	(0.62)	(846)			
(3) Reduction in wages at your job	6.5	10.2	13187	1500	5000	15000
	(0.45)	(1.11)	(1927)			
(4) Changed to a lower-paying job	6.6	13.9	16320	2000	10000	23000
	(0.42)	(1.00)	(1506)			
(5) Loss of government benefits	4.8	4.6	3782	400	943	3000
	(0.36)	(0.66)	(997)			
(6) Worked less because of illness or injury	11.0	9.6	11390	1000	3000	10000
	(0.57)	(0.79)	(2735)			
(7) Worked less to care for others who were sick or injured	6.5	8.4	7232	500	2000	6000
	(0.43)	(1.19)	(990)			
(8) Worked less or stopped working to take care of children	6.4	13.7	12053	1000	5000	20000
	(0.42)	(1.32)	(1177)			
(9) Lost rental income from a property you own	2.3	6.5	8680	2600	7500	10000
	(0.25)	(1.05)	(1007)			
(10) Loss of revenue from a business you own	4.8	18.5	36280	5000	20000	40000
	(0.39)	(1.39)	(5583)			
(11) Loss of income due to a natural disaster	1.7	12.4	17396	1000	3000	18000
	(0.21)	(2.72)	(9323)			
(12) Other significant drop in income	5.3	15.2	18548	2600	7000	20000
	(0.41)	(1.33)	(2698)			
Any signficant drop in income	38.2	16.7	21215	2000	6400	20000
	(0.87)	(0.56)	(1487)			

Notes: Standard errors in parentheses. Inc. lost is calculated based on pre-income drop income. Source: Authors' calculations from the 2023 and 2024 Making Ends Meet surveys.

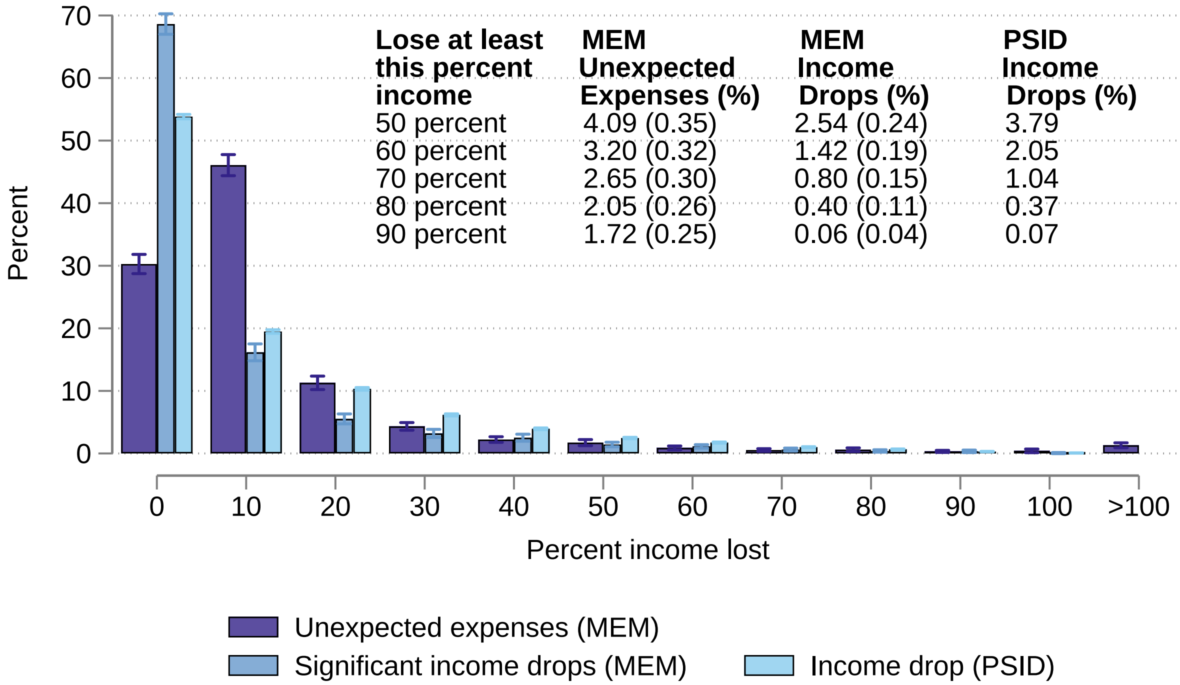
of their income, but only 38 percent of households experienced any income drop. Meanwhile, 75 percent of households experienced a significant unexpected expense, and among these households the mean share of income lost to all unexpected expenses was 15.3 percent. Including households who did not experience an expense or income drop as zeros or reported zero costs, the average household lost 5.4 percent of its pre-drop income to income drops and 10.3 percent to significant unexpected expenses. Hence, on average in our MEM data the average household can expect to lose twice as much to expense shocks as income shocks.

During the time period our data are from the labor market was tight, so income drops may have been milder than usual. For a comparison with data covering recessions, we calculate similar income drops from the Panel Study of Income Dynamics (PSID) from 1969 to 1997 when it was an annual survey. This time period included several recessions which might produce larger income drops (Guvenen, McCay, and Ryan, 2023). 45 percent of families had an income drop in the PSID data; among households with an income drop, the average amount lost was 19.05 percent. Treating not having an income drop as zero (in analogy to our MEM data), the average household lost 8.79 percent to income drops in the PSID. Hence, even when using PSID data to measure income shocks we still find that expense shocks are larger on average.

Figure 2 plots histograms of the severity of income and expense shocks. Small expense shocks—on the order of 10 percent of income or less—were substantially more common than small income drops. Even these relatively small shocks may present a significant problem for liquidity-constrained households (Sabat and Gallagher, 2019; Mello, 2023), of which there are many (Campbell and Mankiw, 1989; Lusardi, Schneider, and Tufano, 2011). The frequency of small but urgent expense shocks among liquidity-constrained households may help explain demand for payday loans and other expensive small-dollar credit (Saldain, 2023; Huang, 2023).

Very large expense shocks were also more common than very large income shocks. The table in Figure 2 examines potentially catastrophic events costing 50 percent or more of income; 4.1 percent of households experienced unexpected expenses of this size, while a similar 3.8 and 2.5 percent of households experienced income drops of this size in the PSID and MEM, respectively.

Figure 2: Income and expense shocks compared to pre-income-drop income



Lose at least this percent income	**MEM Unexpected Expenses (%)**	**MEM Income Drops (%)**	**PSID Income Drops (%)**
50 percent	4.09 (0.35)	2.54 (0.24)	3.79
60 percent	3.20 (0.32)	1.42 (0.19)	2.05
70 percent	2.65 (0.30)	0.80 (0.15)	1.04
80 percent	2.05 (0.26)	0.40 (0.11)	0.37
90 percent	1.72 (0.25)	0.06 (0.04)	0.07

Notes: The share of zero expense or income shocks is slightly different than the share with no shocks because some respondents reported an income or expense shock but did not report a cost (which we include as a zero) or reported a zero cost. The income for each respondent is the income before income drops. The bars show 95 percent confidence intervals and the table parentheses contain standard errors. Source: Authors' calculations from 2022, 2023, and 2024 Making Ends Meet surveys (expense shocks), the 2023 and 2024 surveys (income drops), and 1969-1997 PSID.

However, the largest liquidity shocks households were overwhelmingly expense shocks: 2.05 percent of households experienced unexpected expenses worth at least 80 percent of income, over five times more than suffered a comparable income drop in either MEM or the PSID. 1.72 percent of households experienced unexpected expenses worth at least 90 percent of income, more than 10 times more than suffered a comparable income drop in either MEM or PSID data.

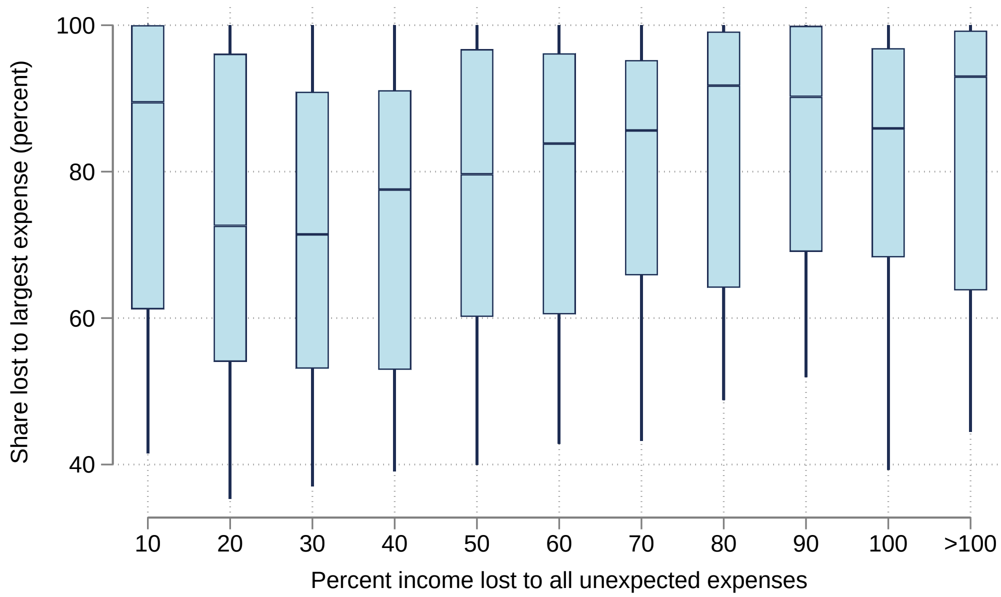
The thickness of the tail of the expense shock distribution is worth highlighting. Even though drops in income of 100 percent are very rare, their major theoretical implications led early researchers to devote considerable effort to precisely estimating their low probability (Carroll, 1992); we estimate expense shocks of this size are many times more common. Previous researchers have noted the importance of expense shocks of this size; for example, a small chance of a very large medical expense may substantially influence consumers' retirement and savings decisions (De Nardi, French, and Jones, 2010). In light of this previous work highlighting the theoretical importance of expense shocks, our empirical estimates are notably large because we account for non-medical expense shocks. For example, our estimate of the probability of an expense shock costing more than 80 percent of income is over three times higher than the frequently-used estimates in Livshits, MacGee, and Tertilt (2007), who—because of the data available to them—only accounted for medical shocks when studying expense shocks of this size.

We emphasize that there is some uncertainty in our estimates, as reflected in the standard errors in Figure 2. The MEM surveys oversample consumers experiencing financial distress, so our data have more power to study tail shocks than a random sample would. Yet tail shocks are by definition rare, leading to notable standard errors.

4.4 Expense shocks often occur together

One reason we find that expense shocks are so important is that different expense shocks often occur in the same year. As already shown in Figure 1, many households experience two or more simultaneous expense shocks; among households with unexpected expenses, over two-thirds experienced more than one.

Figure 3: Distribution of the largest expense by percent income lost to all unexpected expenses



Notes: Vertical lines show the 5th and 95th percentiles, boxes show the 25 and 75th percentiles, and horizontal lines denote the median. Sources: 2022, 2023, and 2024 Making Ends Meet surveys.

To provide more detail on how expense shocks combine, Figure 3 plots the the 5th, 25th, 50th, 75th and 95th percentiles of the largest expense shock's share of the total expense shock. For households that experience only one shock, that shock has a 100 percent share. Figure 3 shows that for many households a combination of shocks, not just the largest, were important. Across the distribution of total expense shock size, the largest unexpected expense accounted for 60 percent or less of all expense shocks for about a quarter of households (the bottom of the box). Even at the median (the line in the box's middle), the largest unexpected expense constituted only about 80 percent of total unexpected expenses. Hence aggregating across many, sometimes small, unexpected expenses shifts mass into the right tail in Figure 2 and helps explain why our estimates for unexpected expenses are so large.

Among expense shocks, medical expense shocks have received by far the most previous attention. While medical expenses can be substantial, they constituted a minority of total expense shocks. On average, unexpected out-of-pocket medical expenses were 20 percent of all unexpected expenses for households with at least some (not necessarily medical) unexpected expenses. For households with a medical expense, the average medical expense was 48 percent of all unexpected expenses. Appendix Figure A-6 shows that these shares are relatively constant across the share of income lost to all unexpected expenses, and so (perhaps surprisingly) extreme shocks are not disproportionately medical expenses. These findings complement those of Miranda-Pinto et al. (2023), who find that the share of expenditures spent on health care varies little between normal and high-expenditure episodes.

These results synthesize previous findings that a wide variety of expense shocks are important. For example, just within the context of mortgage borrowers, researchers have shown that expense shocks including divorce (Low, 2015), medical expense shocks (Gupta et al., 2018; Gallagher, Gopalan, and Grinstein-Weiss, 2019; Deshpande, Gross, and Su, 2021), ARM rate resets (Gupta, 2019), HELOC resets (Jørring, 2023), and property tax payments (Anderson and Dokko, 2016; Wong, 2020), all cause financial distress. Among renters, there is evidence that (often unexpected) increases in rent also cause financial distress (Bhutta, 2023). Some of these expenses may be in theory predictable, but consumers may fail to anticipate expense shocks that they "should" (Jørring, 2023) in the same way they fail to anticipate income drops they "should" (Ganong and Noel, 2019). Indeed, Miranda-Pinto et al. (2023) show theoretically that expense shocks can help explain this kind of behavior.

4.5 Income and expense shocks often occur together

Subsection 4.3 compared expense shocks to income shocks, because income shocks provide a useful and well-studied benchmark. However, we emphasize that expense shocks and income shocks are not mutually exclusive. Indeed, the expense shocks we document provide an additional layer of risk for households on top of the income shocks that have been widely documented.

To understand how income and expense shocks can combine, Figure 4 shows, among households with an income drop, the share of income lost (1) to income drops alone and (2) to income and expense shocks combined.[4] Figure 4 shows that considering expense shocks in addition to income drops shifts the distribution of risks sharply to the right. More than twice as many households with income drops lose 50 percent or more of income to all liquidity shocks than just income shocks.

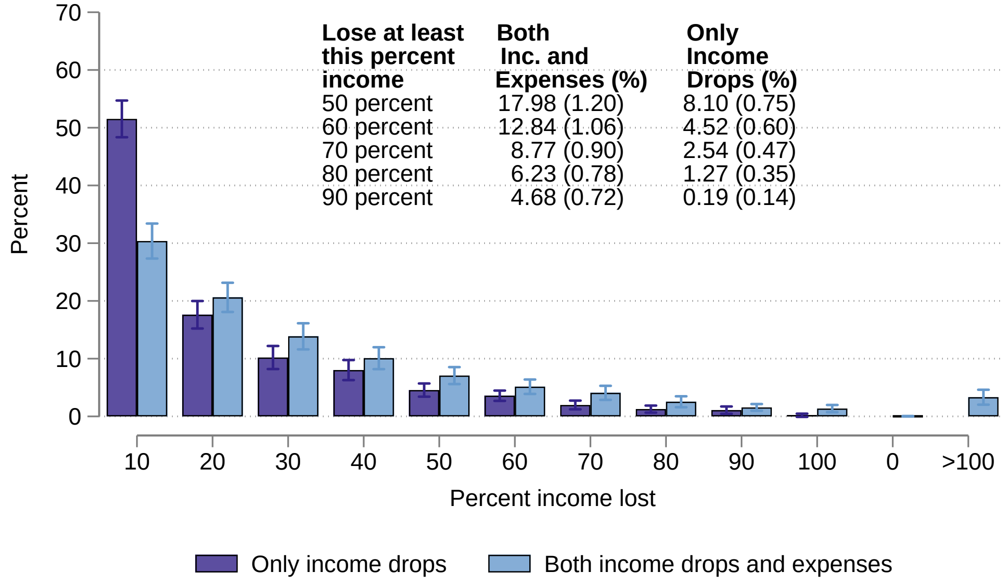
Our result that households often experience multiple concurrent shocks helps to interpret previous empirical findings. Early surveys of defaulters (Gardner and Mills, 1989; Chakravarty and Rhee, 1999; Cutts and Merrill, 2008) typically asked respondents to identify one specific cause of their default; while many respondents listed income or expense shocks, many others could not identify a specific cause and so failed to answer the question or provided hard-to-interpret answers such as "excessive obligations." Thus it was unclear whether these defaults were not triggered by liquidity shocks and so were "strategic" or were triggered by multiple concurrent liquidity shocks. The MEM surveys allowed respondents to list multiple shocks, and we find many households experience shocks that together are much more severe than any specific shock they experience. Similarly, a survey of mortgage defaulters (Low, 2023b) that allowed respondents to list multiple reasons for their default found that 38–58 percent of defaulters report that at least three liquidity shocks contributed to their default. Our findings suggest that future surveys on similar topics should allow respondents to list multiple causes of default or financial distress.

5 How economic models can account for expense shocks

Information we have already presented can help inform structural models. Table 1 shows the probability and size of expense shocks. Table 1 also shows the mean and variance of the log fraction of income lost to expense shocks overall and for specific shocks. Figure 2 shows the probability of expense shocks that cost at least 50, 60, 70, 80, or 90 percent of income so that

[4] We restrict to households that had an income drop because the surveys ask only about income drops and not income increases. Some households experience an income increase and an expense shock, so their total liquidity shock is smaller than an estimate looking at only expense shocks would suggest. By restricting to households that had an income drop, we avoid this problem at the cost of looking only at the 38 percent of households who reported an income drop.

Figure 4: Among households with income drops, the share of income lost to income drops alone and both income and expense shocks



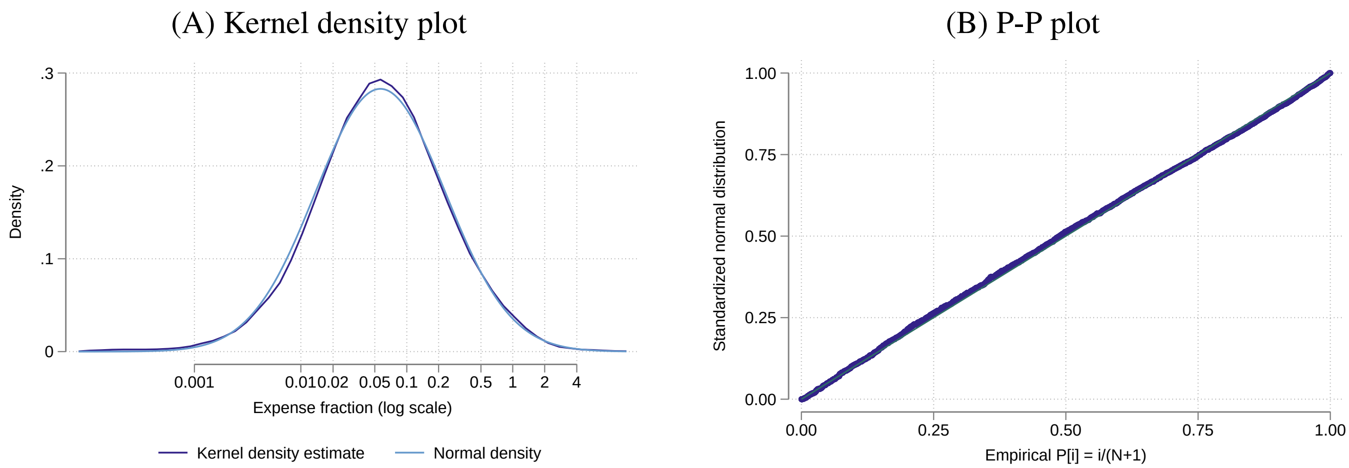
Notes: This figure considers only consumers with an income drop because consumers with income increases are not identified by the survey. Sources: 2023 and 2024 Making Ends Meet surveys.

researchers can account for tail shocks.

In this section, we provide more information on the distribution of expense shocks so that future models can fully account for them. We summarize the expense shock distribution in several ways to give other researchers the ability to incorporate expense shocks in ways they think best; we expect that different models will account for expense shocks in different ways depending on the application. For example, our estimates could be treated as the outcome of an exogenous expense shock process, or as moments to discipline the parameters of an endogenous expense shock process. We provide a simple illustration of this latter approach in Section 6.

We start by showing that expense shocks are approximately log normal. We then examine the demographic distribution of expense shocks, their correlation with income shocks, and their persistence. Expense shocks in our data are not persistent and are only weakly correlated with income shocks, so we think one reasonable approach is for models to account for them by simply increasing the probability and conditional size of temporary income shocks so that they can be

Figure 5: Unexpected expenses compared to normal distribution



Notes: Kernel density is weighted using survey weights. The P-P plot is not weighted. Source: Authors' calculations from 2022, 2023, and 2024 Making Ends Meet surveys.

interpreted more broadly as temporary liquidity shocks. This approach would not require adding any state variables to traditional models.

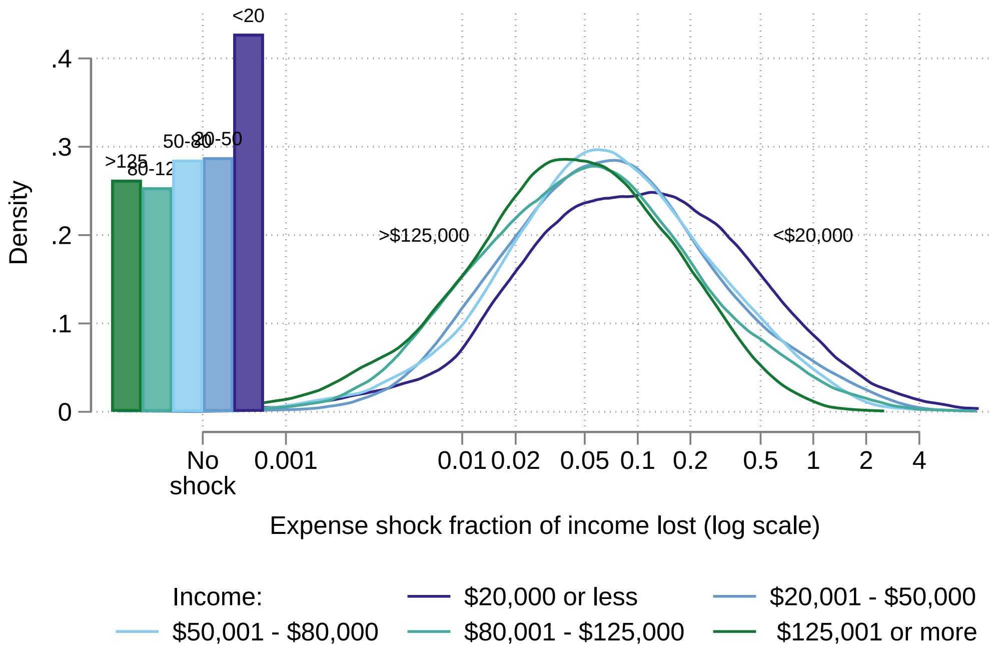
5.1 Expense shocks are approximately log-normal

Figure 5 compares the log fraction of income lost to expense shocks, conditional on having any expense shock, to the normal distribution. Conditional on occurring, the fraction of income lost to expense shocks is very nearly log-normally distributed. Indeed, in the P-P plot it is difficult to see differences from the 45-degree line. Hence, expense shocks can be well approximated with only three parameters: the probability that an expense shock occurs, and the mean and variance of the log-normal distribution. Table 1 presented earlier provides these numbers both for specific expense categories and overall. Next, we provide these numbers for specific demographic groups.

5.2 Income shocks and expense shocks across demographic groups

Table 3 shows how the incidence and distribution of expense shocks varies across demographic groups; averages across demographic groups for several specific expense shocks are in Appendix

Figure 6: Distribution of expense shocks across income groups



Notes: The figure shows the kernel density of the log expense fraction. The bars are the fraction of households with no expense shock or 0 expenses. Sources: 2022, 2023, and 2024 Making Ends Meet surveys.

Table A-4. The first column of Table 3 shows the average amount of income lost to unexpected expenses, including households without shocks. The table also (conservatively) treats respondents who report experiencing a shock, but do not report its cost, as experiencing a zero cost. The second column shows a similar calculation for income drops. The share of income lost to unexpected expenses decreases with income. Income drops are also negatively correlated with income levels.

The next column shows the fraction of households with a non-zero unexpected expense. The final two columns show, conditional on a positive expense shock, the mean log expense share of income lost and the variance of the log. These three parameters summarize the distribution for each group. Across income groups, the share with an expense is relatively constant as is the variance, except for the lowest income group. But because the mean shifts left as income increases, lower income groups face substantially higher probability of shocks greater than 50 percent of income. Figure 6 illustrates this shift.

Table 3 further shows that the average income lost to unexpected expenses does not vary much

Table 3: Income and expense shocks across demographic groups

	Income lost to unexpected expenses (%)	Income lost to income drops (%)	Fraction with non-zero unexp. exp.	Mean ln(fraction unexp. exp.)	Variance ln(fraction unexp. exp.)
Overall	10.3	5.4	0.697	-2.88	2.03
	(0.47)	(0.22)	(0.0078)	(0.030)	(0.074)
Income					
$20,000 or less	16.2	11.0	0.572	-2.32	2.26
	(2.43)	(1.06)	(0.0230)	(0.087)	(0.193)
$20,001 to $50,000	12.6	6.8	0.712	-2.66	1.96
	(0.82)	(0.41)	(0.0133)	(0.050)	(0.137)
$50,001 to $80,000	11.1	5.9	0.715	-2.73	1.91
	(0.99)	(0.54)	(0.0181)	(0.060)	(0.151)
$80,001 to $125,000	10.4	3.9	0.746	-2.96	1.98
	(1.28)	(0.38)	(0.0168)	(0.070)	(0.161)
More than $125,001	6.1	3.1	0.737	-3.25	1.83
	(0.39)	(0.33)	(0.0161)	(0.062)	(0.140)
Education					
Less than H.S.	11.8	6.3	0.650	-2.77	2.09
	(1.24)	(0.51)	(0.0167)	(0.062)	(0.148)
High School	11.1	6.6	0.727	-2.75	1.95
	(0.94)	(0.54)	(0.0187)	(0.066)	(0.191)
Some college	10.0	4.8	0.709	-2.89	2.05
	(0.80)	(0.43)	(0.0186)	(0.072)	(0.178)
College or post-grad.	9.0	4.2	0.724	-3.02	2.00
	(0.57)	(0.28)	(0.0112)	(0.046)	(0.107)
Race and ethnicity					
Non-Hisp. white	10.6	4.5	0.700	-2.88	2.12
	(0.61)	(0.24)	(0.0100)	(0.039)	(0.099)
Black	9.2	7.2	0.684	-3.03	2.06
	(1.18)	(0.71)	(0.0202)	(0.073)	(0.158)
Hispanic	10.2	7.4	0.728	-2.78	1.71
	(0.89)	(0.68)	(0.0189)	(0.064)	(0.166)
Other	10.4	5.3	0.643	-2.78	1.89
	(2.16)	(0.84)	(0.0293)	(0.117)	(0.244)
Age					
<40	9.4	6.9	0.737	-2.93	1.89
	(0.66)	(0.46)	(0.0147)	(0.053)	(0.125)
40-61	10.0	6.3	0.744	-2.95	1.87
	(0.83)	(0.43)	(0.0128)	(0.050)	(0.119)
>61	12.0	2.4	0.591	-2.62	2.23
	(1.27)	(0.29)	(0.0171)	(0.064)	(0.164)
Observations	9681	7653	9685	6464	6464

Notes: All results are survey weighted; standard errors in parentheses. Observations are for the Overall result. Expense shocks greater than ten times income are dropped. Non-zero unexpected expenses includes only respondents who reported a positive non-missing cost for the shock; see Table 1 for the percentage who had a shock, regardless of cost. Source: 2022, 2023, and 2024 Making Ends Meet surveys for expenses, 2023 and 2024 surveys for income drops.

across racial and ethnic groups. Because many of these attributes are correlated, Appendix Table A-3 includes all of the demographics in a series of regressions. Income tends to be the most important attribute; after controlling for the income level, other demographic factors are much less important. There is somewhat more variation in the extent of income drops across groups.

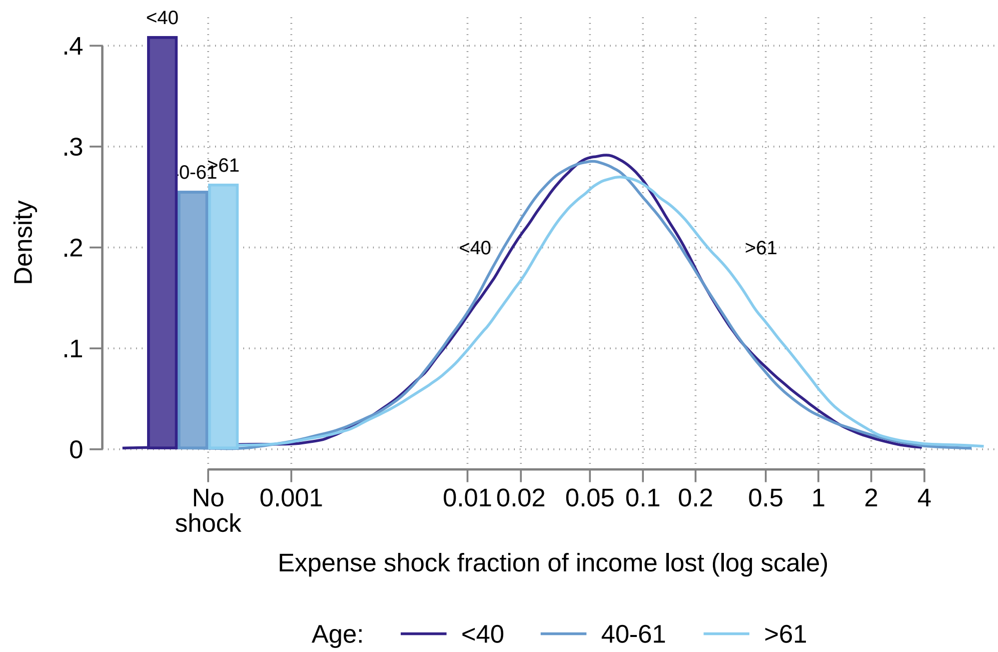
Table 3 also shows that the elderly experience more large expense shocks but fewer small ones. The average income lost to unexpected expenses does not vary much by age in Table 3. People over age 61 are less likely to experience an expense shock, but when they do occur, the mean shock size is significantly higher. The variance is also larger, so there is substantially more weight in the extreme tails as illustrated by Figure 7. Meanwhile, the elderly lose less than half as much of their income to income shocks than younger people. Liquidity risk for older Americans is thus mostly from expenses. While a rich literature already emphasizes the importance of medical expenses for older Americans (De Nardi, French, and Jones, 2010; Blundell et al., 2024), Appendix Table A-4 shows that other expense categories are also important later in life.

5.3 The correlation between income shocks and expense shocks

We show that there is a low positive correlation between income and expense shocks that is partly explained by specific shocks that affect both. Accounting for these specific shocks, income and expense shocks appear approximately independent. The raw correlation between the income share lost to expenses and income drops is 0.08, including households without income or expense shocks. Among only households with positive shocks, the correlation is 0.06. Figure A-5 in Appendix B provides the correlations between specific income and expense shocks. The figure suggests that events that affect both income and expenses explain some of the correlation between income and expense shocks. Households experiencing an unexpected increase in childcare expenses are more likely to report working less to care for children, and vice versa. Households that experience a medical expense are slightly more likely to work less because of illness.

Table 4 examines these correlations in regression form. The dependent variable in the first three columns is the share of income lost to expense shocks (including zeros) while the depen-

Figure 7: Distribution of expense shocks across age groups



Notes: Kernel density of ln expense fraction. Bars are fraction with no expense shock or 0 expenses. Sources: 2022, 2023, and 2024 Making Ends Meet surveys.

Table 4: Relationship between income and expense shocks

	Income lost to unexpected exp. (%)			Income lost to income drops (%)		
Income lost to income drops (%)	0.111*** (0.0243)	0.0852*** (0.0251)	0.0769*** (0.0267)			
Income lost to unexpected expenses (%)				0.0581*** (0.0143)	0.0436*** (0.0139)	0.0407*** (0.0147)
Constant	8.477*** (0.375)	10.58*** (1.140)	10.07*** (1.109)	4.875*** (0.231)	10.53*** (1.070)	10.14*** (1.122)
Observations	7,565	7,457	6,931	7,565	7,457	6,337
R-squared	0.006	0.019	0.017	0.006	0.039	0.035
Controls	None	Income	Income	None	Income	Income
Sample excludes medical and childcare	No	No	Yes	No	No	Yes

Notes: The sample in column 3 excludes respondents with income drops relating to injury, caring for others who are sick, or working less to care for children. The sample in column 6 excludes respondents with unexpected medical expenses or childcare expenses. Source: Authors' calculations from the 2023 and 2024 Making Ends Meet surveys. *** p<0.01, ** p<0.05, * p<0.1

dent variable in the next three columns is the share of income lost to income drops. Without any controls, the two shocks are modestly predictive of each other. Controlling for income weakens this correlation. Excluding income shocks related to illness or childcare (in column 3), or expense shocks related to illness or childcare (in column 6), the modest correlation falls.[5]

5.4 The persistence of income and expense shocks

This section examines shocks' persistence from year to year. We find low persistence of expense shock size but some evidence that people who report experiencing a shock in one year are more likely to report experiencing one the next year. Expense shocks could be (or appear to be) persistent for several reasons including: (1) conditional on experiencing a shock one year, a household could be more likely to experience a new shock the next year; (2) income drops or expenses shocks may be spread out over several years because of an underlying shock such as a medical event; (3) despite the survey instructions, respondents could include shocks from more than 12 months before the survey; and (4) respondents may vary in their propensity to report shocks they experienced. We caution that our sample size is smaller in this section because analyzing shock persistence requires that we observe the same household over two surveys.

Table 5 shows regressions that relate shocks experienced across the panel from 2022 to 2023 and 2023 to 2024. The probit results in Panel (A) are the average marginal effect, and so show the change in predicted probability. Households that experienced an expense shock in one year are about 25 percentage points more likely to experience one the next year and about 9 percentage points more likely to experience one if they had an income drop the previous year. Households that experienced an income drop in 2022 were around 30 percentage points more likely to experience an income drop the next year, depending on the specification, and 14 percentage points more likely if they had an expense shock. These average marginal effects are mostly unaffected by controlling

[5]Table A-5 in the appendix shows two stage regressions of a similar form. First we estimate a probit model for whether the household experienced a shock, and then we estimate an OLS regression of the size of the shock, conditional on having one. The probit regressions suggest that households who experience income shocks are modestly more likely to also experience expense shocks even controlling for income or childcare, but the size of the shocks are uncorrelated.

Table 5: Persistence of income and expense shocks

(A) Probit dep. variable:	Had expense shock			Had income drop		
Had an expense shock	0.264***	0.249***	0.240***		0.136***	0.132***
year before	(0.0271)	(0.0285)	(0.0288)		(0.0250)	(0.0255)
Had an income drop		0.0858***	0.0907***	0.325***	0.285***	0.273***
year before		(0.0268)	(0.0271)	(0.0281)	(0.0287)	(0.0291)
Observations	2,373	2,283	2,245	2,329	2,293	2,253
Control for income	No	No	Yes	No	No	Yes

(B) OLS dep variable:	ln(fraction inc. lost unexpected expenses)		Share of income lost (%) if had shock			
			Expenses	Expenses	Expenses	Income
ln(fraction inc. unexp. exp.	0.174***	0.151***				
year before)	(0.0430)	(0.0422)				
Income lost to expense shocks			0.0393*	0.0367	0.0351	
year before (%)			(0.0224)	(0.0251)	(0.0237)	
Had an expense shock				1.096	1.701	
year before				(2.386)	(2.361)	
Income lost to income drops				0.101	0.105	0.302***
year before (%)				(0.0785)	(0.0806)	(0.0648)
Had an income drop				0.895	0.0160	
year before				(2.800)	(2.835)	
Observations	1,146	1,146	1,551	1,497	1,484	243
R-squared	0.028	0.040	0.003	0.007	0.014	0.097
Control for income	No	Yes	No	No	Yes	No

Notes: Probit results show the average marginal effect. Source: Authors' calculations from the 2022-2023 and 2023-2024 Making Ends Meet survey panels. *** p<0.01, ** p<0.05, * p<0.1

for income the year before.

Among those who experienced an expense shock, there is some persistence of the size of shock. Panel (B) relates the size of shocks, if the household had one, to having a shock the previous year and its size. In log terms, a one point larger expense shock is correlated with a 0.17 point larger shock the next year, conditional on experiencing a shock in both years. Yet columns 3 through 5 suggest a low correlation in percentage terms. Consistent with the literature finding that income shocks are persistent, the last column suggests the size of income shocks is correlated from year to year, although the sample size is small.

6 A model of endogenous expense shocks

In this section, we explore some implications of our empirical results in a simple quantitative model that endogenizes consumers' spending response to exogenous preference shocks. The utility specification, from De Nardi, French, and Jones (2010), has been used in the healthcare literature (White, 2021; Khwaja and White, 2024) to endogenize medical spending responses to health shocks. We take code to solve and simulate the model from the publicly-available HARK repository; readers can quickly access the code and some basic results here.

The simplicity of the model brings several advantages; for example, the model's mechanisms are clear and we can use it to explore the implications of expense shocks for a variety of topics in household finance and macroeconomics. However, because the model is so simple, none of our specific quantitative results should be viewed as robust. Instead, our model demonstrates that our empirical results have important quantitative implications for a wide variety of topics. We hope that the broader research community will establish in detail what these implications are, using a variety of tools including more sophisticated models.

6.1 Model specification

The core of the model is a standard infinite-horizon consumption-savings problem. The income vector $\vec{y}$ is exogenous and stochastic, with temporary and persistent shock components.[6] Consumers choose standard consumption c and discount the future exponentially at rate β. They have access to one liquid, risk-free asset a that earns rate of return R.

The model's only departure from this standard framework is that, in addition to facing stochastic income risk, consumers also face exogenous stochastic utility shocks η. In response to these shocks (their car breaking down), consumers choose how much they spend x on unexpected expenses (whether to scrap the car, fix it, or replace it). Consumers with higher income or wealth endogenously choose to spend more on a given expense shock.

Utility is additively separable in normal consumption c and effective shock consumption $\frac{x}{\eta}$. It is CRRA in both, with parameters γ and ν respectively.

$$u(c, x) = \frac{c^{1-\gamma}}{1-\gamma} + \frac{(\frac{x}{\eta})^{1-\nu}}{1-\nu} \tag{1}$$

With this specification, consumer utility is not homothetic. If $\nu > \gamma$, consumers are more risk averse over x than c, so spending on expense shocks will be less responsive to wealth for a given shock η. Thus, while consumers with higher income or wealth will choose to spend more on x given η, they will do so less than proportionally, and so the fraction of income spent on expense shocks will fall with income. Given our empirical finding that lower-income consumers spend proportionally more on expense shocks (see Figure 6), this is an attractive feature of the model.

With utility u given by Equation 1, the Bellman equation can be written:

$$V(a, \vec{y}, \eta) = \max_{c,x} u(c, x) + \beta E_{\vec{y}',\eta'} V(a', \vec{y}', \eta') \tag{2}$$

subject to:

[6] Temporary and persistent income shocks enter the model in distinct but standard ways. We write $\vec{y}$ as a vector to note these distinctions while economizing on notation.

$$a' \geq \underline{a}(\vec{y}) \tag{3}$$

$$R^{-1}a' + c + x = a + \vec{y} \tag{4}$$

where Equation 3 is the exogenous borrowing limit and Equation 4 is the budget constraint.

The Euler inequalities give some intuition for the model and its implications. Taking first order conditions with respect to c and x and using the envelope theorem yields:

$$\frac{\partial u(c,x)}{\partial c} = \frac{\partial u(c,x)}{\partial x} \tag{5}$$
$$\frac{\partial u(c,x)}{\partial c} \geq \beta R E\left[\frac{\partial u(c',x')}{\partial c'}\right] \tag{6}$$
$$\frac{\partial u(c,x)}{\partial x} \geq \beta R E\left[\frac{\partial u(c',x')}{\partial x'}\right]. \tag{7}$$

For liquidity-constrained households, Equation 3 binds and marginal utility today is strictly greater than expected marginal utility tomorrow; Expressions 6 and 7 become strict inequalities. For these households, the observable expense shock x may be low even if the unobservable spending need η is high. In this sense, the liquidity constraint in the model sometimes generates a disconnect between large values of η and small values of x; the utility costs of spending needs may be high even if expense shock spending is low. The interaction of expense shocks with the liquidity constraint has important and testable policy implications that we explore in Subsection 6.3 and Subsection 6.4.

6.2 Calibration and model fit

We calibrate two versions of the model. In the "Endogenous Expense Shock" (EES) version of the model, η shocks are first drawn to be either 0, "small" (as defined below), or from a thick-tailed Pareto distribution. Using Figure 2, we set the probability of no expense shock to 30 percent, and the probability of a "small" η of .00002 to 56 percent. These choices come close to replicating our empirical results for small expense shocks on the order of 10 percent of income or less. Given these choices, we calibrate the scale parameter of the Pareto distribution so that the endogenous consumer spending x to exogenous shocks η approximates the mean (from Table 1) and tails (from Figure 2) of the expense shock distribution in MEM data. In particular, we target the percent of expense shocks worth at least 70 and 90 percent of income. We calibrate ν to match the relationship between expense shocks and income documented in Figure 11; higher values of ν make expense shocks more of a necessity good, leading them to represent a higher fraction of income for lower-income consumers.

In a second, "No Expense Shock (NES)," version of the model, η_t is always (arbitrarily close to) zero. This collapses the model to a standard consumption-savings model with CRRA utility and no expense shocks. By comparing NES with EES, we can study the theoretical implications of endogenous expense shocks in a model that is consistent with the empirical moments we target.

In reality, households hold much of their wealth in illiquid assets. Therefore one-asset models like EES and NES typically must choose between matching consumers' liquid wealth or their total wealth including illiquid assets (see Kaplan and Violante, 2022, for a detailed discussion). Because liquid wealth is particularly relevant to the questions we study, we target liquid wealth levels; in particular we set the discount factor β in both versions of the model to match an average ratio of liquid wealth to income of 0.6 (Kaplan and Violante, 2022). Later, we briefly explore agents' demand for illiquid assets in EES as a first step towards understanding models with expense shocks that could match both liquid and illiquid wealth levels.

We set the coefficient of relative risk aversion γ on normal consumption c to a standard value of 2, the risk-free interest rate on liquid assets to 1 percent, and the borrowing constraint to 18.5 percent of permanent income following Kaplan and Violante (2014).

We set the variance of the temporary and persistent components of income shocks respectively to $.0116$ and $.0334$, from PSID data following Low (2023a). However, the standard temporary-persistent lognormal income process does not replicate the left skewness of income shocks (Guvenen, Ozkan, and Madera, 2024; Crawley and Theloudis, 2024). In order to avoid overstating the role of expense shocks relative to income shocks, we therefore augment this standard income process with a discrete temporary "disaster" income shock. As shown in Figure 2, about 2 percent of PSID respondents report a drop in income of 60 percent or more. Because many of these large income drops persist for more than a year,[7] we allow in the model for a 5 percent chance of a temporary 70 percent drop in income.

Unsurprisingly, the calibrated models fit their targets well. In EES the average expense shock including (excluding) zeros costs 10.42 percent (14.6 percent) of income; recall from Table 1 and Table 3 in the MEM data we obtain 10.5[8] (15.3 percent) of income. In EES 2.40 percent and 1.50 percent of expense shocks cost more than 70 percent and 90 percent of permanent income, respectively; the targets from the MEM data are 2.65 percent and 1.72 percent. Figure 8 presents a bar chart of normalized spending on expense shocks, by income category in EES and the data; with a value of $\nu = 3.724$, EES fits the data well. Hence, while NES neglects expense shocks, EES replicates several important empirical facts about expense shocks that we document.

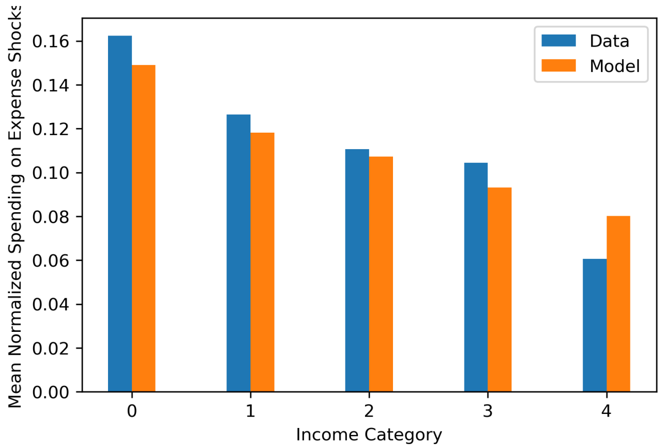
Agents in EES face more liquidity risk than agents in NES, so all else equal they have a stronger precautionary motive. To counteract this and achieve the same mean wealth-to-income ratio, agents in EES must have lower discount factors ($\beta = .916$) than in NES ($\beta = .946$). This is a simple illustration of an important point: incorporating expense shocks into calibrated quantitative models will affect other parameters, which will have other downstream effects that depend on the targeted moments and the specific parameters that change in response to expense shocks.

Another important point is that neither NES nor EES replicates the fraction of households with zero (or negative) liquid wealth. Median normalized wealth is 0.586 in EES and .479 in NES; 5.1 percent of agents in EES and 6.4 percent of agents in NES have nonpositive wealth. For comparison, Kaplan and Violante (2022) estimate median normalized liquid wealth is *zero*, and roughly 15 percent of households have nonpositive *total* wealth (including illiquid assets). Kaplan

[7] Low (2023a) finds that only roughly half resolve within a year.

[8] In Table 3, we find that the average expense shock including zeros is 10.3 percent. However, this statistic includes a few survey respondents that did not report their income but did report no expense shock, which we impute to be 0 percent of income. The 10.5 percent number we target restricts the sample to respondents who reported their income for consistency with Figure 8, which requires knowing respondents' income.

Figure 8: Normalized Spending on Expense Shocks in EES vs. Data



Notes: MEM respondents are placed into income categories, based on whether they make less than \$20k, \$20-\$50k, \$50-\$80k, \$80k-\$125k, or more than \$125k. 12.0%, 21.3%, 18.9%, 20.0%, and 27.8% of MEM respondents are in each of these categories, respectively. In the model, we divide agents into comparable categories by placing the 12.0% of agents with the lowest permanent income in the first category, the next highest 21.3% in the second category, etc. Given these categories, the figure shows the average percent of permanent income spent on expense shocks in each of these categories.

and Violante (2022) explain that one-asset models like ours typically do not match the percent of households with zero or negative liquid wealth unless they target it during calibration, because risk-averse optimizing agents avoid being near the liquidity constraint. Relative to the models studied in Kaplan and Violante (2022), this problem is particularly acute because we also allow for the "disaster" income shock. The possibility of this disaster income shock makes agents especially eager to avoid being near the borrowing constraint if possible, shifting median wealth closer to mean wealth.[9] Adding expense shocks to the model strengthens the precautionary motive and exacerbates the problem, which explains why (despite the lower discount factor) EES performs even worse than NES on this front.

Why so many households hold so little liquid wealth in the face of so much liquidity risk—including expense shocks—is outside the scope of our simple model, and we view it as a critical question for future research. Rather than changing the discount factor, consumption-savings models could change other parameters to explain agents' wealth holdings in the face of expense

[9]If we calibrate a version of NES without the disaster income shock to match mean normalized wealth of .6, the model-predicted median normalized wealth is .25. This is quite close to the baseline model-predicted median wealth of .2 reported in Column 5 Table 1 of Kaplan and Violante (2022).

shock risk. For example, agents could be less risk-averse, have quasi-hyperbolic (Laibson, 1997) or temptation (Gul and Pesendorfer, 2001) preferences, underestimate risk (Balleer et al., 2021; Wang, 2023) etc. Some of these approaches may perform better on matching the lower tail of the wealth distribution.

In the next two subsections, we contrast NES and EES to explore some of the potential implications of expense shocks for household finance and macroeconomics. A common theme is that, with expense shocks, income shocks are no longer the only mechanism to generate a high marginal value of liquidity. In EES even agents without income shocks may be liquidity-constrained because they have urgent spending needs outside typical models; for this reason, they may default on their payment obligations for liquidity considerations unrelated to income, or have high MPCs out of transitory income windfalls that traditional models would not predict.

6.3 Model results: Household finance

A long and ongoing debate in household finance, spanning multiple literatures, concerns the relative extent that liquidity shocks versus long-run financial ("strategic") considerations play in causing households to default on various payment obligations (e.g. Foote and Willen, 2018; Indarte, 2023).

Livshits, MacGee, and Tertilt (2007) emphasize the importance of accounting for expense shocks for this debate in the context of bankruptcy. Following their lead, in this subsection we briefly consider the theoretical role of expense shocks in a stylized default experiment. Understanding the implications of expense shocks for default is especially urgent given our finding that expense shocks are several times more common than the benchmark estimates used in Livshits, MacGee, and Tertilt (2007) and many papers since.

Specifically, we assume that agents in the models are suddenly and unexpectedly given the ability to default on a payment obligation they had been exogenously making with unmodeled income.[10] In effect, this gives agents the opportunity to claim extra liquidity; defaulting increases

[10] We could also explore agents' default decisions for a new and unexpected payment obligation out of modeled

their liquid wealth by d, which we set to equal to 25 percent of their income, and so in magnitude this experiment corresponds very roughly to consumer default on mortgage or rent payments. It is well-known that in many contexts consumers default on payment obligations less than pure financial considerations would suggest; to account for this many models of bankruptcy (Exler and Tertilt, 2020) and mortgage default (Foote and Willen, 2018) allow for non-financial default costs and calibrate them to match aggregate default rates. In this spirit, we assume that defaulting incurs a cost δ in terms of permanent income, and we set δ in the two models to match an aggregate default rate of .5 percent, which is roughly the annual foreclosure rate.

To achieve this default rate, NES sets default costs to equal 5 percent of permanent income, while EES sets costs that are 8.1 percent of permanent income, more than 50 percent higher. EES requires higher default costs to match the same default rate, even though it has fewer agents with very low liquid wealth, in part because (due to expense shocks) it still has more liquidity-constrained consumers that value the liquidity that defaulting provides. NES does not allow for defaults driven by expense shocks, so in order to target the same default rate as EES it sets default costs to be lower. Hence defaults in NES are more strategic than in EES, in the sense that they are driven less by liquidity constraints and more by wealth maximization.

In the spirit of Livshits, MacGee, and Tertilt (2007), we next explore the implications of expense shocks for default policy. In particular, we consider two policies a social planner may consider to reduce default rates. The first, "wage garnishment", punishes defaulters by permanently reducing their income by 1 percent. The second, a "liquidity injection", provides agents with a one-time payment worth 10 percent of their permanent level of income, whether or not they default.

Wage garnishment is more effective at reducing default rates in NES (default rates fall to .21 percent) than in EES (default rates fall only to .30 percent). However, liquidity injections are less effective in NES (default rates fall only to .39 percent) than in EES (where they fall to .29 percent). Because allowing for expense shocks leads defaults in the model to be more liquidity-driven

income, but this would require defining utility below the borrowing constraint.

and less strategic, we find that optimal default policy should be more accommodating towards defaulters because the ability to default provides valuable insurance to agents in the face of severe liquidity shocks.

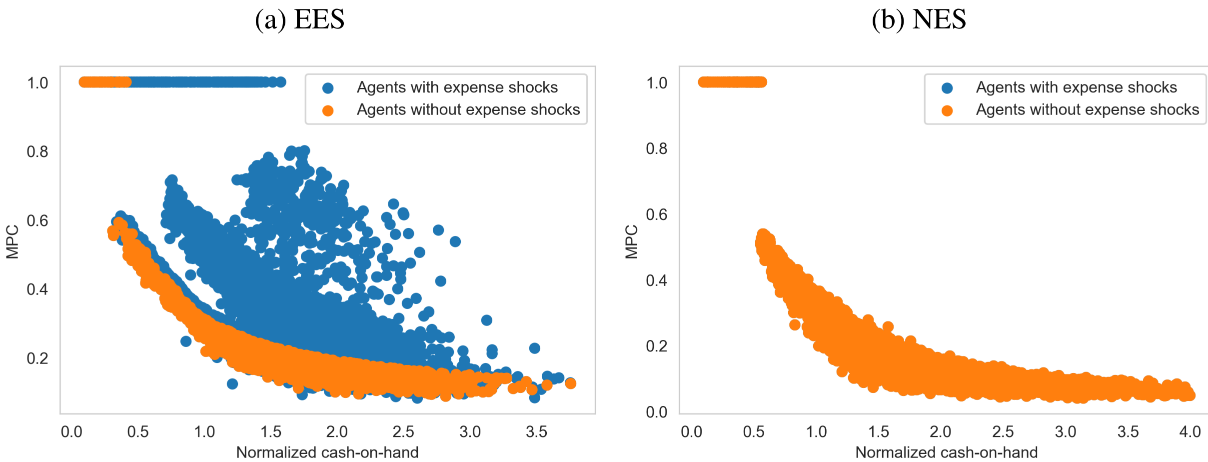
Hence we obtain the same basic result as Livshits, MacGee, and Tertilt (2007) for the same basic reason. However our model is much more stylized; therefore its results, though less conclusive, are more generalizable. The important lessons of Livshits, MacGee, and Tertilt (2007) have so far been mostly confined to the bankruptcy literature; our findings suggest that, because expense shocks are so large and so frequent, household default on a wide variety of payment obligations is likely less strategic than typically modeled. One application of our result is to mortgage default; models of mortgage default typically do not allow for the expense shocks we document (Foote and Willen, 2018), but expense shocks help explain recent empirical results that liquidity shocks—not strategic considerations—drive almost all mortgage defaults among households with stable income (Ganong and Noel, 2023; Low, 2023b). Another application is to the burgeoning structural literature on housing insecurity (İmrohoroğlu and Zhao, 2022; Favilukis, Mabille, and van Nieuwerburgh, 2023; Corbae, Glover, and Nattinger, 2023; Abramson, 2024; Abramson and van Nieuwerburgh, 2024), which studies the events that lead families to become homeless. These models often account for health shocks but the other the expense shocks we document. Our results also speak to a debate in the life insurance lapsation literature regarding the importance of liquidity shocks versus interest rate considerations in driving lapsation (see Koijen, Lee, and van Nieuwerburgh (2024) for a discussion). Fang and Kung (2020) find that idiosyncratic shocks that are uncorrelated with income and health are important for explaining life insurance lapsation, especially among younger households, which is consistent with our results. Our simple model suggests that our empirical results should inform future models on these and other topics related to debt or bill nonpayment.

6.4 Model results: Macroeconomics

Consumers' marginal propensity to consume (MPC) out of fiscal transfers is a central object of interest in macroeconomics (Kaplan and Violante, 2022; Crawley and Theloudis, 2024). As a result, developing models that are consistent with the evidence on MPCs has become a priority. Basic models predict a simple, monotonically decreasing relationship between household liquidity and MPCs, since wealthier households are less likely to need the fiscal transfers to smooth over income shocks. But a number of empirical studies have documented that the relationship between available measures of liquidity and MPCs is much more complex; many poor households have low MPCs, while many rich households have high ones. For an exhaustive review of this evidence, see Miranda-Pinto et al. (2023) or Crawley and Theloudis (2024) .

In our models, we examine agents' MPCs by giving them small additional liquidity and examining the proportion they spend immediately, on both c and x. Figure 9 provides a scatterplot of MPCs against cash-on-hand in the two versions of the model, breaking results out separately for agents experiencing nonzero expense shocks (blue dots) or not (orange dots.) Of course in NES, no agents experience expense shocks. For agents without expense shocks, the joint distributions of MPCs and cash-on-hand both follow the typical pattern in such simple models: agents with very little cash-on-hand often have high MPCs as they use the fiscal transfers to smooth over income shocks, but MPCs fall quickly with cash-on-hand because liquid households do not need the transfers to smooth consumption. Expense shocks introduce more liquidity risk into the model and so more households are liquidity-constrained. Moreover, because agents without income shocks can still experience severe expense shocks, expense shocks help to explain—as with the nonpayment decisions analyzed in Subsection 6.3—why even some moderate- or high-income households appear so constrained. Hence EES has a wider and higher range of MPCs even at higher levels of cash-on-hand, partially helping to reconcile the model with evidence that household observables are surprisingly poor predictors of MPCs (Lewis, Melcangi, and Pilossoph, 2024). Miranda-Pinto et al. (2023) embed expense shocks into a richer model and find that expense shocks help explain other important features of the data.

Figure 9: Scatterplot of MPCs against Normalized Cash-on-Hand

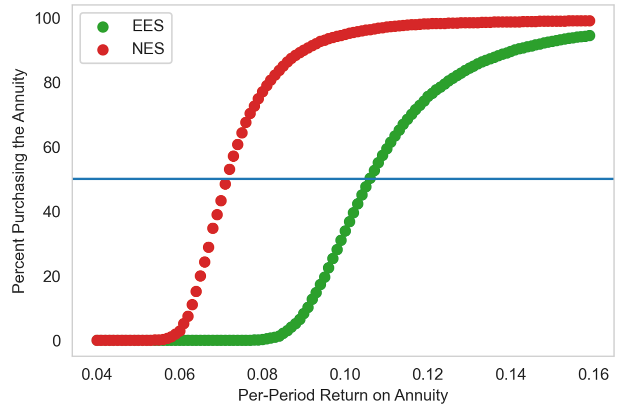


Notes: The figures show a scatterplot of MPCs on the y-axis against normalized cash-on-hand on the x-axis, for agents with (blue dots) and without (orange dots) expense shocks. The figure on the left is the model with expense shocks; the figure on the right is the model without expense shocks.

While realistic expense shocks help the model in many respects, they also exacerbate a different puzzle. Many households have substantial illiquid wealth but almost no liquid wealth (e.g. Laibson, Repetto, and Tobacman, 2003); this fact is considered critical for macroeconomic models to match, in order to explain both the level of aggregate wealth in the economy and hand-to-mouth behavior among cash-poor households (Kaplan and Violante, 2014, 2022). Models with both liquid and illiquid assets have been developed that can match some important features of the data, but in order for agents to simultaneously hold little liquid wealth (and so expose themselves to liquidity risk) and substantial illiquid wealth, these models typically require a sizable interest rate gap between the two assets that is often criticized as counterfactually high (Beshears et al., 2018; Kaplan and Violante, 2022).

Introducing expense shocks into EES increases the liquidity risk in the model and so increases agents' demand for the liquid asset; in order to keep liquid asset holdings in line with the data, as discussed in Subsection 6.2 the calibration strategy decreases agents' discount factor. This strategy roughly aligns demand for the liquid asset between EES, NES, and the data as intended. But to examine the impact of this calibration choice on the demand for an illiquid asset, we provide agents in both models with an unexpected, one-time opportunity to purchase an annuity that permanently

Figure 10: Annuity Demand in the Models



Notes: For a given per-period return on an annuity (x-axis), the y-axis shows the percent of agents in the models that would purchase the annuity. The horizontal blue line denotes where 50 percent of agents purchase the annuity.

increases agents' income.[11] We vary the per-period return on the annuity, and plot the percent of agents in each model that would purchase the annuity for a given return in Figure 10. Because agents in EES have lower discount factors, they require a significantly higher return on the illiquid annuity before they purchase it. For example, 50 percent of agents in NES would purchase the annuity if it offered a per-period return of roughly 7 percent; the return would have to be more than 10 percent for 50 percent of agents in EES to purchase it. By exposing households to much more liquidity risk than typically modeled, expense shocks appear to exacerbate the puzzle of why so many households hold such a small fraction of their wealth in liquid form.

7 Implications of expense shocks

The previous section models households' responses to unexpected and urgent spending needs. The model distinguishes between the underlying shock η and the amount a household spends x in response. For example, in response to a car breaking down, a household with liquid resources may fix it while a liquidity-constrained household may not, and instead pay a high but unmeasured utility cost. In this section, we show support for two of the model's predictions: (1) that measured

[11]We set the price of the annuity to be very low so that virtually all agents can afford the annuity.

expense shocks depend on household liquidity, and (2) they are correlated with financial distress.

While the model captures one important source of endogeneity, expense shocks may also be endogenous to other household choices and characteristics. Many expense shocks are endogenous to insurance or maintenance decisions made before the shocks occurred. Many of the most important shocks we measure such as medical expenses, home repairs, and auto repairs can be viewed as replacement or repair of durable goods subject to stochastic depreciation shocks. The amount households spend on insurance or routine maintenance affects their exposure to these shocks; for example higher-income households may be less exposed to expense shocks because they have more health, home, or auto insurance. However, higher-income households could also be more exposed to expense shocks because they are more likely to own cars or homes at all.

In addition, because many expense shocks can be viewed as replacement or repair of durable goods, over longer time horizons it may be the *timing* of the shocks that is unexpected rather than the *amount*. People may save to cover these expenses and self-insure. Lower-income or less wealthy households with less dependable durable goods may have less control over the timing of these shocks.

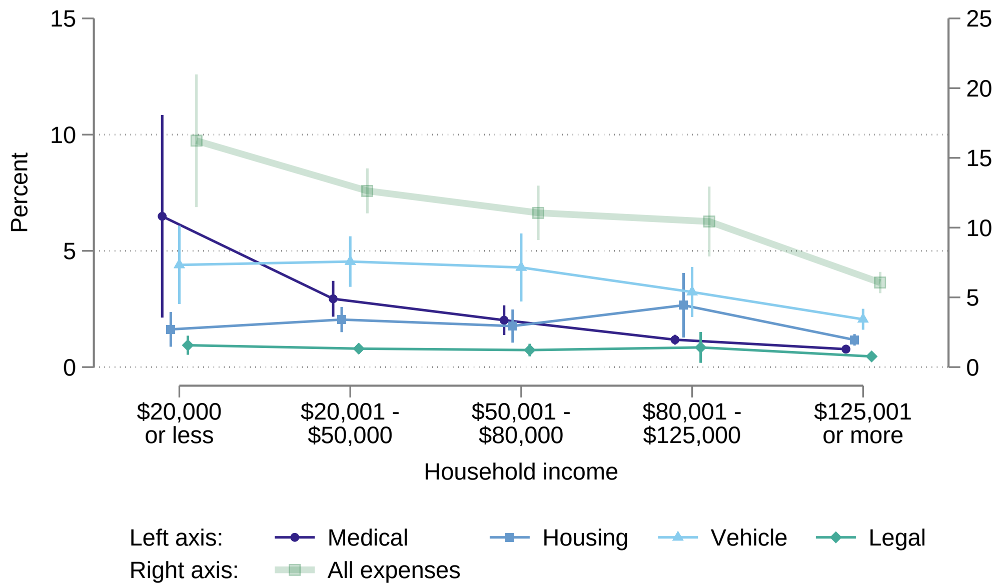
7.1 Expense shocks are partly endogenous

Income and expense shocks are to some extent endogenous; indeed previous work using the MEM survey (Fulford and Rush, 2020) shows that households in financial difficulty often seek new income and cut back on expenses. Many previous studies have shown that the endogeneity of income can have important policy implications (Low, Meghir, and Pistaferri, 2010; Zator, 2024). In this subsection we provide evidence on the endogeneity of expense shocks.

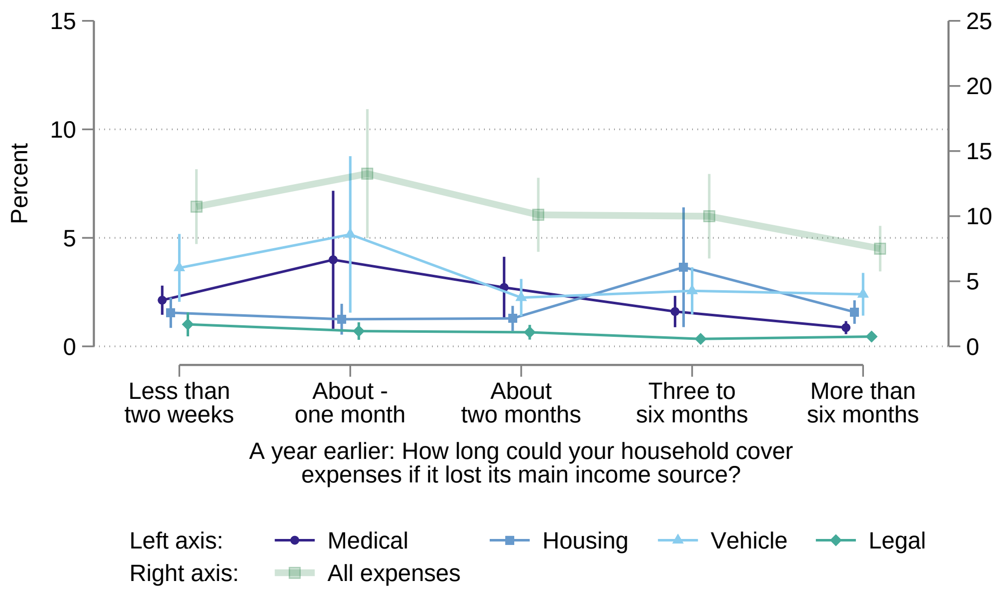
To help characterize the extent of different endogeneity forms, Figure 11 shows how expense shocks vary with income and available liquidity (we show the distribution by other groups in Section 5). The figure shows the share of income lost to all expense shocks (including households with no expense shocks) on the right axis and the share of income lost to the largest kinds of expense shocks on the left axis.

Figure 11: Share of income lost to expense shocks by income and available liquidity

Panel (A): Share lost by income



Panel (B): Share lost by liquidity



Notes: The share lost includes zeros for consumers who did not experience that shock. Panel (B) uses the respondents' answer to the liquidity question in the prior year and has a smaller sample size. Source: Authors' calculations from the 2022, 2023, and 2024 Making Ends Meet Surveys.

Figure 11 shows that expense shocks decline on average as income increases, so expense shocks are necessity and not luxury goods. This decline is inconsistent with the hypothesis that high income households choose to spend more on expense shocks on average. On the other hand, the decline is consistent with several other approaches. First, it suggests that expense shocks are generally negative and financially destabilizing events (Livshits, MacGee, and Tertilt, 2007). Second, it suggests lower-income households are more exposed to shocks, which would explain why lower-income households have stronger precautionary motives (Fulford, 2020).

On the other hand, on average expense shocks decline only slightly with with liquidity in Panel (B), which is consistent with the model prediction that liquidity constraints sometimes prevent households from spending on shocks. Panel (B) suggests that our measured expense shocks may be limited by available liquidity, so for constrained households the utility costs of spending needs may be high even when spending is low. Section 6 models this observation explicitly. Panel (B) is also consistent with the argument that liquidity constraints prevent some households from maintaining (Kluender, 2023; Fang and Kung, 2020) or using (Gross, Layton, and Prinz, 2022) insurance that would protect them from expense shocks.

Within expense shock categories, the negative correlation with income is strongest for medical expenses. While all households are subject to medical shocks, only households with the income to own a vehicle or home are subject to vehicle and home repair expenses. Moreover, unlike other expenses, medical expenses often do not require cash or credit in advance, so this decline could indicate that liquidity constraints matter more for other expenses. This negative correlation could also arise because higher-income consumers have access to more or better health insurance, although we observe the decline both for households with and without health insurance.

More broadly, lower-income consumers could be more exposed to expense shocks if (as in our model) demand for expense shock spending is not homothetic. It is also possible that financial distress itself increases expenditure risk; for example eviction or foreclosure exposes families to moving costs (Diamond, Guren, and Tan, 2020; Collinson et al., 2024).

Credit scores are highly predictive of households' credit access, so how shocks vary by credit

Table 6: Income and expense shocks across credit score groups

	Income lost to unexpected expenses (%)	Income lost to income drops (%)	Fraction with unexpected expense	Fraction difficulty paying bills	Fraction did not pay all expense
Credit score one year before survey					
300-540	7.8	10.8	0.748	0.713	0.503
	(0.63)	(1.18)	(0.0227)	(0.0318)	(0.0392)
540-599	11.1	8.2	0.742	0.724	0.463
	(1.51)	(0.77)	(0.0218)	(0.0285)	(0.0344)
600-659	9.9	6.8	0.724	0.632	0.397
	(0.95)	(0.71)	(0.0216)	(0.0278)	(0.0356)
660-719	11.9	4.9	0.657	0.424	0.301
	(1.81)	(0.55)	(0.0233)	(0.0282)	(0.0364)
720-779	10.3	4.0	0.715	0.295	0.203
	(0.93)	(0.37)	(0.0177)	(0.0204)	(0.0305)
780-850	9.5	3.4	0.666	0.124	0.193
	(0.71)	(0.30)	(0.0131)	(0.0103)	(0.0360)
Observations	9502	7498	9506	5067	2212

Notes: Credit score is as of the end of December 12 months before the survey. Income drops and unexpected expenses include zeros for households without such a loss. Standard errors for means or coefficients in parentheses. All results are survey weighted. Source: 2022, 2023, and 2024 Making Ends Meet surveys except for income drops which is only 2023 and 2024.

score provides information on the relationship between liquidity and expense shocks.[12] Table 6 shows how income and expense shocks vary by credit score. We measure the credit score one year before each survey to avoid a mechanical connection between income and expense shocks and credit score.

People with lower credit scores lose more income to income drops the subsequent year but do not have larger unexpected expenses. One reason appears to be because of available liquidity. The third column shows that lower credit score respondents are about as likely, or possibly more likely, to have a non-zero unexpected expense. The fourth column shows that they are much more likely to report having “difficulty paying a bill or expense” in the previous year. Among those with

[12]For example, in response to the survey question “If you lost your main source of income, about how long could you cover expenses by borrowing, using savings, selling assets, or seeking help from family or friends?” 53 percent of consumers with lagged scores between 300 and 499 answered less than two weeks, while only 3 percent answered six months or more. Among consumers with lagged scores between 781-850, only 3 percent answered less than two weeks while 53 percent answered six months or more.

difficulty, half of lower credit score respondents selected that they did not pay all of the bill or expense that they had difficulty with, a much higher percentage than high credit score respondents. These questions were in a different section of the survey than the expense shock questions, so we do not know whether the respondent did not pay all of a specific unexpected expense.

We take the results in Figure 11 and Table 6 as evidence that observed expense shocks are limited by available liquidity; many respondents would spend more if they could, so the utility costs of urgent spending needs can be high even if spending on those needs is low, a key prediction of the model in Section 6.

7.2 Expense shocks are correlated with financial distress

Section 4 shows that, in terms of size and frequency, expense shocks are quantitatively comparable to income shocks. Other work with MEM shows that when households have difficulty paying bills, they frequently point to both expense shocks and income shocks as the cause (Fulford and Rush, 2020). However, income shocks and expense shocks may have different implications for individual and macroeconomic outcomes. In this subsection we use our unique data to explore the correlation between expense shocks' size and financial distress.

Table 7 shows average marginal effects from a series of logit regressions that include indicators for experiencing an expense or income shock of different sizes. The outcome variable is a survey question that asked "At any time in the past 12 months have you or your household had difficulty paying for a bill or expense?" Because "having difficulty" may mean different things to different respondents, the surveys asked respondents who had difficulty if they had difficulty paying for food, among other options. We interpret having difficulty paying for food as a sign of severe financial distress with potentially high marginal utility costs. The first two columns of Table 7 control for log household income (before any income drops), education, and credit score a year before the survey.

Table 7 shows that expense shocks and income shocks are correlated with having difficulty

Table 7: Shocks and financial distress

	Had difficulty	Had difficulty with food	Had difficulty	Had difficulty with food
Expense (0, 20]	0.160***	0.0989***	0.136***	0.0804***
	(0.0100)	(0.00886)	(0.0110)	(0.00954)
Expense (20,40]	0.200***	0.129***	0.199***	0.121***
	(0.0178)	(0.0162)	(0.0201)	(0.0179)
Expense (40, 60]	0.215***	0.120***	0.215***	0.121***
	(0.0301)	(0.0273)	(0.0342)	(0.0305)
Expense (60, 80]	0.118***	0.111***	0.145***	0.126***
	(0.0381)	(0.0343)	(0.0449)	(0.0405)
Expense (80, .)	0.165***	0.148***	0.184***	0.169***
	(0.0325)	(0.0301)	(0.0376)	(0.0357)
Income drop (0, 20]	0.157***	0.133***	0.238***	0.193***
	(0.0118)	(0.0106)	(0.0129)	(0.0120)
Income drop (20,40]	0.214***	0.153***	0.308***	0.230***
	(0.0202)	(0.0182)	(0.0213)	(0.0215)
Income drop (40, 60]	0.292***	0.209***	0.390***	0.302***
	(0.0273)	(0.0250)	(0.0270)	(0.0291)
Income drop (60, 80]	0.340***	0.317***	0.416***	0.366***
	(0.0393)	(0.0388)	(0.0382)	(0.0438)
Income drop (80, .)	0.394***	0.462***	0.385***	0.415***
	(0.0479)	(0.0554)	(0.0538)	(0.0621)
Observations	8,904	8,536	9,370	8,971
Controls	Yes	Yes	No	No

Notes: The table presents average marginal effects from logit regressions. The bins are 20 percent bins of expense and income drops as a percent of pre-drop income. The zero expense bin and zero income drop bin are excluded, so the coefficients are relative to zero income or expenses. "Had difficulty" denotes that the respondent answered yes to "At any time in the past 12 months have your or your household had difficulty paying for a bill or expense?" "Had difficulty with food" denotes the respondent answered yes both to "had difficulty" and to a followup question for difficulty paying for food. Controls are: log household income (before income drops), education, and lagged credit score. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Source: Authors' calculations from the 2022, 2023, and 2024 Making Ends Meet surveys.

paying for expenses and having difficulty paying for food.[13] The indicator for not having a shock is excluded, so for example Table 7 shows that for an otherwise average household the logit model estimates that an expense shock between 0 and 20 percent of income predicts a 16 percent higher probability of difficulty paying bills or expenses, and a 10 percent higher probability of difficulty paying for food.

Moderate expense shocks (around 40 percent of income or less) are just as predictive of financial distress as comparably-sized income shocks. However—and perhaps surprisingly—the conditional correlation between expense shocks and financial distress varies little with their size, while larger income shocks are more predictive of financial distress. As a result, the very largest income shocks have average marginal effects that are roughly three times larger than those of comparably-sized expense shocks.

One potential explanation for this result is that paying for large expense shocks likely requires significant liquidity, and households with significant liquidity are unlikely to have difficulty paying for bills or expenses.[14] This explanation is consistent with our model's prediction that the expense shocks we observe are paid by households with the liquidity to pay them. It is also consistent with our results in Table 6 that lower credit score consumers are much more likely to report not paying for bills or expenses, and with previous findings (Adams et al., 2022) that some constrained consumers incur large utility costs to avoid paying for expense shocks. Because some urgent spending needs go unmet, measured expense shocks likely underestimate the size and frequency of urgent expense needs.

While very large expense shocks are less predictive of financial distress than similarly sized income shocks, they are also more common. For example, Figure 2 shows that expense shocks costing more than 60 percent of income are 1.5 times more common than similarly sized income drops and expense shocks more than 80 percent of income are 5 times more common. Together, these

[13] One potential explanation for the literature's focus on medical expense shocks is the argument that medical shocks may be more predictive of financial distress than other expense shocks. When we run versions of the logit regressions behind Table 7, we find little evidence that the relationship between expense shocks and financial distress depends on the proportion of unexpected expenses that come from medical expenses. However, expense shocks with any medical spending component are somewhat more predictive of financial distress.

[14] Another potential explanation is that large income drops are likely more persistent than large expense shocks.

results broadly suggest that financial distress is as related to expense shocks as to income shocks. This finding is consistent with causal evidence from the mortgage default literature (Ganong and Noel, 2023; Low, 2023b), but more broadly applicable in household finance and macroeconomics.

8 Discussion and conclusion

In this paper, we use unique survey data to empirically quantify, for the first time, all the expense shocks that households face. We find quantitatively that expense shocks are at least as large as income shocks, so typical research neglecting them understates the liquidity shocks households face by at least half on average. Relative to important and influential previous work emphasizing the importance of expense shocks (Livshits, MacGee, and Tertilt, 2007), we find that expense shocks of any size are almost ten times more common, while particularly large expense shocks (on the order of 80 percent of income) are over three times more common. Our expense shock estimates are so much larger than previous ones because our data allow us to measure all expense shocks, not just a limited subset such as medical expenses. Our results demonstrate that households are subject to liquidity shocks that together are much larger and more common than typically modeled and allow future research to fully account for expense shocks.

Our results have important implications for many topics in economics and household finance. Informed in part by our simple model developed in Section 6, we discuss how our empirical results may help resolve puzzles or inform debates in several literatures below.

Consumption smoothing and insurance A benchmark prediction of standard models is that risk-averse agents should smooth consumption in the face of income shocks. Based on this prediction a large literature estimates the pass-through of income shocks to consumption, and the implications for the ability of households to self-insure against liquidity shocks and other topics (for a review, see Crawley and Theloudis, 2024). However, when agents face expense shocks as well as income shocks, it is no longer clear that smoother spending is indicative of more insurance (Blundell et al., 2024). Indeed, volatile spending may in some cases demonstrate effective insurance, as it could indicate agents have the ability to spend when expense shocks occur. Supporting this mechanism, we find evidence that some households are constrained in how much they spend in response to expense shocks.

Precautionary saving An extensive structural literature emphasizes the importance of liquidity risk and precautionary wealth for macroeconomic outcomes (for reviews see Kaplan and Violante (2022) or Cherrier, Duarte, and Saidi (2023)). This literature typically finds that models in which agents have full information and rational expectations ("FIRE") about income risk are able to match levels of precautionary savings with reasonable preference parameters. However, an already large and ever-growing literature documents many empirical departures from FIRE models (for one review see Beshears et al., 2018). Many of these departures would generally lead agents to accumulate less precautionary wealth, such as quasi-hyperbolic (Laibson, 1997) or temptation (Gul and Pesendorfer, 2001) preferences, or underestimated income risk (Wang, 2023). In light of the substantial empirical evidence behind this latter set of findings, it may seem puzzling that FIRE models without these ingredients can match households' liquid wealth levels.

Our paper could help to resolve the tension between these two literatures by demonstrating that, in addition to income risk (which FIRE models account for), households are also subject to considerable expense shock risk (which FIRE models abstract from).[15] In the face of this extra risk, agents in FIRE Models should accumulate more precautionary wealth. Nonstandard preferences or beliefs could help constrain agents' liquid wealth accumulation to observed (and often low) levels, even in the face of additional risk.

This reconciliation seems promising to us because it is consistent with survey evidence that consumers are more motivated to accumulate precautionary saving for expense shocks than income shocks (Fulford, 2015, 2020), and with previous theoretical models that argue expense shocks drive much precautionary saving (Kotlikoff, 1986; Hubbard, Skinner, and Zeldes, 1994; De Nardi, French, and Jones, 2010).[16]

[15] Complementary papers argue that households also face more income risk than FIRE models typically account for (Guvenen, Ozkan, and Madera, 2024; Ganong et al., 2024).

[16] However there is also evidence that households underestimate their exposure to expense shocks (Sussman and

Social networks We find that “unplanned gifts or loans" to a family member or friend are common and can be costly. Transfers from social and family networks can help families smooth over shocks, but demands from these networks can also cause financial distress. While an extensive literature studies these sharing networks’ consequences in developing countries (see, for example, Kinnan and Townsend (2012); Fafchamps and Lund (2003)) and their potential to cause poverty traps (Hoff and Sen, 2006), our results suggest they are important in the U.S. as well.

Consumption heterogeneity and macroeconomics The distribution of the marginal propensity to consume (MPC) across households and over the business cycle is one of the most important and controversial question in macroeconomics (Kaplan and Violante, 2022). Our model shows that, because of the large and frequent expense shocks we estimate, typical measures of cash-on-hand are not a sufficient statistic for MPCs; even some households with stable income may have high MPCs because of unexpected spending needs. This finding is consistent with evidence that there is substantial unobserved heterogeneity in MPCs (Lewis, Melcangi, and Pilossoph, 2024; Boehm, Fize, and Jaravel, 2023; Colarieti, Mei, and Stantcheva, 2024), and with the argument of Miranda-Pinto et al. (2023) who show that expense shocks have a number of important and realistic implications for MPCS. For example, the expense shock model of Miranda-Pinto et al. (2023) is consistent with evidence that MPCs of lower income consumers are countercyclical (Gross, Notowidigdo, and Wang, 2020; Jeon and Walsh, 2023), and that the relationship between MPCs and household income is U-shaped during expansions (Jeon and Walsh, 2023).

Miranda-Pinto et al. (2023) explore other macroeconomic implications of expense shocks; for example they find that expense shocks increase the welfare costs of income shocks by an order of magnitude. Other papers that explore some implications of expense shocks in macroeconomic models include Telyukova (2013) and Ferro (2022).

Payday Loans Interest rates on payday loans are remarkably high—they often have an annualized rate above 300 percent —and many payday loan borrowers pay this interest for a long time by

Alter, 2012; Berman, Tran, and Zauberman, 2016; Howard et al., 2022).

rolling their loans over repeatedly. A frequent argument is that frequent expense shocks help explain this behavior (Saldain, 2023; Huang, 2023). We find strong evidence that expense shocks are considerable, especially among lower-income consumers who are particularly likely to use payday loans.

Mortgage default Many foreclosed homeowners have positive home equity (Ambrose and Capone, 1998), but typical models predict abovewater homeowners do not default (Foote and Willen, 2018). Abovewater default is financially costly and so challenging to generate in a structural model; liquidity shocks beyond income shocks help to explain why so many abovewater households are so constrained that they default (Low, 2015). This is especially true because foreclosure also involves many non-financial costs (Diamond, Guren, and Tan, 2020) and because most abovewater mortgage delinquencies do not result in foreclosure (Ambrose and Capone, 1998), so to match abovewater foreclosure rates a realistic model must generate a large number of homeowners in severe financial distress in order to match the smaller number that experience foreclosure (Low, 2023a). In this paper, we show that expense shocks are surprisingly frequent and large, helping to explain why abovewater default is so common. This finding is consistent with evidence in Ganong and Noel (2023) and Low (2023b) that expense shocks contribute to many mortgage defaults.

Bankruptcy We show that, after accounting for non-medical expense shocks, expenditure shocks are almost ten times as common (and severe expense shocks several times more common) than bankruptcy models typically assume. As shown in our stylized model, larger expenditure shocks increase the tendency of households to default on loans. But in order to keep default rates stable at empirically observed levels, this in turn implies that unobserved bankruptcy costs must be higher than they are in typical models, as empirical evidence suggests (Gross, Notowidigdo, and Wang, 2014; Gross et al., 2021; Albanesi and Nosal, 2022). The implication that many bankruptcies are likely driven by expense shocks besides, or in addition to, medical expense shocks is consistent with evidence that medical expense shocks directly cause only a minority of bankruptcies (Dobkin et al., 2018a,b), yet contribute to many or most bankruptcies (Himmelstein et al., 2005). It is also consistent with evidence that the medical expense shocks that contribute to bankruptcy are on average modest in size (Himmelstein et al., 2005),[17] while also being consistent with evidence that liquidity is a much stronger driver of bankruptcy than moral hazard (Indarte, 2023).

Credit scores and default on other loans As shown in Section 6, the moral hazard and strategic default considerations discussed above for mortgage default and bankruptcy also apply to other credit topics. Indeed, most defaults do not end in bankruptcy; civil judgments resulting in wage garnishment or asset seizures are more common (Fulford and Nagypál, 2023). There are several active policy debates that revolve around consumer reporting and scoring, including what kinds of defaults should appear on credit reports, how long they should remain on them, how much wage garnishment should be allowed, and what credit scores proxy for (Gibbs et al., 2023; Chatterjee et al., 2023). Our results inform these debates by showing that households—especially lower income households—face larger risks than previously assumed so liquidity shocks are more important, and strategic default less important, in explaining default than typically modeled.

[17]Because they find that about half of people declaring bankruptcy report health shocks as a contributing factor, Himmelstein et al. (2005) are often criticized as implying an implausibly large role of health shocks in driving bankruptcy. But they also find that out-of-pocket medical expenses averaged only about $12,000 among people declaring bankruptcy, a number several times smaller than the average health expense shock estimated in Livshits, MacGee, and Tertilt (2007). These findings suggest that medical expense shocks are often fairly modest in size relative to other concurrent liquidity shocks contributing to bankruptcy. This point was made by critics (Dranove and Millenson, 2006) of Himmelstein et al. (2005), and we find evidence for it in Figure A-6.

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A Data construction

A.1 Duplicate income drops

Several income drop categories can reasonably overlap. For example, in Table 2 someone might "Work less because of illness or injury" and have a "Reduction in work hours" from the same event. When calculating the total income lost in a year we attempt to remove extra costs that represent the same event where it was reasonable for the respondent to include both. For example, if the respondent selected both "illness or injury" and "reduction in work hours" and put the same value for "how much income did you lose" for both, we include only one drop in our calculation of total income drops.

Tables A-1 and A-2 show the combinations where respondents gave the same cost for more than one income drop. The income drop codes correspond to the row numbers in Table 2. The first column shows the number of consumers with that combination. Some events, such as working less to care for children (8), others who were sick or injured (7), or for illness or injury (6) could reasonably be read to be the reason behind unemployment (1), reduction in work hours (2), and reduction in wages (3) and these combinations are common. For other combinations, it is less obvious that the two events overlap despite having identical values.

The last column records whether we decided to suppress extra values. Our decision rule is that putting the exact same value for events that could plausibly overlap suggests that the events were the same to the respondent, so we suppress extra costs when calculating totals except where it is difficult to see an overlap between the events.

Because there is inherently a subjective element in the decision rule, we report income drops without any suppression. The number of consumers affected is not large, but experiencing multiple large events of the same size even for a few consumers increases the impact of income drops. Compared to the last row in Table 2, the income share lost if experienced is 1.7 percentage points higher at 19.73 percent. The mean cost is \$21,644, the 25th percentile, \$1,880, the median \$7,800, and the 75th percentile \$21,500.

A.2 The January 2022 Making Ends Meet survey

The January 2022 Making Ends Meet survey asked nearly identical expense questions to the 2023 and 2024 surveys,[18] but had a different block of income questions. This appendix discusses the income questions and how we calculate an approximate income fraction lost for comparison with the January 2023 follow up survey.

The January 2022 survey asked respondents: "In the past 12 months, have you or someone in your household experienced a significant drop in income from any of the following?" and provides a list of 12 possibilities. The survey gave one column for "You" and a separate column for "Someone else in your household," allowing us to break these out, but only asked for a check in the column if the respondent experienced the event, not an active no. The 2022 survey included a retired option. We exclude retirement from the reporting and discussion as a mostly voluntary and planned income drop.

Relative to the 2023 and 2024 surveys, asking about you and your household separately has a similar incidence of households experiencing an income drop, at 32.9 percent in 2022 (calculating incidence as either "You" or "Someone else in your household" experienced at least one income drop and defining the potential responses as respondents who answered the household income question).

A followup question asked respondents who experienced a significant income drop "about how much your monthly income dropped" and "how many months did this last?" for the largest income drop if there was more than one. We calculate a yearly income drop by multiplying the monthly income drop by the months (capped at 12) that the drop lasted. We have examined several methods for calculating an approximate total income drop given the question asks only about the largest. All of them are imperfect and yield income drops that are larger as a fraction of income than the average experienced in 2023. We describe and implement an approach that gives a reasonable comparison to 2023 and 2024, but acknowledge it makes several assumptions.

[18]Relative to the later surveys, on the 2022 survey the "unplanned gift or loan" option read "giving a gift or loan to a family member or friend outside your household," the "medical or dental expense" option did not include "out-of-pocket" and the 2023 and 2024 surveys had a new option "moving costs."

In 2023, we calculate the ratio of subsequent income drops for households that experienced more than one. The second drop is, on weighted average, 50 percent of the first income drop. The third drop is 54.9 percent of the second drop and the fourth drop (of which there are not many) is 63.3 percent of the third drop. We apply these ratios to the "largest income drop" in the 2022 survey for households that experienced more than one type of drop (treating either you or someone else in the household experiencing a drop as one event). We do not calculate income drop for events more than four.

Using this approach, the weighted mean income lost to income drops is 24.2 percent, the 25th percentile is 5.2 percent, the median is 14.6 percent, and the 75th percentile is 35.1 percent each of which are several percentage points larger than their corresponding values in Table 2.

Other approaches produced larger falls. One approach was to calculate the average income lost for households that had only one income drop in 2022, then apply that income drop calculate smaller income drops for households that experienced more than one drop.

The income adjustments do affect the share of income lost to expenses because these rely on the pre-drop income. However, because the correlation between expense drops and income drops is low, the impact is small. Indeed, the expenses shocks we calculate in 2022 are nearly identical to the 2023 shocks (with standard errors in parentheses): 68.5 percent (2.1) experienced an expense shock, with the mean income lost 14.9 percent (1.2) nearly the same as in Table 1. The 25th percentile lost to expense shocks is 2.5 percent, the median is 6.3 percent, and the 75th percentile is 15.7 percent, compared to 2.7 percent, 6.6 percent, and 15.9 percent in 2023.

B Conditional expectation of shocks

This section examines the share of people who had one shock who also had another. These matrices help understand whether some types of shocks often accompany others. Because some of the cell sample sizes are small, the standard errors for these estimates are relatively large (and are not shown for space), so we report them because they help identify interesting patterns but do not place large weight on any particular estimate.

Figure A-3 shows unexpected expenses conditional on experiencing other unexpected expenses. In Figure A-3, 45 percent of people who had an unexpected significant moving cost also had an unexpected increase in childcare expenses, while only 16 percent of people with an unexpected medical expense also had an increase in childcare expenses.

Figure A-4 shows income drops conditional on experiencing other income drops.

Finally, Figure A-5 shows conditional means for unexpected expenses and income drops. The top panel shows how often a household that had experience the unexpected expense on the left also experienced the income drop on the bottom. The bottom panel switches the conditional, showing how often a household that had experienced the income drop on the bottom also experienced the expense drop on the left.

Figure A-1: Unexpected expense and income drop questions in the 2023 Making Ends Meet survey

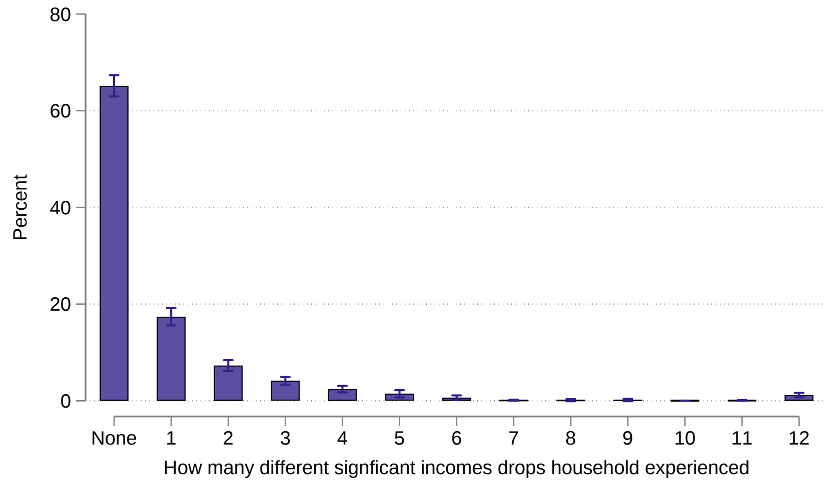
33. In the past 12 months, has your household experienced a significant unexpected expense from any of the following?

	No	Yes	If yes, about how much was the cost?
A major out-of-pocket medical or dental expense	☐	☐	$ ________ .00
An unplanned gift or loan to a family member or friend outside your household	☐	☐	$ ________ .00
A major vehicle repair or replacement	☐	☐	$ ________ .00
A major house or appliance repair	☐	☐	$ ________ .00
A computer or mobile phone repair or replacement	☐	☐	$ ________ .00
Legal expenses, taxes, or fines	☐	☐	$ ________ .00
Increase in childcare or dependent care expenses	☐	☐	$ ________ .00
Moving costs	☐	☐	$ ________ .00
Some other major unexpected expense	☐	☐	$ ________ .00

34. In the past 12 months, has your household experienced a significant drop in income from any of the following?

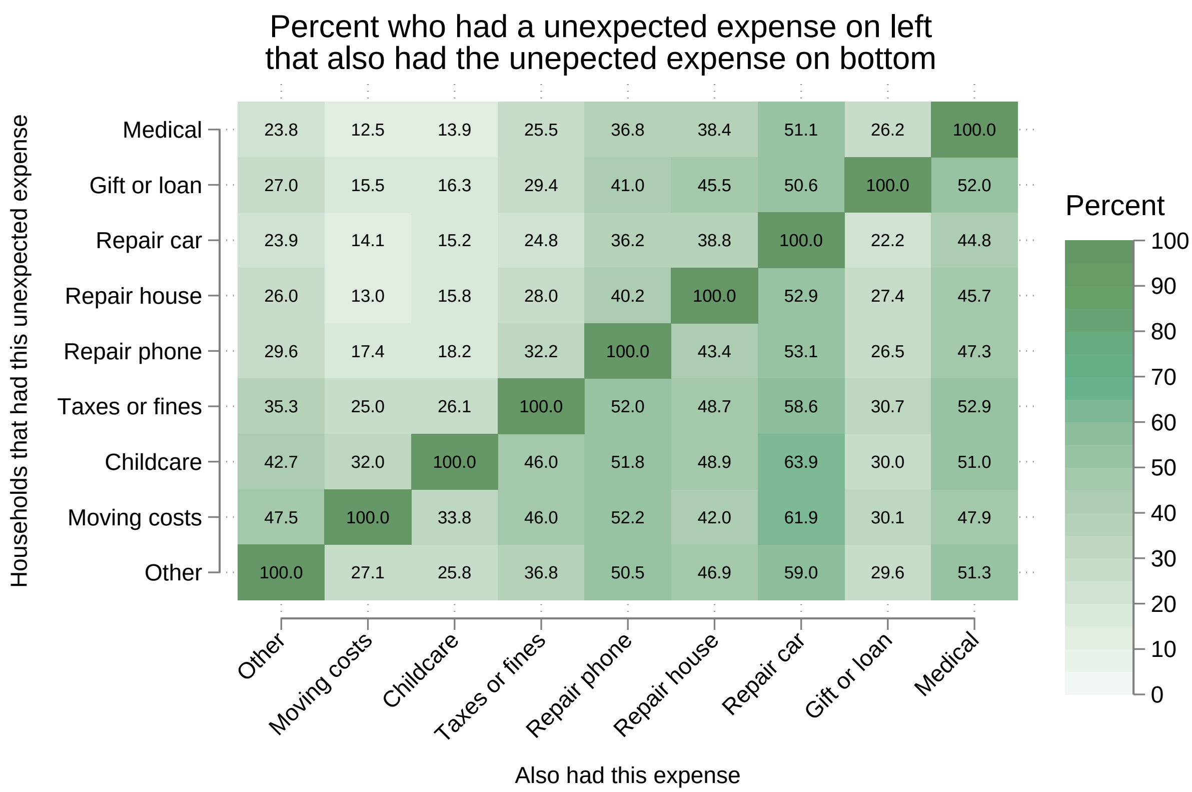
	No	Yes	If yes, about how much income did you lose because of this circumstance over the past 12 months?
Period of unemployment or furlough	☐	☐	$ ________ .00
Reduction in work hours	☐	☐	$ ________ .00
Reduction in wages at your job	☐	☐	$ ________ .00
Changed to a lower-paying job	☐	☐	$ ________ .00
Loss of government benefits	☐	☐	$ ________ .00
Worked less because of illness or injury	☐	☐	$ ________ .00
Worked less to care for others who were sick or injured	☐	☐	$ ________ .00
Worked less or stopped working to take care of children	☐	☐	$ ________ .00
Lost rental income from a property you own	☐	☐	$ ________ .00
Loss of revenue from a business you own	☐	☐	$ ________ .00
Loss of income due to a natural disaster	☐	☐	$ ________ .00
Other significant drop in income	☐	☐	$ ________ .00

Figure A-2: How many different significant income drops households experience



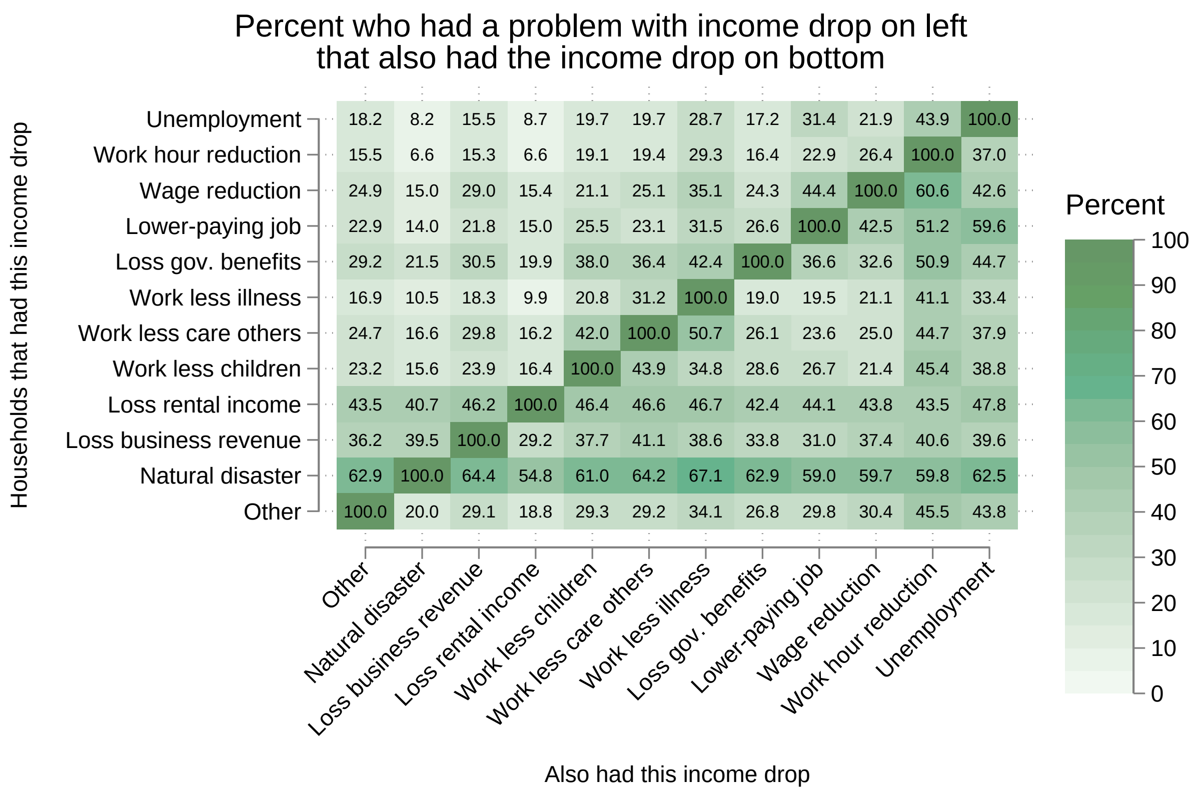
Notes: Source: Authors' calculations from the 2023 and 2024 Making Ends Meet surveys.

Figure A-3: Expenses conditional on expenses



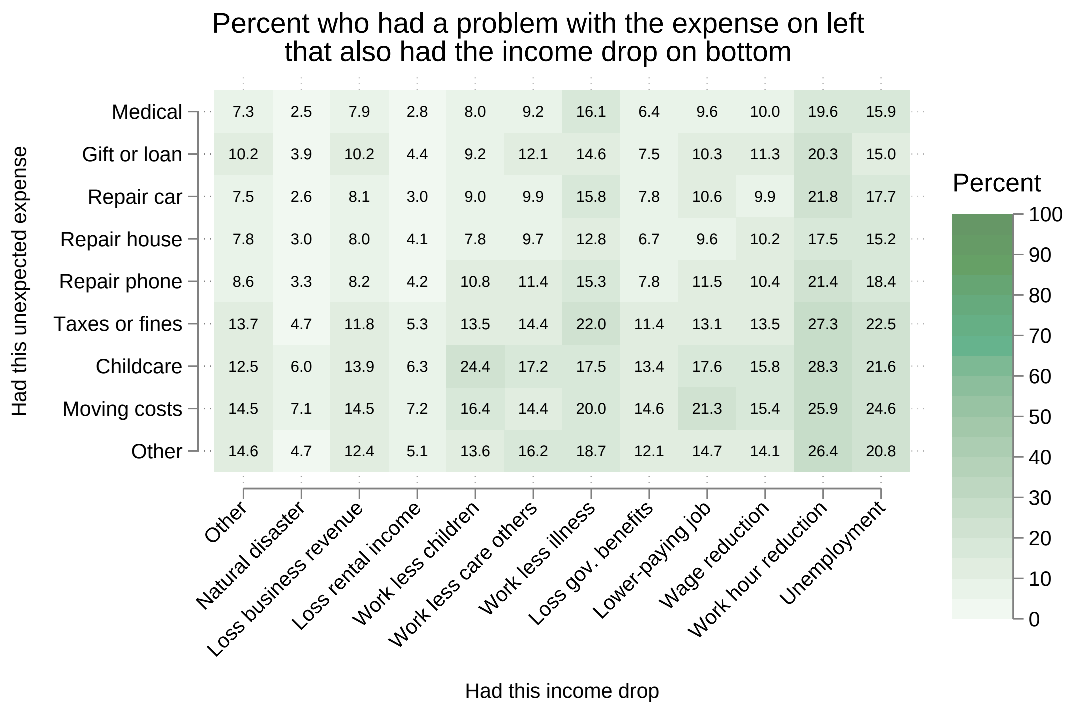
Notes: Each cell shows the conditional share of the population with the expense on the left that also had the expense on the bottom. Source: 2023 and 2024 Making Ends Meet surveys.

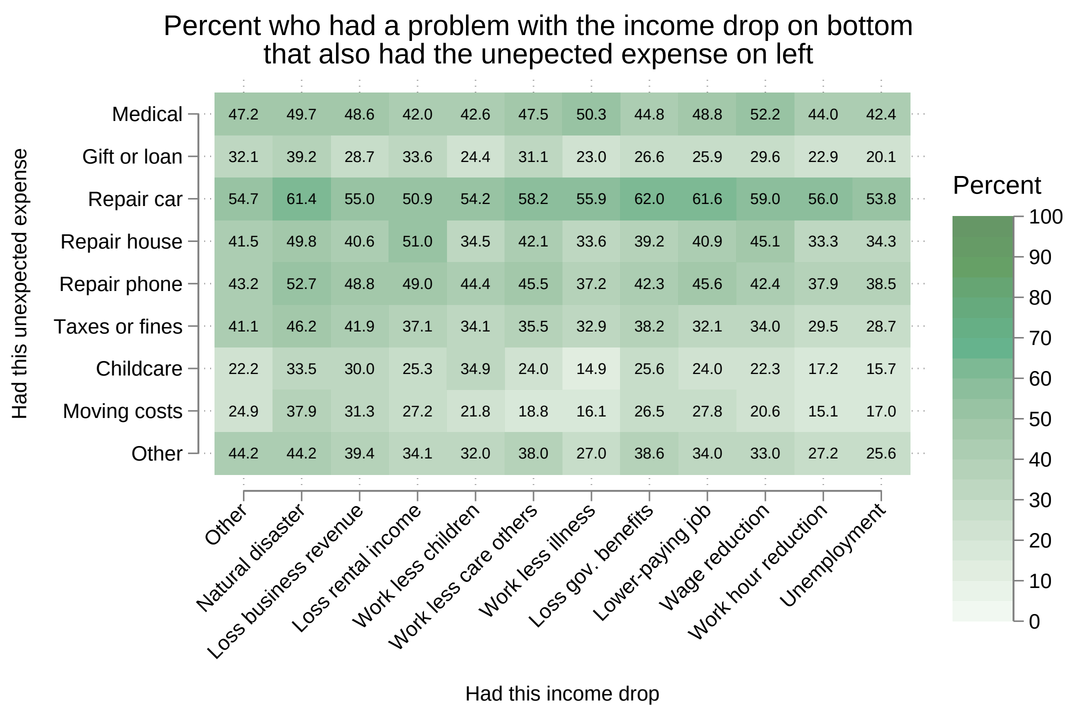
Figure A-4: Income drops conditional on income drops



Notes: Each cell shows the conditional share of the population with the income drop on the left that also had the income drop on the bottom. Source: 2023 and 2024 Making Ends Meet surveys.

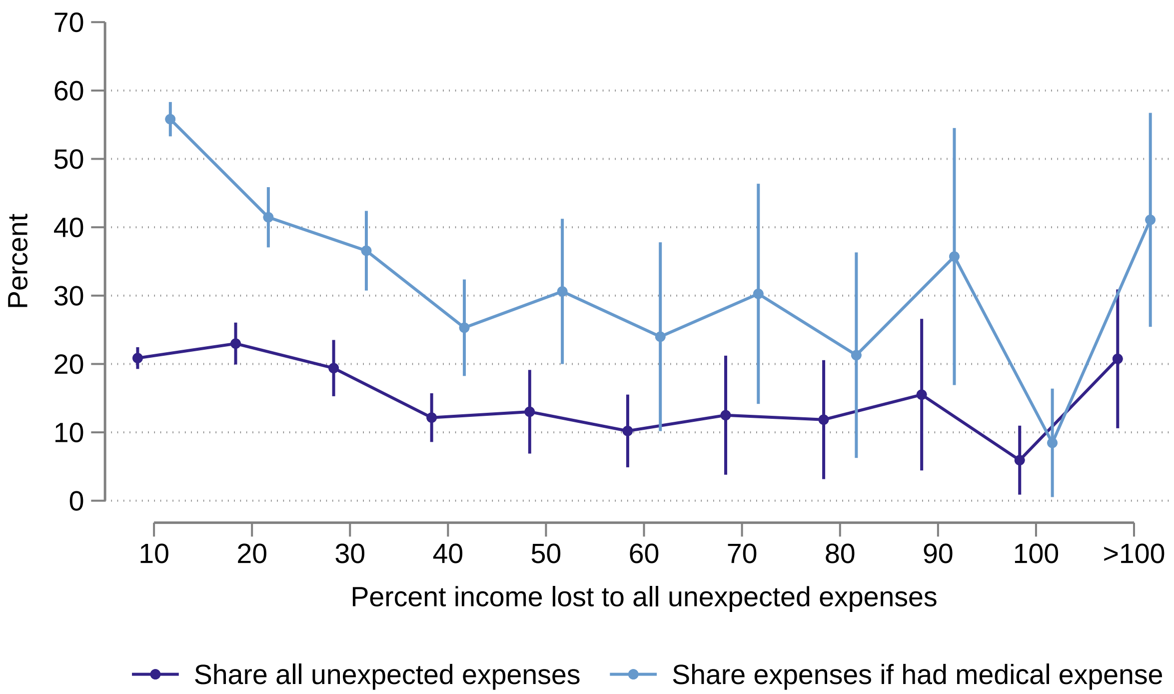
Figure A-5: Income conditional on expenses and expenses conditional on income





Notes: Each cell shows the conditional share of the population with the expense on the left that had the income drop on the bottom (top panel) or the share with the income drop that had the unexpected expense (bottom panel) Source: 2023 and and 2024 Making Ends Meet survey.

Figure A-6: Share of medical expenses in all unexpected expenses by share of income lost to all unexpected expenses



Notes: In the first (lower) line, the share of medical expenses in all unexpected expenses includes medical expenses as zero when the household did not have one. In the second (higher) line, medical expenses are never zero because only households with a medical expense are included. The second line therefore shows that, except for the lowest percent of income lost, for households with a medical expense the medical expense was only around 40 percent of all unexpected expenses. Drop lines show 95 percent confidence intervals. Source: 2022, 2023, and 2024 Making Ends Meet surveys.

Table A-1: Duplicate income events with more than one consumer

Consumers	Income drop code				Suppress extra
16	2	3	0	0	Y
14	1	2	0	0	Y
13	7	8	0	0	Y
12	1	6	0	0	Y
10	6	7	0	0	Y
8	1	8	0	0	Y
7	1	2	6	0	Y
7	2	6	0	0	Y
7	2	8	0	0	Y
7	3	4	0	0	Y
5	1	2	3	0	Y
4	1	4	0	0	Y
4	2	12	0	0	N
4	3	12	0	0	Y
4	4	8	0	0	Y
4	6	8	0	0	Y
3	2	3	4	0	Y
3	2	4	0	0	Y
3	2	7	0	0	Y
3	3	6	0	0	Y
3	4	6	0	0	Y
3	5	6	0	0	N
3	5	12	0	0	N
3	6	10	0	0	Y
2	1	2	8	0	Y
2	1	2	12	0	Y
2	1	3	0	0	Y
2	1	7	0	0	Y
2	1	10	0	0	Y
2	2	10	0	0	Y
2	4	12	0	0	Y

Notes: The income drop codes correspond to Table 2 where 0 means no other code was selected with the same income drop amount. The table includes events where the consumer selected more than one income drop and gave the same cost of the event. We include only one income drop when calculating the total income drop for the events marked with a Y. Source: Authors' calculations from the 2023 Making Ends Meet surveys.

Table A-2: Duplicate income events with only one consumer

Consumers	Income drop code				Suppress extra
1	1	2	3	6	Y
1	1	2	3	10	N
1	1	2	4	0	Y
1	1	2	5	0	N
1	1	2	6	7	Y
1	1	2	6	12	Y
1	1	3	12	0	Y
1	1	4	6	0	Y
1	1	4	7	0	Y
1	1	5	0	0	N
1	1	6	7	0	Y
1	1	6	7	8	Y
1	1	6	7	12	Y
1	1	6	8	0	Y
1	1	6	10	0	Y
1	1	6	11	0	Y
1	1	11	0	0	Y
1	1	12	0	0	N
1	2	3	6	0	Y
1	2	3	6	8	Y
1	2	3	7	0	Y
1	2	3	11	0	Y
1	2	5	6	7	N
1	2	5	12	0	N
1	2	6	7	0	Y
1	2	6	7	11	Y
1	2	7	8	0	Y
1	3	4	12	0	Y
1	3	7	0	0	Y
1	5	7	0	0	N
1	6	7	8	0	Y
1	6	7	11	0	Y
1	6	7	12	0	N
1	6	9	0	0	N
1	6	11	0	0	Y
1	6	12	0	0	N
1	7	10	0	0	Y
1	8	9	0	0	N
1	9	11	0	0	Y
1	10	11	0	0	Y
1	10	12	0	0	N
1	11	12	0	0	N

Notes: The income drop codes correspond to Table 2 where 0 means no other code was selected with the same income drop amount. The table includes events where the consumer selected more than one income drop and gave the same cost of the event. We include only one income drop when calculating the total income drop for the events marked with a Y. Source: Authors' calculations from the 2023 Making Ends Meet surveys.

Table A-3: Income and expense shocks regressions across demographic groups

	Income lost to unexpected expenses (%) OLS	Indicator have unexp. expense OLS	ln(fraction unexp. exp.) OLS	Income lost to income drops (%) OLS	Indicator have income drop OLS
Inc. \$20,001 to \$50,000	-5.408*	0.127***	-0.394***	-4.773***	0.0157
	(3.232)	(0.0295)	(0.112)	(1.255)	(0.0305)
Inc. \$50,001 to \$80,000	-8.370**	0.0904***	-0.533***	-6.322***	-0.0470
	(3.532)	(0.0339)	(0.123)	(1.338)	(0.0339)
Inc. \$80,001 to \$125,000	-8.757**	0.107***	-0.741***	-8.669***	-0.0814**
	(3.785)	(0.0362)	(0.141)	(1.317)	(0.0370)
More than \$125,001	-13.84***	0.0862**	-1.075***	-9.845***	-0.134***
	(3.562)	(0.0389)	(0.135)	(1.374)	(0.0407)
High School	1.586	0.0689**	0.194*	2.513***	0.0478
	(1.769)	(0.0270)	(0.0992)	(0.798)	(0.0293)
Some college	-0.117	0.0381	0.0777	0.910	0.0135
	(1.728)	(0.0272)	(0.102)	(0.719)	(0.0296)
College or post-grad.	0.948	0.0410	0.106	1.463**	-0.0278
	(1.596)	(0.0252)	(0.0954)	(0.634)	(0.0261)
Black	-3.010	0.00793	-0.342***	0.614	0.120***
	(1.835)	(0.0245)	(0.0943)	(0.829)	(0.0292)
Hispanic	-1.428	0.0235	0.0358	1.335*	0.0944***
	(1.210)	(0.0241)	(0.0842)	(0.799)	(0.0298)
Other	0.816	-0.0537	0.192	0.887	-0.0207
	(2.896)	(0.0357)	(0.146)	(1.034)	(0.0330)
Age 40-61	1.620	-0.00870	0.0819	-0.202	-0.0693***
	(1.083)	(0.0194)	(0.0720)	(0.618)	(0.0225)
Age >61	4.077***	-0.0939***	0.371***	-3.515***	-0.201***
	(1.573)	(0.0238)	(0.0881)	(0.557)	(0.0252)
Share finances with	0.128	0.0490**	-0.0219	0.391	0.0491**
spouse or partner	(1.709)	(0.0212)	(0.0719)	(0.602)	(0.0229)
Have financial	1.839*	0.113***	0.137**	2.399***	0.0839***
dependents	(0.974)	(0.0180)	(0.0649)	(0.541)	(0.0203)
Indicator survey	0.373	0.0159	0.0668		
in 2023	(1.433)	(0.0206)	(0.0854)		
Indicator survey	1.365	0.0595***	0.0525	0.688	0.0419***
in 2024	(1.397)	(0.0202)	(0.0847)	(0.420)	(0.0146)
Constant	15.38***	0.485***	-2.496***	9.824***	0.329***
	(3.230)	(0.0357)	(0.140)	(1.252)	(0.0337)
Observations	7,844	7,844	5,368	5,892	5,892
R-squared	0.016	0.051	0.063	0.071	0.082

Notes: Excluded group: income below \$20,000, less than high school, white, age < 40, no financial spouse or partner, no financial dependents, indicator for survey in 2022. Regression coefficients are reported, not odds ratios. All results are survey weighted. Source: 2022, 2023, and 2024 Making Ends Meet surveys for unexpected expenses, 2023 and 2024 surveys for income drops. *** p<0.01, ** p<0.05, * p<0.1

Table A-4: Individual expense shocks across demographic groups

	Income lost to unexpected expenses (%)				
	Medical	Housing	Vehicle	Legal and fines	Unplanned gifts
Overall	2.3	1.8	3.5	0.9	0.7
	(0.29)	(0.17)	(0.25)	(0.26)	(0.10)
Income					
$20,000 or less	7.3	1.6	4.4	0.9	0.9
	(2.31)	(0.38)	(0.86)	(0.21)	(0.47)
$20,001 to $50,000	3.0	2.0	4.8	2.0	0.7
	(0.39)	(0.28)	(0.60)	(1.22)	(0.12)
$50,001 to $80,000	2.0	1.8	4.3	0.7	0.9
	(0.33)	(0.36)	(0.75)	(0.14)	(0.29)
$80,001 to $125,000	1.2	2.7	3.2	0.8	0.8
	(0.11)	(0.71)	(0.55)	(0.34)	(0.18)
More than $125,001	0.8	1.2	2.1	0.5	0.6
	(0.09)	(0.13)	(0.23)	(0.08)	(0.15)
Education					
Less than H.S.	3.2	1.3	4.5	0.7	0.8
	(0.84)	(0.17)	(0.70)	(0.12)	(0.26)
High School	2.5	2.2	4.0	0.7	0.5
	(0.49)	(0.63)	(0.52)	(0.12)	(0.06)
Some college	2.6	1.9	3.1	0.5	0.7
	(0.60)	(0.36)	(0.36)	(0.09)	(0.18)
College or post-grad.	1.3	1.9	2.7	1.4	0.9
	(0.17)	(0.29)	(0.20)	(0.73)	(0.15)
Race and ethnicity					
White	2.5	1.9	3.5	1.1	0.8
	(0.43)	(0.19)	(0.27)	(0.42)	(0.13)
Black	2.0	1.1	3.8	0.7	0.5
	(0.64)	(0.28)	(1.02)	(0.12)	(0.09)
Hispanic	2.1	1.4	3.7	0.7	0.9
	(0.30)	(0.34)	(0.55)	(0.10)	(0.35)
Other	1.1	2.6	2.5	0.6	0.5
	(0.15)	(1.24)	(0.90)	(0.18)	(0.15)
Age					
<40	1.7	1.6	3.4	0.7	0.4
	(0.21)	(0.40)	(0.39)	(0.12)	(0.05)
40-61	2.0	1.7	3.1	0.8	0.6
	(0.36)	(0.26)	(0.34)	(0.21)	(0.17)
>61	3.4	2.1	4.3	0.5	1.2
	(1.02)	(0.33)	(0.71)	(0.08)	(0.21)
Observations	9382	9433	9433	9466	9503

Notes: People without the shock are included as zeros, so the calculation is the expected loss due to that expense. All results are survey weighted. Source: 2022, 2023, and 2024 Making Ends Meet surveys. Observations are for the Overall calculation.

Table A-5: Relationship between income and expense shocks

(A) Probit dependent variable: Had expense shock				
Had an income drop	0.238***	0.229***	0.208***	0.205***
	(0.0149)	(0.0188)	(0.0186)	(0.0194)
Share of income lost to		0.000669	0.00160**	0.00158*
income drops (%)		(0.000772)	(0.000748)	(0.000811)
Observations	7,598	7,598	7,490	6,962
(B) OLS dep variable: Share of income lost to expenses (%) if had shock				
Had an income drop		-0.809	-1.408	-1.331
		(1.379)	(1.306)	(1.329)
Share of income lost to	0.0507*	0.0661*	0.0154	0.00698
income drops (%)	(0.0277)	(0.0398)	(0.0395)	(0.0402)
Observations	5,170	5,170	5,170	4,904
R-squared	0.001	0.002	0.037	0.035
(C) Probit dependent variable: Had income drop				
Had an expense shock	0.245***	0.247***	0.251***	0.249***
	(0.0154)	(0.0155)	(0.0159)	(0.0166)
Share of income lost to		-0.000152	-0.000370**	-0.000495*
expenses (%)		(0.000159)	(0.000186)	(0.000259)
Observations	7,598	7,598	7,490	6,362
(D) OLS dep. variable: Share of income lost to income drops (%) if had shock				
Had an expense shock		0.481	1.977	2.063
		(1.531)	(1.496)	(1.521)
Share of income lost to	0.0607	0.0587	0.0285	0.0206
expenses (%)	(0.0404)	(0.0417)	(0.0346)	(0.0346)
Observations	2,312	2,312	2,312	2,158
R-squared	0.004	0.004	0.085	0.076
Control for income	No	No	Yes	Yes
Exclude childcare	No	No	No	Yes

Notes: Probit results show the average marginal effect. Source: Authors' calculations from the 2023 and 2024 Making Ends Meet surveys.