

# Coping with Costs

Big Data on Expense Volatility  
and Medical Payments



# About the Institute

The global economy has never been more complex, more interconnected, or faster moving. Yet economists, businesses, nonprofit leaders, and policy makers have lacked access to real-time data and the analytic tools to provide a comprehensive perspective. The results—made painfully clear by the Global Financial Crisis and its aftermath—have been unrealized potential, inequitable growth, and preventable market failures.

The JPMorgan Chase Institute is harnessing the scale and scope of one of the world's leading firms to explain the global economy as it truly exists. Its mission is to help decision-makers—policymakers, businesses, and nonprofit leaders—appreciate the scale, granularity, diversity, and interconnectedness of the global economic system and use better facts, timely data, and thoughtful analysis to make smarter decisions to advance global prosperity. Drawing on JPMorgan Chase's unique proprietary data, expertise, and market access, the Institute develops analyses and insights on the inner workings of the global economy, frames critical problems, and convenes stakeholders and leading thinkers.

The JPMorgan Chase Institute is a global think tank dedicated to delivering data-rich analyses and expert insights for the public good.

## Acknowledgments

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## Contact

For more information the JPMorgan Chase Institute or this report, please see our website [www.jpmchaseinstitute.com](http://www.jpmchaseinstitute.com) or e-mail [institute@jpmchase.com](mailto:institute@jpmchase.com).

# Coping with Costs:

## Big Data on Expense Volatility and Medical Payments

Diana Farrell  
Fiona Greig

## Contents

2	Executive Summary
6	Introduction
7	Coping with Costs: Big Data on Expense Volatility and Medical Payments
23	Implications
25	Data Asset
32	References
34	Endnotes
37	Suggested Citation

# Executive Summary

Americans across the income spectrum experience tremendous income and expense volatility, and this volatility has been on the rise. This volatility tests the financial resilience of American families. In *Weathering Volatility*, we estimated that median-income families needed \$4,800 in liquid assets to weather 90 percent of the income and expense volatility observed, but that they had only \$3,000—a shortfall of \$1,800. In *Paychecks, Paydays, and the Online Platform Economy* we documented that most income volatility stems from labor income and, specifically, variation in take-home pay within a job rather than job transitions.

In this report, the JPMorgan Chase Institute assembled a de-identified data asset of nearly 250,000 Chase customers between 2013 and 2015 in order to study how consumers' expenses vary over time and how their financial behavior changes when faced with extraordinary payments. This high-frequency panel of family finances—weighted to represent the age and income distribution of the nation—provides a first ever look into the components of expense volatility based on real financial transactions and the changes to family income, expenses, assets, and liabilities that coincide with extraordinary medical payments.

## Data

From a universe of 35 million checking account customers, we assembled a de-identified data asset comprised of roughly 250,000 core Chase customers for whom we could categorize at least 80 percent of expenses. These families met the following five sampling criteria:

**35 MILLION** CHECKING ACCOUNT CUSTOMERS

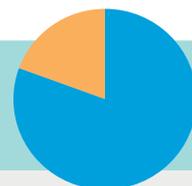


**250,000**

CORE CHASE CHECKING ACCOUNT CUSTOMERS

- Had at least five outflows from their checking account in every month
- Had a Chase consumer credit product and therefore a credit bureau record on file
- Spent less than 20 percent of total expenses through channels that cannot be categorized (e.g. checks, cash)
- Used their debit or credit card at least once each month and have transacted at least once in the following categories: Grocery, Restaurant, Fuel or Transit, Clothing, Miscellaneous Retail, Drug Store, Home Supply or Improvement, and Entertainment
- Made at least one housing payment in each year.

WE CAN CATEGORIZE AT LEAST **80 PERCENT** OF EXPENSES



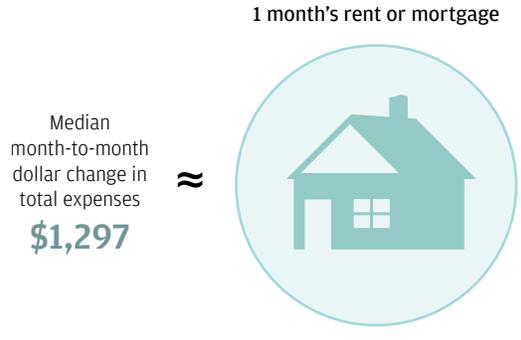
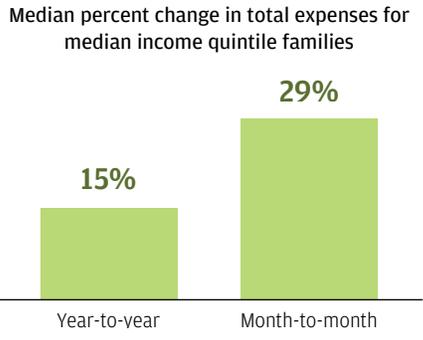
Source: JPMorgan Chase Institute

# Finding One

Expenses fluctuated by nearly \$1,300 or 29 percent on a month-to-month basis for median-income households.

High frequency data highlighted that expenses were more volatile on a month-to-month than year-to-year basis.

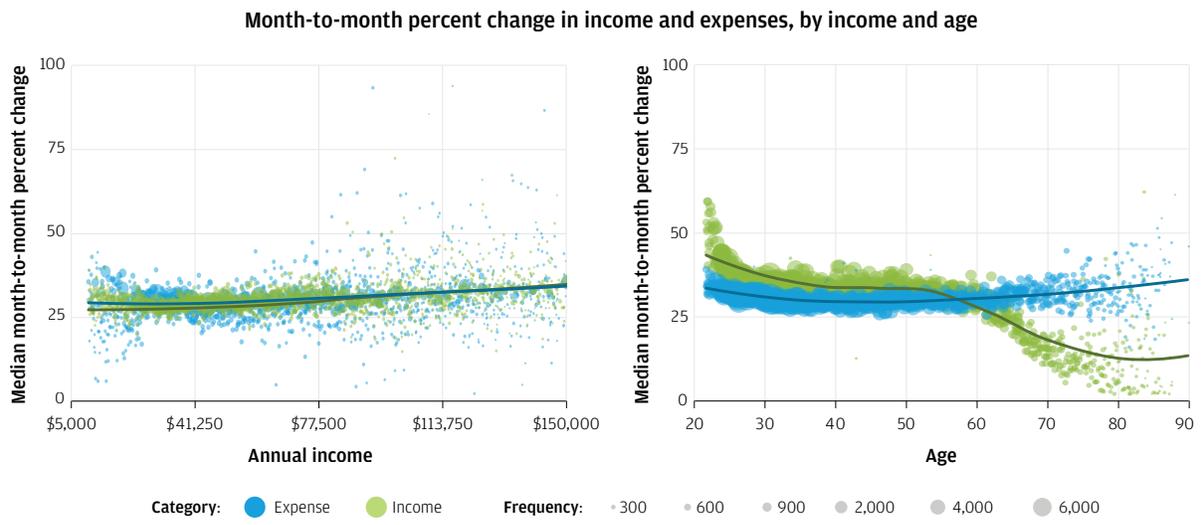
In dollar terms, monthly fluctuations in total expenses were roughly equivalent to a family's rent or mortgage payment.



Source: JPMorgan Chase Institute

# Finding Two

Expense volatility was high across the income and age spectrum. While older families typically had less volatile incomes, they exhibited a larger range of income and expense volatility.



Source: JPMorgan Chase Institute

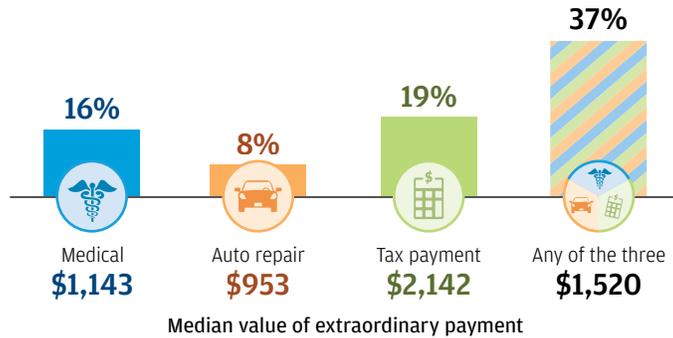
## Finding Three

Almost four in ten families—particularly middle-income and older families—made an extraordinary payment of over \$1,500 related to medical services, auto repair, or taxes.

We defined an extraordinary payment as:

- **Large in magnitude:** At least \$400 in magnitude and more than 1 percent of annual income
- **Unusual:** More than 2 standard deviations away from the individual's normal monthly mean expense in this category

Percent of families with at least one extraordinary payment within a year



Source: JPMorgan Chase Institute

## Finding Four

Extraordinary medical payments were more likely to occur in months with higher income and specifically during tax season.

Extraordinary medical payments were more likely to occur in months with higher income. Total income was \$163 or 4 percent higher in months with a major medical payment. The income increase stemmed mostly from tax refunds and not labor income and was still small in magnitude compared to the mean medical payment of \$2,089.

Decomposition of dollar (percent) difference in income in month with a major medical payment relative to the baseline\*



Source: JPMorgan Chase Institute

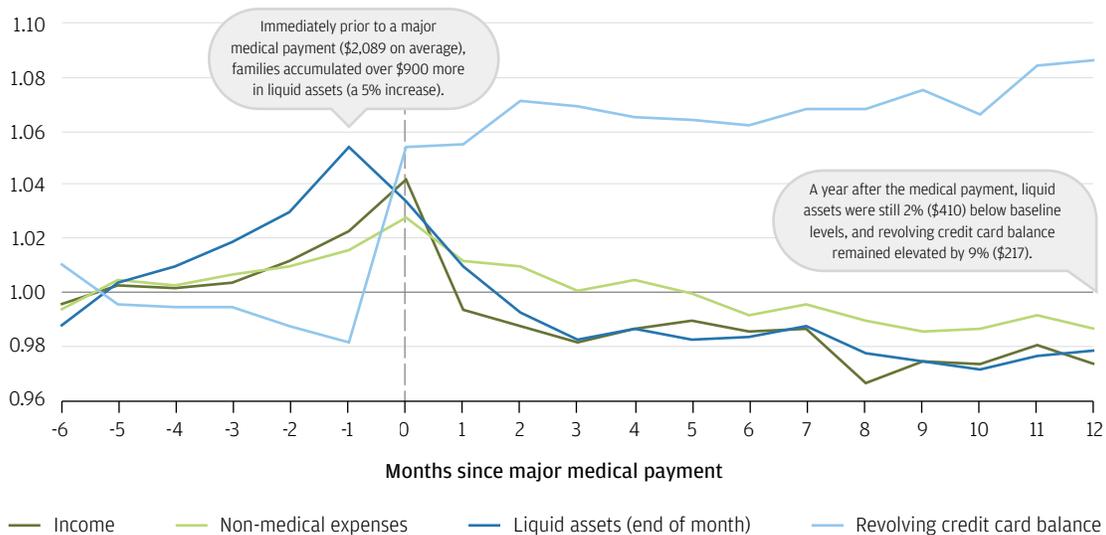
\* Baseline period corresponds to four to six months prior to the payment month. Totals may not reflect sums due to rounding.

## Finding Five

Prior to a major medical payment, families garnered significant liquid assets but did not recover financially within 12 months after the payment.

Major medical payments coincided with short-term improvements in income, assets, and liabilities, as well as lasting negative changes in not just assets and liabilities but also income and non-medical expenses.

Ratio of income, non-medical expenses, liquid assets, and revolving credit card balance before and after major medical payment relative to baseline\*



Source: JPMorgan Chase Institute

\* Baseline period corresponds to four to six months prior to the payment month.

## Conclusion

These findings highlight the critical role liquid assets play in managing expense spikes and the need for policies and solutions to promote emergency savings. While many families experienced an increase in income in the month in which they made a major medical payment, liquid assets were the primary source of funding to cover the medical payment. Our evidence also underscores the connections between financial health and physical health. First, the timing of medical payments was linked to ability to pay. Families may have delayed either medical treatment or payment of their medical bill until they were able to pay. The second link is that major medical payments were associated with lower income, non-medical expenses, and liquid assets and higher credit card debt a year later. This highlights the reality that families are not fully insured against the economic consequences of major health events. Older families in particular could benefit from more customized solutions as they exhibited a greater range in income and expense volatility and were also more likely to make major medical payments. More broadly, better solutions could help families accumulate liquid assets and predict, manage, and afford expense spikes. Integrated, high-frequency data of income, expenses, assets, and liabilities shed new light on expense volatility and how behavior changes with this volatility. This is critical to improving policies and solutions to strengthen the financial resilience of American families.

# Introduction

Americans across the income spectrum experience tremendous income and expense volatility, and this volatility has been on the rise.<sup>1</sup> This volatility tests the financial resilience of American families. In *Weathering Volatility*, we estimated that median-income families needed \$4,800 in liquid assets to weather 90 percent of the income and expense volatility observed, but that they had only \$3,000—a shortfall of \$1,800. In *Paychecks, Paydays and the Online Platform Economy* we documented that most income volatility stems from labor income and, specifically, variation in take-home pay within jobs.

In this report, we examine the sources of expense volatility and the changes in financial behavior that coincide with extraordinary medical payments. Expense volatility can stem from a number of different sources. First, it could result from a change in income—previous literature has provided evidence for significant changes to household consumption in response to both permanent and transitory income shocks as well as anticipated income changes.<sup>2</sup> This response is due in part to the fact that a high proportion of families (across the wealth spectrum no less) face short-term liquidity constraints.<sup>3</sup>

Second, expense volatility could also stem from an unanticipated expense shock, such as a large medical or vehicle repair bill, against which families are not fully insured. Many studies of financial resilience, relying on self-reported survey responses, indicate that Americans struggle to manage large unexpected or extraordinary payments. The 2015 Survey of Household Economics and Decisionmaking indicates that 32 percent of adults are not prepared for a three-month long financial disruption and that 46 percent are not prepared to cover a \$400 emergency expense without borrowing or selling something.<sup>4</sup> They might also curtail expenses in some categories in order to cope with an expense shock in another category.

In this report, the JPMorgan Chase Institute assembled a de-identified data asset of roughly 250,000 Chase customers between 2013 and 2015 to study how expenses vary over time and how families' financial behavior changes when faced with extraordinary medical payments.<sup>5</sup> For the purposes of our research, the unit of analysis is the primary account holder, whom we subsequently refer to as a family.<sup>6</sup> This month-to-month panel of family finances—weighted to represent the age and income distribution of the nation—provides a first-ever look into the components of expense volatility based on real financial transactions and the changes to family income, expenses, assets, and liabilities that coincide with extraordinary medical payments.<sup>7</sup> A full description of our data asset can be found in the Data Asset section.

## Our findings are as follows:

**Finding 1:** Expenses fluctuated by nearly \$1,300 or 29 percent on a month-to-month basis for median-income households.

**Finding 2:** Expense volatility was high across the income and age spectrum. While older families typically had less volatile incomes, they exhibited a larger range of income and expense volatility.

**Finding 3:** Almost four in ten families per year—particularly middle-income and older families—made an extraordinary payment of over \$1,500 related to medical services, auto repair, or taxes.

**Finding 4:** Extraordinary medical payments were more likely to occur in months with higher income and specifically during tax season.

**Finding 5:** Prior to a major medical payment, families garnered substantial liquid assets but did not recover financially within 12 months after the payment.

These findings highlight the critical role liquid assets play in managing expense spikes and the need for policies and solutions to promote emergency savings. While many families experienced an increase in income in the month in which they made a major medical payment, liquid assets were the primary source of funding to cover the medical payment. Our evidence also underscores the connections between financial health and physical health. First, the timing of medical payments was linked to ability to pay. Families may have delayed either receipt of medical treatment or payment of their medical bill until they were able to pay. The second link is that major medical payments were associated with lower income, non-medical expenses, and liquid assets and higher credit card debt a year later. This highlights the reality that families are not fully insured against the economic consequences of major health events. Older families in particular could benefit from more customized solutions, as they exhibited a greater range in income and expense volatility and were also more likely to make major medical payments. More broadly, better solutions could help families accumulate liquid assets and predict, manage, and afford expense spikes. Integrated, high-frequency data of income, expenses, assets, and liabilities shed new light on expense volatility and how behavior changes with this volatility. This is critical to improving policies and solutions to strengthen the financial resilience of American families.

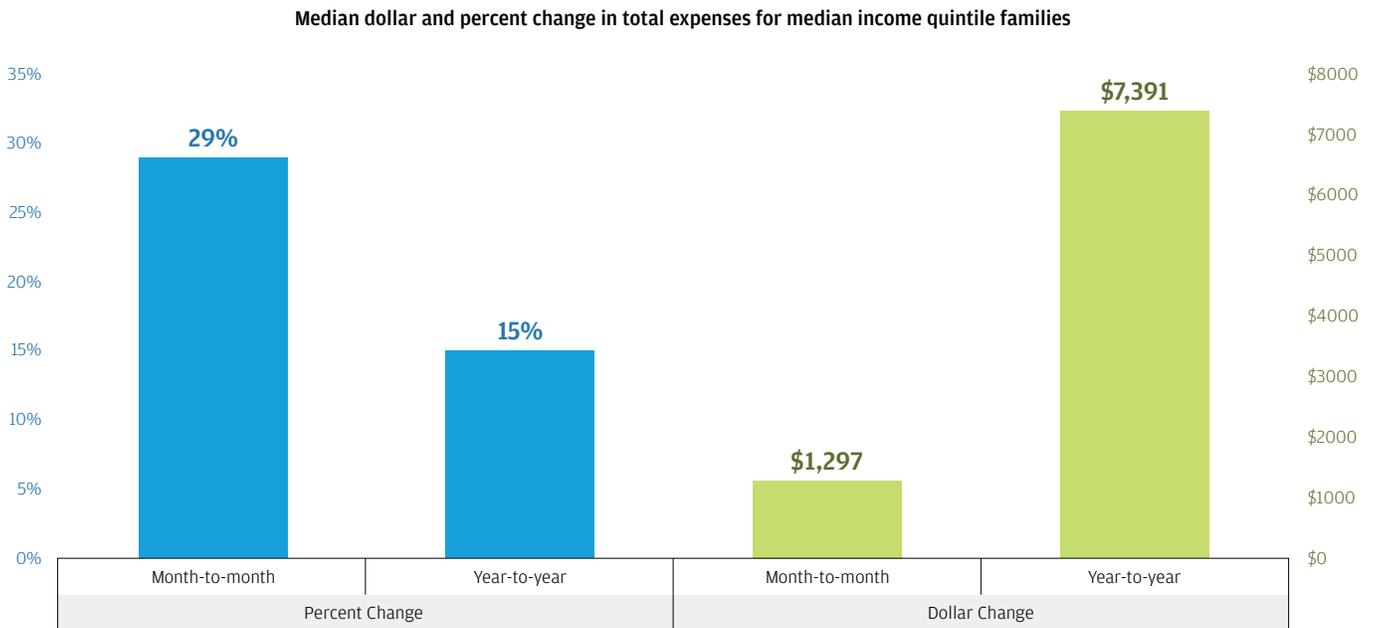
# Findings

## Finding One

Expenses fluctuated by nearly \$1,300 or 29 percent on a month-to-month basis for median-income households.

Expense volatility—increases or decreases in expenses—is an important input to a household’s economic wellbeing. While some level of expense volatility occurs naturally, unusually large expense spikes could be more difficult to manage. On an absolute basis, the median-income family experienced a \$7,391 change in expenses on a year-to-year basis and a \$1,297 change in expenses on a month-to-month basis compared to median total monthly expenses of \$3,889.<sup>8</sup> These were equivalent to a change of 29 percent month-to-month and 15 percent year-to-year or roughly a month’s rent or mortgage payment (Figure 1).<sup>9</sup>

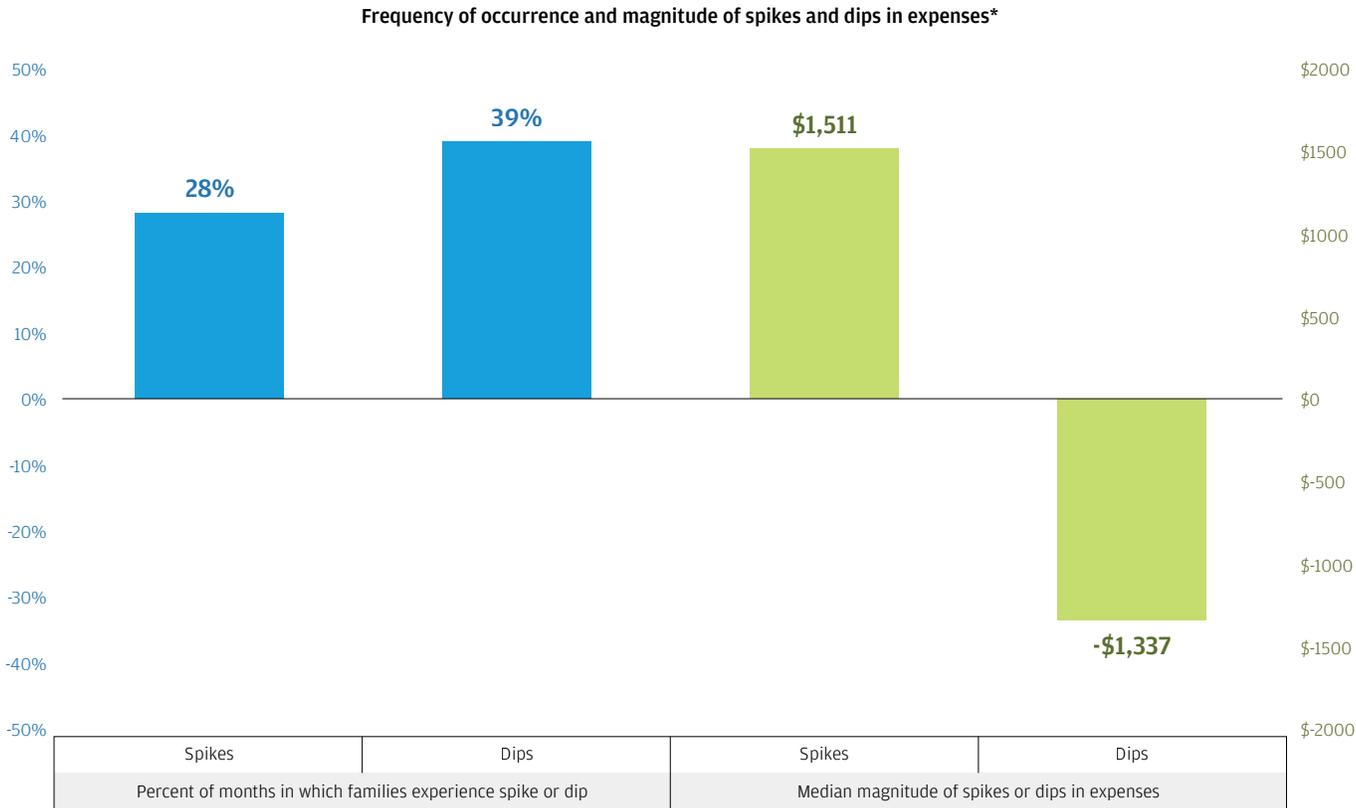
Figure 1: Expenses fluctuated by nearly \$1,300 or 29 percent on a month-to-month basis for median-income households



Source: JPMorgan Chase Institute

We examined positive and negative deviations in monthly expenses from mean monthly expenses over the prior 12 months. We defined expense spikes and dips as deviations that are greater than 1 percent of annual income. Dips in expenses occurred more frequently than spikes, but they were offset by spikes that were 13 percent larger in magnitude (Figure 2). Families experienced spikes in expenses 28 percent of the time and dips in expenses 39 percent of the time. However, the median size of a spike was \$1,511 compared to a median dip of -\$1,337.

Figure 2: Spikes in expenses were larger in magnitude but occurred less frequently than dips



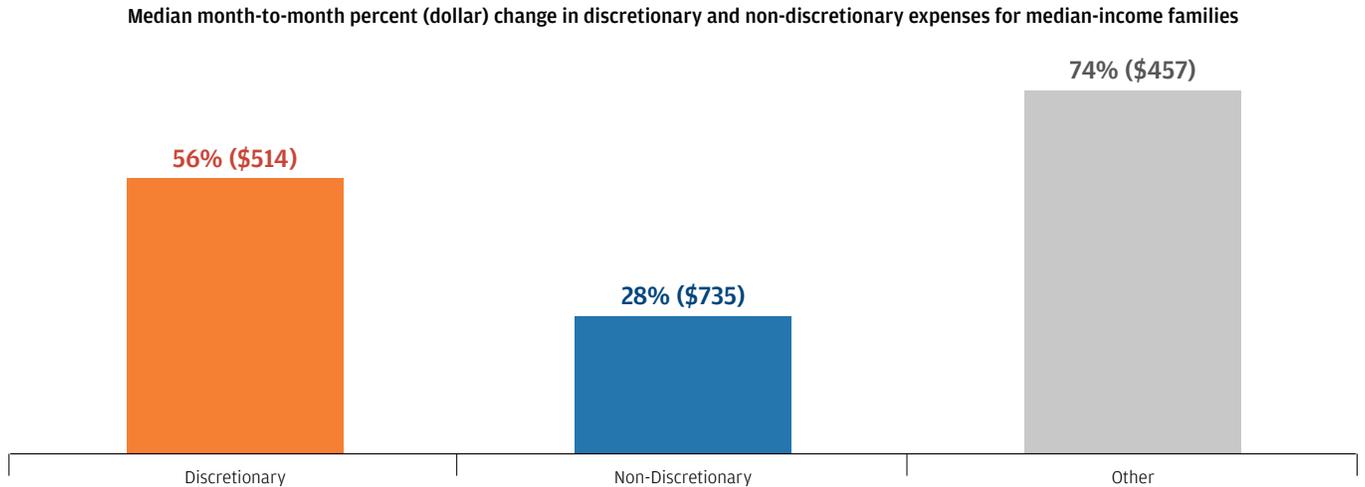
\* We examined positive and negative deviations in monthly expenses from mean monthly expenses over the prior year. We defined expense spikes and dips as deviations that are greater than 1 percent of annual income.

Source: JPMorgan Chase Institute

In evaluating expense volatility, an important distinction is whether the expenses represent non-discretionary expenses—everyday necessities such as groceries, housing, and bills—or discretionary expenses—one-time durable purchases and leisure expenses (see Figure 4 for a list of categories considered non-discretionary versus discretionary, and the Data Asset section for more detail on this categorization). Among middle-income households (with incomes between \$38,800 and \$63,000), 63 percent of expenses was non-discretionary, 24 percent of expenses was discretionary, and 13 percent could not be categorized because it came from paper checks, cash withdrawals, and other unknown expenses.

Discretionary expenses were more volatile in percentage terms than non-discretionary expenses (Figure 3).<sup>10</sup> Discretionary expenses, which include travel, restaurants, and retail, fluctuated on a month-to-month basis by 56 percent or \$514. Non-discretionary expenses, which include housing, groceries, and utilities, fluctuated by 28 percent or \$735 on a month-to-month basis. The remaining category of other expenses varied by 74 percent on a month-to-month basis. Total expenses were less volatile (29 percent, as indicated in Figure 1) than each of the component parts because a spike within one category can be offset by a dip in another category.

**Figure 3: Discretionary expenses were more volatile than non-discretionary expenses**



Source: JPMorgan Chase Institute

Month-to-month fluctuations in expenses were roughly equivalent to a month's rent or mortgage payment.

In order to understand how discretionary expenses were more volatile than non-discretionary expenses, we evaluated the frequency and magnitude of payments as well as the volatility of monthly payment amounts in dollar and percentage terms for each expense category (Figure 4).<sup>11</sup> These four dimensions illustrate the distinct ways in which each category behaved and contributed to volatility. In Figure 4, darker shading within each dimension represents a greater contribution to volatility.

Within discretionary expenses, travel and hotel expenses were volatile across multiple dimensions. The median family only made a travel and hotel payment 19 percent of the time (about two months out of a year), and when they did, the mean value was \$356. Travel and hotel payments were large and infrequent, and amounts (in months with a travel and hotel payment) varied by \$111 or 64 percent. The patterns evident in Figure 4 show that certain discretionary expense categories contributed more volatility because they were either infrequent but large or they were volatile in payment amounts. This was the case not just for travel and hotel, but also for retail, services, durables, and automobile expenses.

Figure 4: Both non-discretionary and discretionary categories contributed to expense volatility\*

Category**		Frequency and magnitude of payments		Volatility of monthly payment amounts	
		Median percent of months when payment is observed	Median value of non-zero monthly payments	Median dollar value change between non-zero payments	Median percent change between non-zero payments
Discretionary	Restaurant / Entertainment	100%	\$273	\$133	54%
	Non-durable Retail	94%	\$199	\$157	95%
	Other Services	92%	\$167	\$142	99%
	Durable Retail	72%	\$187	\$159	113%
	Automobiles	33%	\$156	\$85	99%
	Travel and Hotel	19%	\$356	\$111	64%
	School	6%	\$100	\$9	22%
Non-Discretionary	Grocery	100%	\$384	\$157	46%
	Utilities	100%	\$323	\$115	40%
	Fuel	100%	\$148	\$59	45%
	Auto Loans***	100%	\$422	\$0	0%
	Student Loans***	97%	\$251	\$0	0%
	Insurance (Non-health)	89%	\$246	\$72	34%
	Housing****	83%	\$1,245	\$382	49%
	Other Debt	72%	\$44	\$6	23%
	Drugstore Retail	67%	\$47	\$32	97%
	Discount Store	53%	\$95	\$55	92%
	Medical	44%	\$139	\$71	86%
	Transit	25%	\$38	\$11	59%
	Tax	6%	\$508	\$35	22%

\* Darker shading represents a greater contribution to volatility

\*\* See the Data Asset section (Figure 27) for more detail on this categorization.

\*\*\* In this sample, the median family does not have an auto or student loan. Forty-one percent of families have an auto loan and 37 percent of families have a student loan.

\*\*\*\* We estimate the conditional absolute dollar change in housing expenses based on electronic and check-based payments, as described in the Data Asset section. When we include only electronic payments the conditional absolute dollar change in housing expenses is substantially lower (\$187 or just 21 percent).

Expenses in some non-discretionary categories also contributed to volatility but did so in distinct ways. Housing, for example, is relatively stable in frequency (payments in 83 percent of months) but varied considerably in dollar terms (\$382). This might reflect families making late payments in certain months, resulting in multiple payments in some months and zero or one payment in other months.<sup>12</sup> Grocery and utilities expenses also occurred every month but varied considerably in payment amounts.

Out-of-pocket medical payments contributed to volatility by being sporadic in frequency and variable in payment amount. These payments were made 44 percent of the time or roughly five months out of the year, with payments (in months with a payment) typically \$139 and varying considerably in percentage terms—by 86 percent or \$71. Drugstore and discount store expenses also behaved in a similar fashion. Tax payments were a unique case and contributed volatility by virtue of being infrequent (6 percent of months), but large when they occurred (\$508).

**Finding  
Two**

Expense volatility was high across the income and age spectrum. While older families typically had less volatile incomes, they exhibited a larger range of income and expense volatility.

Expense volatility did not differ much across the income spectrum (Figure 5).<sup>13</sup> Monthly expense fluctuations increased with income in dollar terms, from \$833 among the lowest income quintile to \$2,906 among the highest income quintile. In percentage terms, however, they were relatively consistent across the income spectrum, ranging from 28 percent among the second income quintile to 34 percent among the top income quintile. Across the income spectrum, income appeared to be as volatile as expenses on a month-to-month basis.<sup>14</sup>

Expense volatility was also consistent throughout the age distribution (Figure 6). In aggregate, while income fluctuated more than expenses among young people, the opposite was true among older adults. In particular, while the typical family's income volatility decreased from around 29 percent among those under 64 to 19 percent among adults 75 and over, expense volatility remained higher at roughly 31 percent across all age cohorts. In other words, older families experienced higher expense volatility with more fixed incomes.

While expense volatility was relatively consistent across the age spectrum, there was a greater range in expense volatility among older families. Some older families experienced very high levels of expense volatility while others experienced low levels of expense volatility. The same was true for income.<sup>15</sup> The greater range in income and expense volatility among older families points to the potential need for more tailored financial and insurance products, or public policies to help older populations mitigate or manage this volatility.

Figure 5: Expense volatility was similar across the income spectrum and comparable in magnitude to income volatility

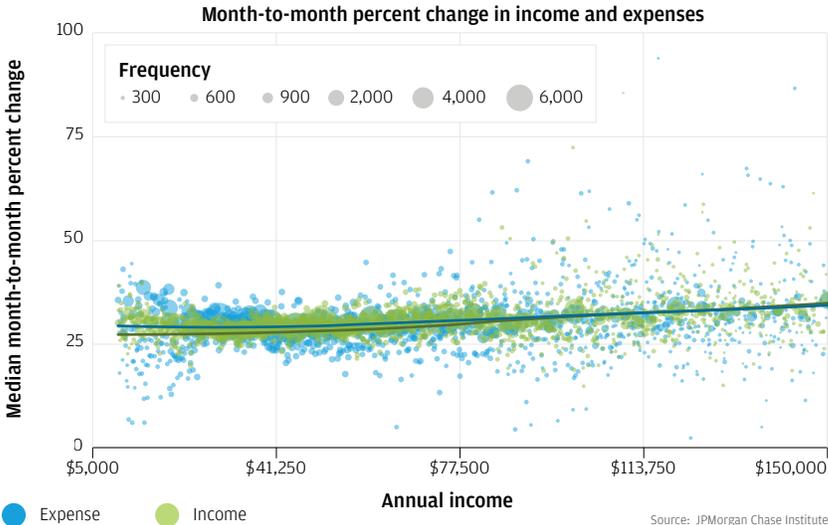
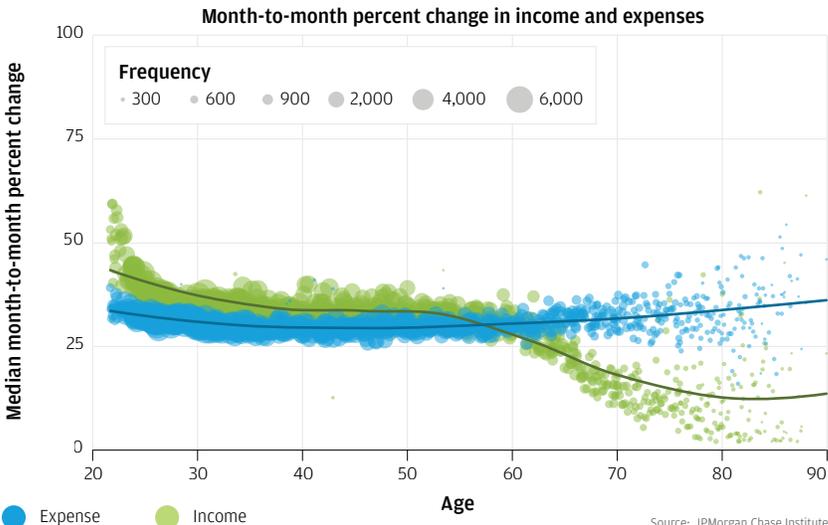


Figure 6: Older families experienced more dispersion in expense volatility and lower income volatility



Income and expense volatility can be difficult to manage if families do not have sufficient liquidity to weather adverse fluctuations. This is especially the case if income and expense fluctuations do not move in tandem. As illustrated in Figure 7, income and expense fluctuations were only slightly positively correlated. A 1 percent increase in income was associated with just a 0.07 percent increase in expenses, and this correlation was consistently low across the income and age spectrum.

While the levels of expense volatility remained similar across the income and age spectrum, the sources of volatility differed. We see from Figure 3 that, at the aggregate level, discretionary expenses were more volatile than non-discretionary expenses. However, low-income and older families spent a smaller fraction of their total budget on discretionary categories. Specifically, families in the lowest income quintile spent 5 percentage points more at grocery, discount and drug stores. They also spent 3 percentage points more on utilities, and 2 percentage points more on fuel and transit than those in the highest income quintile (Figure 8). Conversely, high-income families spent 4 percentage points more on travel and hotel and 2 percentage points more on durable retail. High-income families also made larger tax payments as a fraction of total expenses.

Figure 7: Income and expense fluctuations were only slightly positively correlated

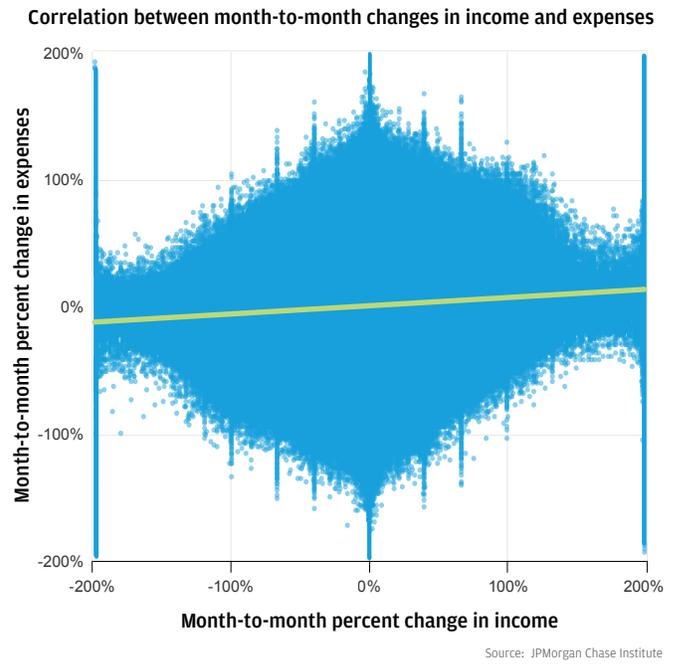
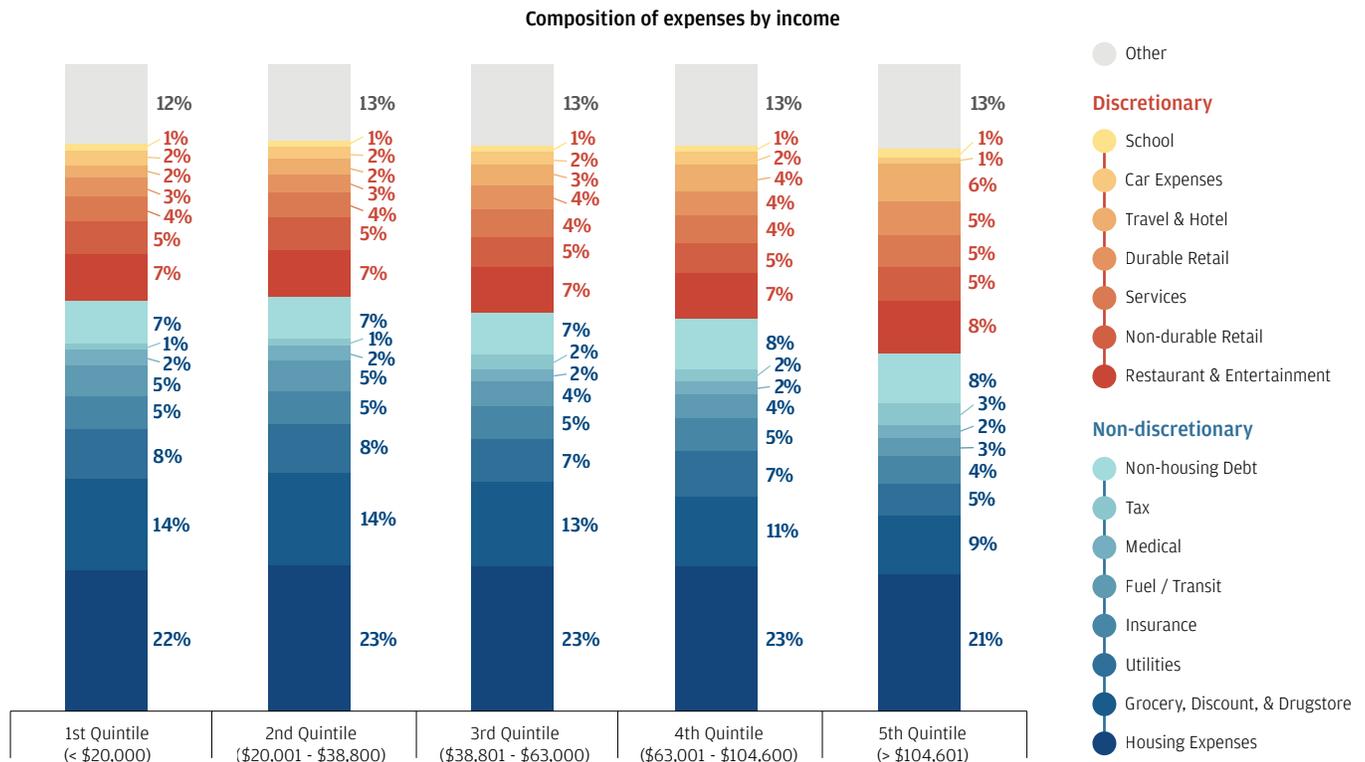
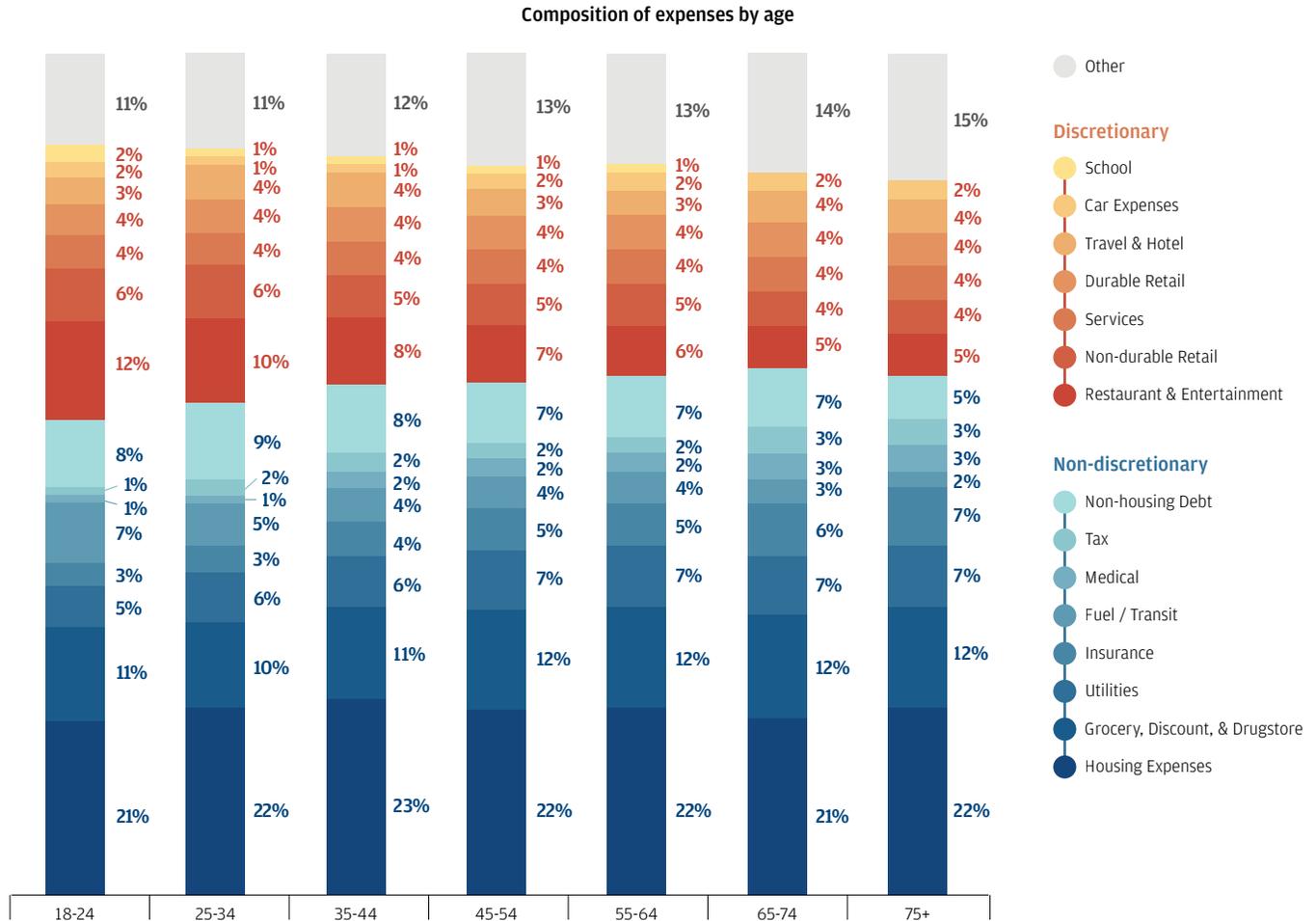


Figure 8: Low-income families spent a smaller fraction of total expenses on discretionary categories



Older families spent a smaller fraction of their total budget on discretionary categories compared to younger families. Families over 75 spent 7 percentage points less on restaurants and entertainment than families between the ages of 18 and 24 and 2 percentage points less on non-durable retail purchases. Conversely, families over 75 spent considerably more than young families (18-24) on insurance (4 percentage points more), medical services, and tax payments (2 percentage points more on each).

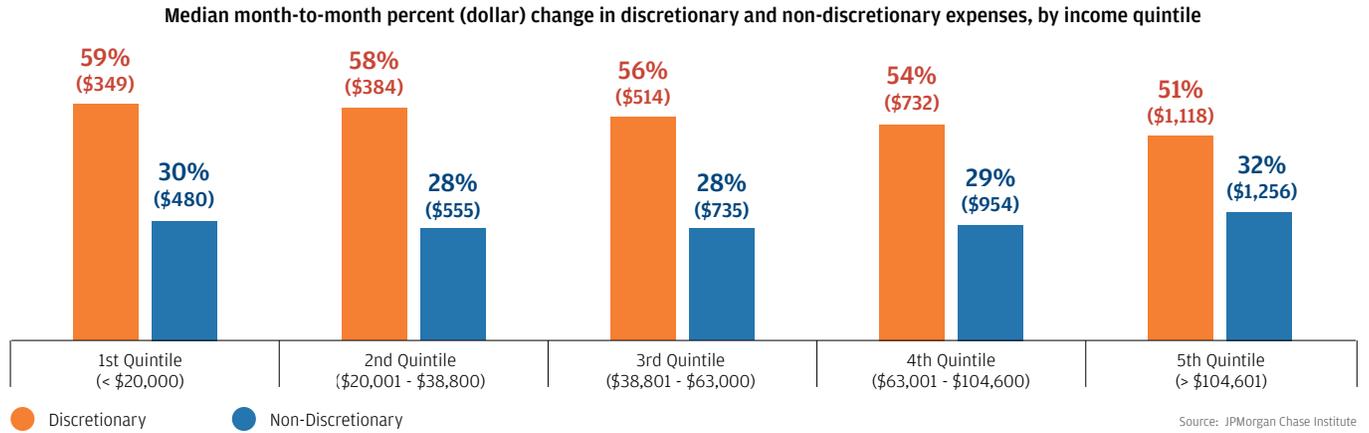
Figure 9: Older families spent less on discretionary categories compared to younger families



Source: JPMorgan Chase Institute

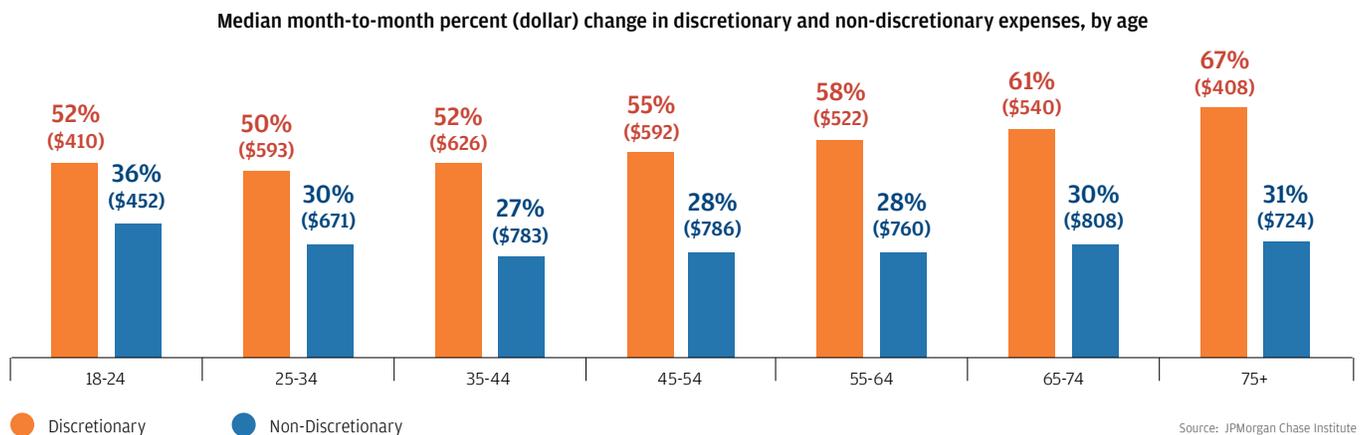
Although lower-income families spent a smaller fraction of their total expenses on discretionary categories than high-income families, discretionary expenses were more volatile for lower-income families relative to other income groups. Among families in the lowest income quintile, discretionary expenses fluctuated on a month-to-month basis by 59 percent (\$349) compared to 51 percent (\$1,118) among families in the top income quintile. Volatility in non-discretionary expenses was consistent across income groups. Thus discretionary expenses were an important component of expense volatility among low-income families.

Figure 10: Discretionary expenses were more volatile among low-income families



Volatility in discretionary categories also increased with age. Among families over 75, discretionary expenses fluctuated on a month-to-month basis by 67 percent compared to 52 percent or less among families younger than 45 years old. Notably, volatility in non-discretionary categories was slightly higher among young families under 25 (36 percent) compared to the general population (28 percent). Thus, younger families experienced volatility across most expense categories, while volatility among older families stemmed particularly from discretionary categories.

Figure 11: Volatility in discretionary categories increased with age



Families over 65 years of age were more than twice as likely as families under 25 to have made an extraordinary medical or tax payment.

**Finding Three**

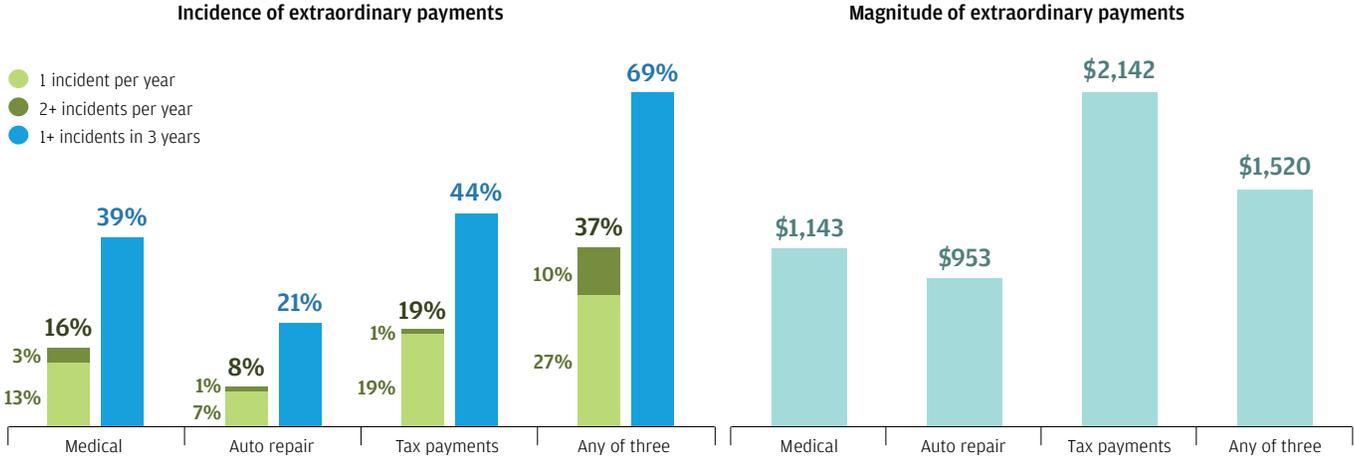
Almost four in ten families per year—particularly middle-income and older families—made an extraordinary payment of over \$1,500 related to medical services, auto repair, or taxes.

We explore the incidence and magnitude of extraordinary payments related to medical services, auto repair, and taxes—three types of expenses that have a higher likelihood of being unexpected in timing or magnitude and are thus potentially more difficult to weather. We define “extraordinary” as monthly expenses that were at least \$400, more than 1 percent of annual income, and more than two standard deviations away from the family’s average monthly expense in this category.<sup>16</sup> These three criteria ensured that the magnitude of the expense was both large and unusual for each family across the income spectrum.

It is important to note that in studying medical payments, the timing between event and payment matters. In our findings, we only observe when a payment was made, and not when the medical condition occurred or medical treatment was received. In reality, when a person has a medical event, he or she could treat it immediately or later, and he or she could pay for that treatment immediately or later.<sup>17</sup> Thus our lens on medical payments might be separated in time from the onset of a medical event and the receipt of medical treatment. The same logic applies to auto-repair payments. Nonetheless a major payment could have important bearing on the cash flow and financial resilience of a family. We explore this in Findings 4 and 5.

We observe that 37 percent of families made an extraordinary payment related to medical services, auto repair, or taxes in a given year, and one in ten made more than one of these extraordinary payments. Almost seven in ten families (69 percent) made a payment of these sorts over a three year period (Figure 12).<sup>18</sup> The median magnitude of these payments was \$1,520. Sixteen percent of families made an extraordinary medical payment in a given year with a median value of \$1,143, and 8 percent of families made an extraordinary auto repair payment in a given year with a median value of \$953. In comparison, extraordinary tax payments were slightly more common, occurring among 19 percent of families, and were much larger in magnitude (median value of \$2,142) than medical or auto repair payments. One notable exception is that families were three times more likely to experience more than one extraordinary medical related payment within a year (3 percent of families) relative to auto repairs (1 percent of families) or tax payments (1 percent of families).

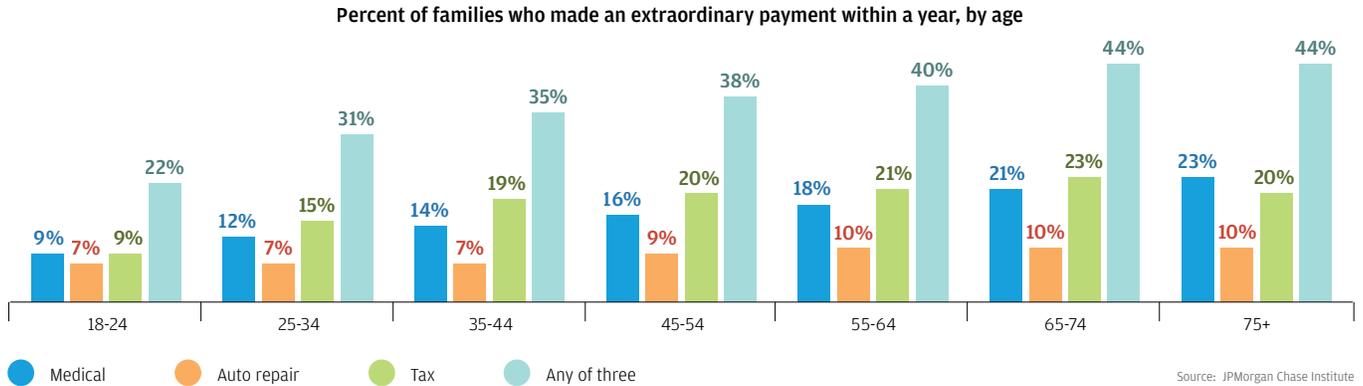
**Figure 12: Thirty-seven percent of families made an extraordinary payment of over \$1,500 related to medical services, auto repair, or taxes per year**



Source: JPMorgan Chase Institute

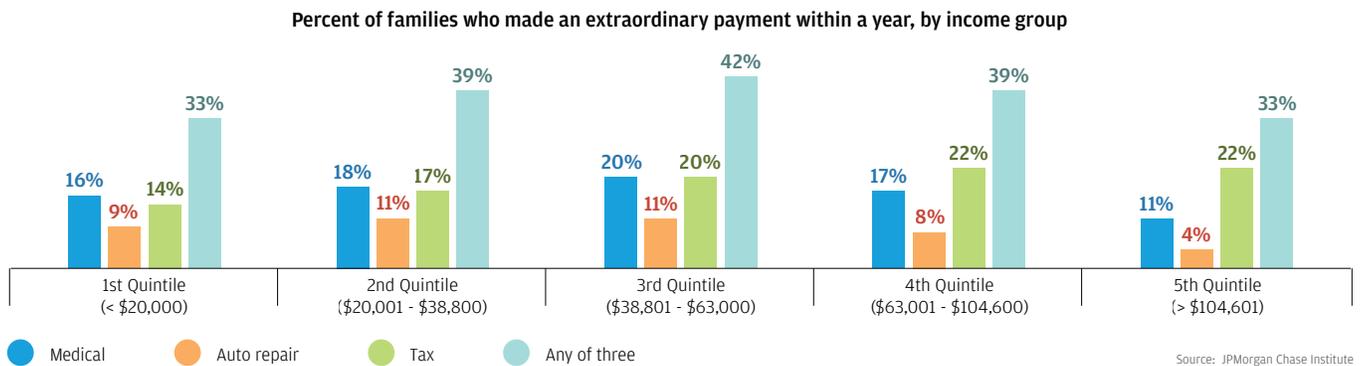
Older families had the highest incidence of extraordinary payments across all three types of payments (Figure 13). In particular, families over 65 years of age were more than twice as likely as families under 25 to have made an extraordinary medical payment. And they were also more likely to have made tax- and auto-related payments than young families. All told, 44 percent of families 65 and older made an extraordinary payment related to medical services, auto repair, or taxes compared to just 22 percent among families under 25.

**Figure 13: Older families were more likely to have made an extraordinary payment related to medical services, auto repair, or taxes**



The incidence of extraordinary payments varied less starkly by income.<sup>19</sup> Families in the middle income quintile were the most likely to have made extraordinary payments—42 percent of middle-income families experienced any of the three extraordinary payments compared to 33 percent among both the lowest and highest income quintiles. Families in the top income quintile were more likely to have made an extraordinary tax-related payment and less likely to have made health or auto-related payments. Therefore, while expense volatility was high across the income spectrum, middle-income families were most likely to have made extraordinary payments that might be difficult to forecast and plan for.

**Figure 14: Middle-income families were most likely to have made extraordinary payments**



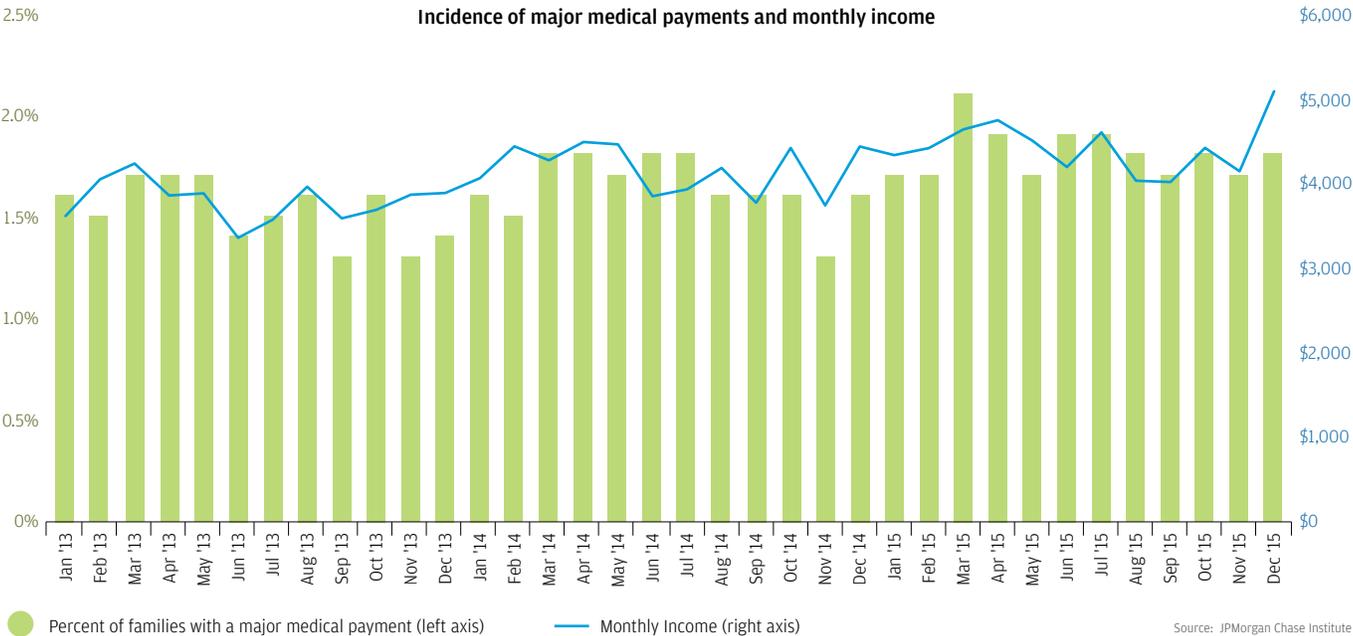
We examined changes in families’ overall financial behavior that coincided with an extraordinary medical payment. These behavior changes could be changes in income or expenses—an increase or decrease in income or non-medical expenses. Alternatively, they could be changes in assets or liabilities—an increase or decrease in liquid assets or credit card borrowing. We focus here on extraordinary medical payments because health emergencies are cited as the most common economic hardships experienced by American families (Federal Reserve Board, 2016).<sup>20</sup> For this analysis, we selected a sub-sample of over 54,000 families who made exactly one major medical payment between 2013 and 2015 out of a total sample of 96,000 families who had ever made extraordinary medical payments. The mean medical payment among this sample was \$2,089, comparable to the general population mean of \$1,898, and 80 percent of the payments were between \$483 (10th percentile) and \$4,197 (90th percentile).

**Finding  
Four**

**Extraordinary medical payments were more likely to occur in months with higher income and specifically during tax season.**

Extraordinary medical payments were more likely to occur in months with higher income—the correlation between aggregate mean income and the incidence of extraordinary medical payments across months was 0.64. This stands in contrast to our earlier finding that changes in income and total expenses do not typically move in tandem. To better understand the correlation between income and incidence of extraordinary medical payments, we examined the path of each income component around the time of the major medical payment relative to the mean over a baseline period between four and six months prior to the payment (Figure 16).<sup>21</sup> Total income increased by roughly 4 percent or \$163 in the month in which families experienced a major medical payment.

**Figure 15: In aggregate the incidence of major medical payments correlated with monthly income**



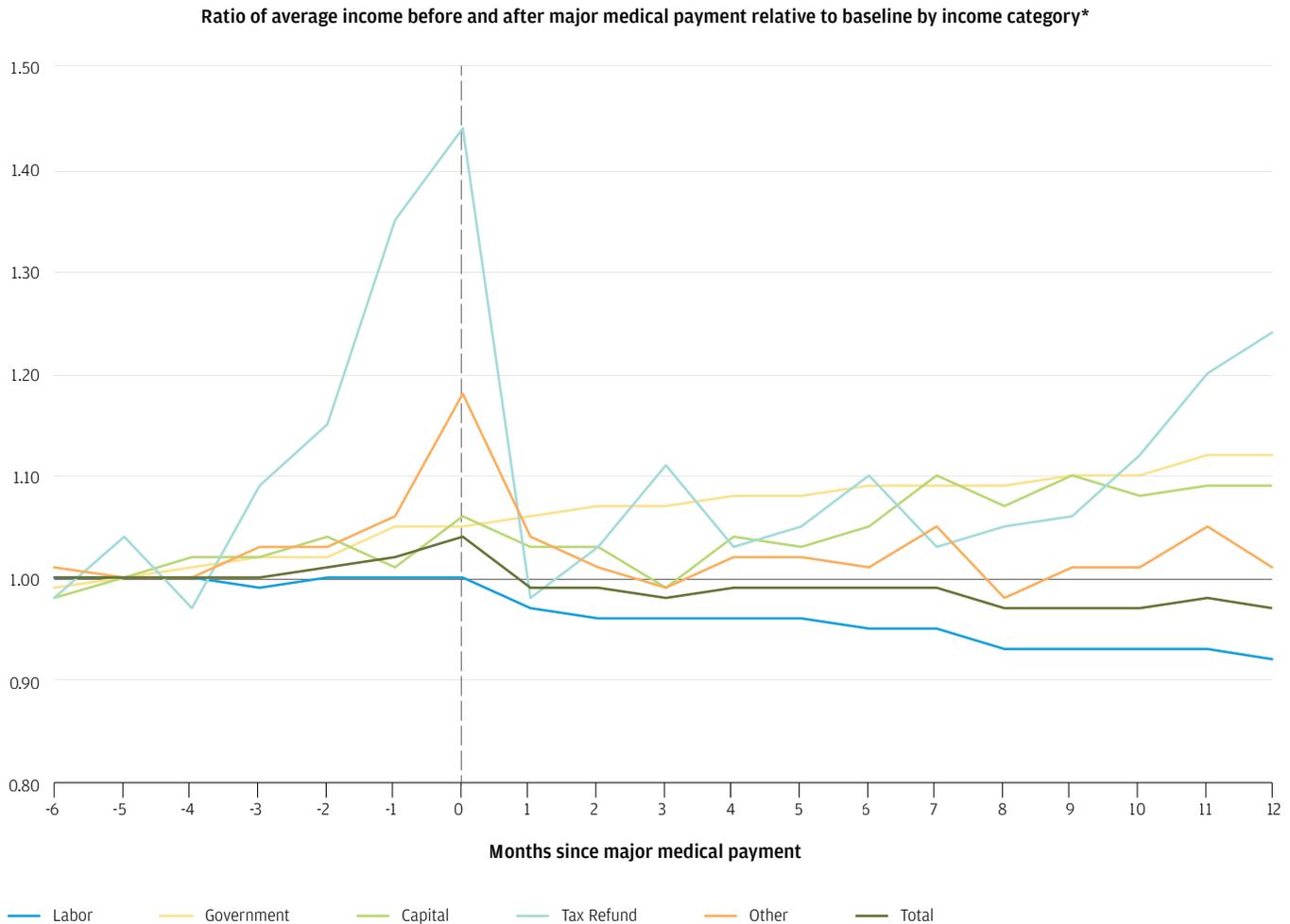
Tax refunds were a key contributor to the correlation between income and medical payments. Extraordinary medical payments were most common in March and April, occurring among 1.8 percent of families compared to 1.4 percent of families in November, the month with the lowest incidence. Sixteen percent of families with an extraordinary medical payment received a tax refund within the three months leading up to the expense, resulting in a 44 percent increase in income from tax refunds in the month with a major medical payment.<sup>22</sup> Tax payments represented 66 percent (\$50) of the (\$77) increase in known income categories (Figure 17).

It is possible that factors other than tax refunds could cause the incidence of medical payments to be higher in March and April, resulting in a spurious correlation between tax refunds and medical payments. For example, a common feature of insurance plans is a deductible, an initial amount of healthcare expenses that must be paid for by the insured individual. For many insurance plans, the deductible resets on January 1. As a result healthcare expenses incurred in the beginning of the calendar year might need to be paid for by the insured individual, resulting in a bill in March or April.

The remaining 34 percent (\$27) of the increase in known income categories came from other government and capital income. Other government income, including social security payments and unemployment insurance, increased by 5 percent in the month prior to the major medical payment and continued to rise subsequently. Capital income, which includes annuities, dividends, and interest income, was 6 percent higher when the major medical payment occurred. Uncategorized income was also 18 percent higher during a major medical payment, accounting for the remaining \$87 of the \$163 increase in total income. This category, which includes all cash and paper check deposits, could represent a range of sources, including transfers from friends and family, business income, and tax refunds received by paper check.<sup>23</sup>

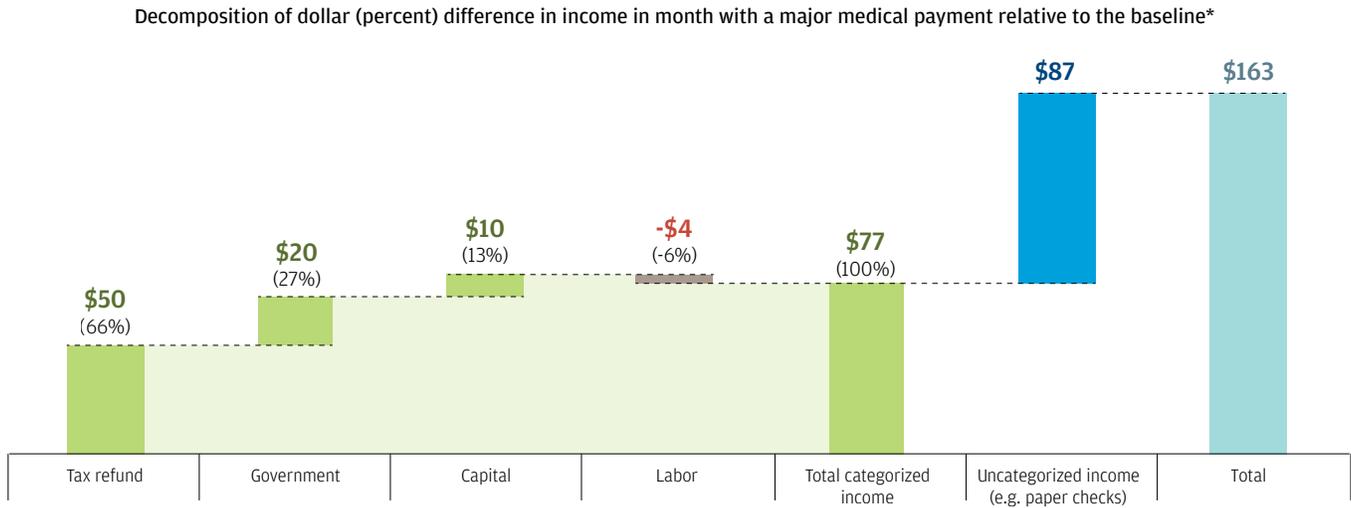
The income increase did not appear to be labor related. Directly deposited labor income was 1 percent lower when the major medical payment occurred and continued to decrease subsequently to 92 percent of the pre-expense baseline after 12 months. This loss of labor income was only partially offset by a rise in government income which rose to 12 percent above the baseline after 12 months. In aggregate, total income did not recover within a 12 month timeframe. This suggests that some of the health expense might have been concurrent with significant health events which had an impact on earnings. It also highlights that American families are not fully insured against the economic consequences of major health events.<sup>24</sup>

**Figure 16: Income from tax refunds was 44 percent higher than baseline at the time of an extraordinary medical payment**



\* t = 0 is the month with major medical payment. Baseline period corresponds to four to six months prior to the payment month.

Figure 17: Tax refund accounted for most of the increase in total categorized income



\* Baseline period corresponds to four to six months prior to the payment month.

Source: JPMorgan Chase Institute

The correlation between income and incidents of extraordinary medical payments has multiple potential mechanisms. First, families might have experienced a health event but delayed payment until they were able to pay. In other words, they might be paying off medical debt. The Consumer Financial Protection Bureau (2014) estimated that nearly one in five consumers with a credit bureau record (19 percent) have medical debt. Receipt of tax refunds, and the Earned Income Tax Credit in particular, has been linked to repayment of unsecured debt, which could include medical debt.<sup>25</sup>

Second, families might have delayed healthcare consumption until they were able to pay. Previous research has found evidence linking healthcare consumption to liquidity constraints. The American Psychological Association (2015) found that 12 percent of adults reported skipping a visit to the doctor when they needed health care because of financial concerns. Others have found evidence of increased healthcare spending after receipt of tax rebates.<sup>26</sup> More broadly, many have documented that families with lower income and wealth utilize less healthcare even after controlling for medical need.<sup>27</sup>

A somewhat less likely mechanism is that families generated more labor income in order to afford a necessary healthcare expense. We do not find that labor income contributed significantly to the rise in total income, and others have shown that family members are limited in their ability to offset each others' income shocks.<sup>28</sup> Nonetheless, with the rise of the Online Platform Economy and contingent work more generally, it may now be easier to increase earnings when necessary.<sup>29</sup>

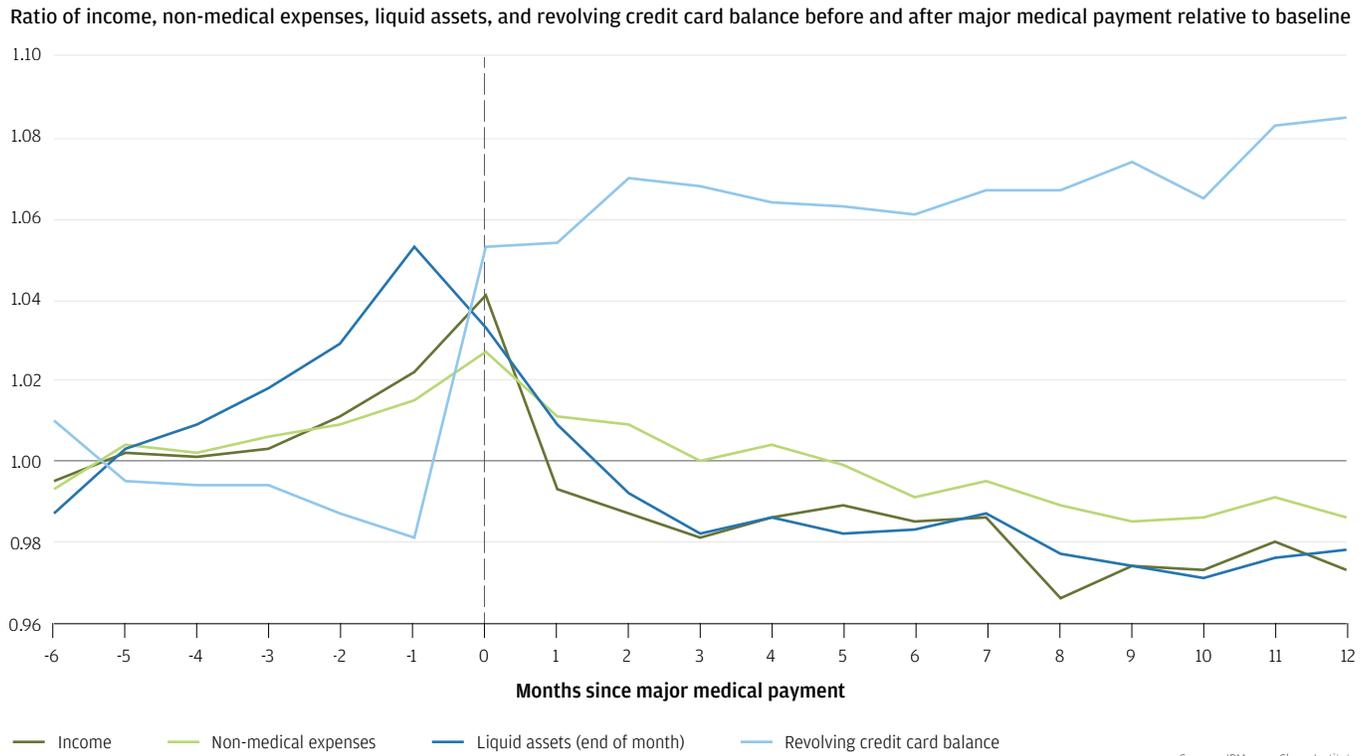
Major medical payments coincided with income increases, suggesting that families delayed payment or healthcare consumption until they were able to pay.

**Finding Five**

**Prior to a major medical payment, families garnered substantial liquid assets but did not recover financially within 12 months after the payment.**

When a major medical payment occurred, in aggregate, families experienced changes in not just their income and expenses but also their liquid assets and borrowing. This was often by necessity—the \$163 increase in income (4 percent relative to baseline, in aggregate) would not have been sufficient to fully pay for a major medical payment that was at least \$400 and \$2,089 on average. We examined the path of income, non-medical expenses, end-of-month liquid assets in observed accounts, and revolving balance on observed credit cards around the time of payment in comparison to the mean over a baseline period between four and six months prior to the payment (Figure 18).<sup>30</sup> We highlight behavior immediately prior to as well as 12 months after the medical payment relative to the baseline (Figure 19).

**Figure 18: Families increased income, spent down liquid assets and also increased credit card debt in the event of an extraordinary medical payment**



Total income increased by 4 percent (\$163) in the month with the major medical payment relative to the baseline. At the same time, non-medical expenses also increased by 3 percent (\$121) (Figure 19). Specifically 48 percent of families increased their income, and 52 percent of families increased their non-medical expenses in the month with the major medical payment relative to the baseline. This might suggest that some families delayed healthcare expenses until they had extra income to spend, and when they did so, they also increased expenses in other categories.

We observed that families increased their liquid assets and decreased their revolving credit card balance immediately prior to the medical payment. Specifically, families marshalled a 5 percent or \$919 increase in liquid assets in the month prior to the major medical payment and immediately spent assets down. This highlights the extent to which families accumulated and used assets over a very short time horizon—53 percent of families increased their liquid assets one month prior to the medical payment, many of whom immediately spent them down in the month with a medical payment as shown in Figure 18.<sup>31</sup>

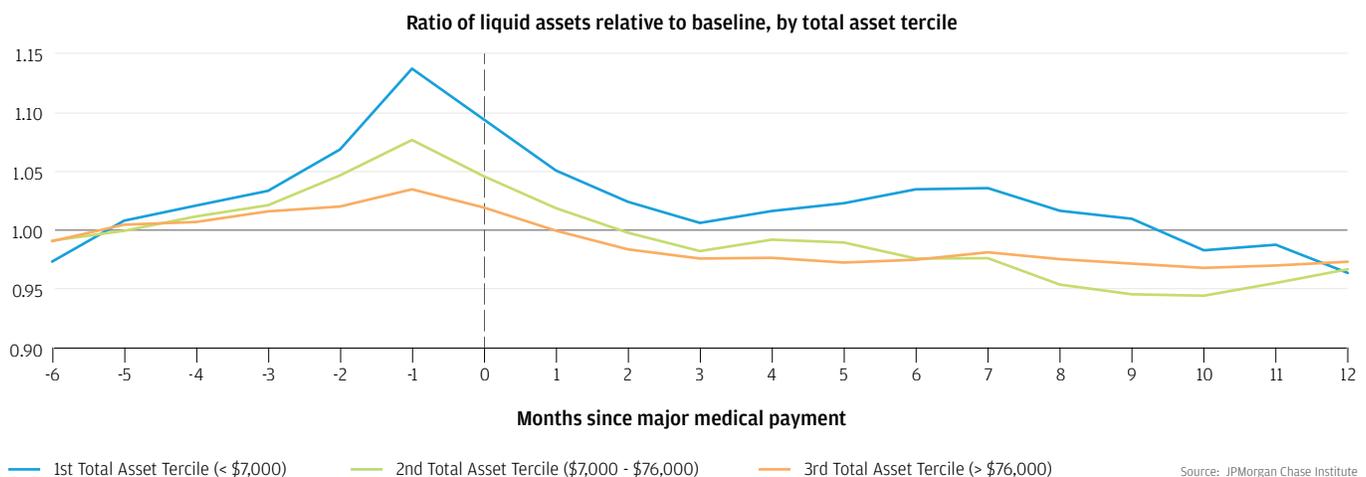
**Figure 19: Families made multiple changes across the income statement and balance sheet prior to the medical payment and did not recover relative to the baseline within 12 months after the payment**

		Pre-payment compared to baseline*			One-year post payment compared to baseline		
		Percent change	Dollar change	Percent exhibiting aggregate trend**	Percent change	Dollar change	Percent exhibiting aggregate trend***
Income statement	Income	4%	\$163	48%	-3%	-\$112	43%
	Non-medical expenses	3%	\$121	52%	-1%	-\$56	47%
Balance sheet	Liquid assets	5%	\$919	53%	-2%	-\$410	48%
	Revolving credit card balance	-2%	-\$39	34%	9%	\$217	32%

\* Pre-payment behavior timeframe is considered month 0 for income and non-medical expenses, which are flow variables, and month -1 for liquid assets and revolving balance, which are stock variables. Baseline period corresponds to four to six months prior to the payment month.  
 \*\* The aggregate trend was considered an increase for income, non-medical expenses, and liquid assets and a decrease for revolving credit.  
 \*\*\* The aggregate trend was considered a decrease for income, non-medical expenses, and liquid assets and an increase for revolving credit.

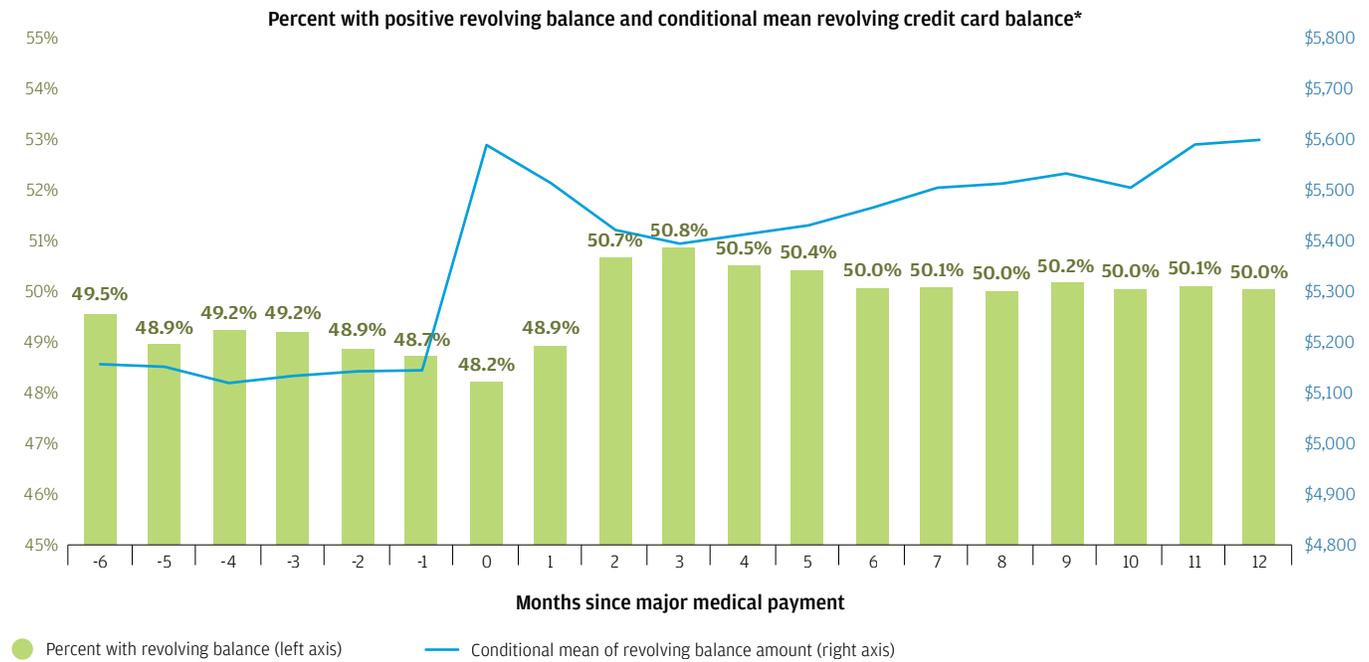
We also studied whether the run up in liquid assets prior to the medical payment was driven by families with high versus low total estimated assets (in both observed and unobserved accounts).<sup>32</sup> Families with less than \$7,000 in total estimated assets increased their liquid assets more, in both percentage and absolute terms, than families with higher total assets.<sup>33</sup> Specifically, families in the lowest asset tercile increased their liquid assets by 14 percent (\$1,102), compared to 8 percent (\$869) among the middle tercile, and just 3 percent (\$891) among the highest tercile prior to the major medical payment (Figure 20).<sup>34</sup> This suggests that families with lower total assets were more likely to have been liquidity-constrained prior to the medical payment and were either paying off outstanding medical bills or had left a medical condition untreated until they were able to pay for the out-of-pocket expenses.

**Figure 20: Families with lower total financial assets were more likely to experience a liquid asset spike prior to the major medical payment**



Families also decreased their liabilities immediately prior to the medical payment (Figure 18). Revolving credit card balances decreased by 2 percent (-\$39) relative to the baseline immediately prior to the medical payment. After payment, revolving credit increased by roughly 5 percent in the month with the extraordinary medical payment. While the percent of families with a positive revolving balance increased by just 2 percentage points from 49 percent in the baseline period to 51 percent two months after the major medical payment, the mean balance increased by \$392 in the month after the major expense (Figure 21).

**Figure 21: The percent of families with a revolving credit card balance and the level of the revolving balance both increased after a major medical payment**



\* Conditional mean revolving balance represents the mean balance among families with a positive revolving balance. Source: JPMorgan Chase Institute

It is worth acknowledging that changes to income, non-medical expenses, liquid assets, and credit card debt in the aggregate population do not necessarily imply that every family simultaneously exhibited each of these changes. While just 6 percent of families exhibited all four of the prepayment behaviors listed in Figure 19, 90 percent of families exhibited at least one, including 62 percent of families that exhibited two or more. The most commonly observed behavior was to increase liquid assets in the month with the major medical payment, but just 8 percent of families did this exclusively. Put differently, most families exhibited multiple changes prior to payment.

More significantly, as evident in Figures 18 and 19, a year after a major medical payment families had not fully recovered financially relative to the baseline. In aggregate, comparing 12 months after the medical payment to the baseline period, income was 3 percent (\$112) lower, non-medical expenses were 1 percent (\$56) lower, liquid assets were 2 percent lower (\$410), and revolving balance was 9 percent (\$217) higher (Figure 19). Not every family was impacted identically—among families that made an extraordinary medical payment, 48 percent remained with lower liquid assets, 47 percent remained with lower non-medical expenses, 43 percent had lower income, and 32 percent had higher revolving credit 12 months after the major medical payment compared to the baseline period. Nonetheless 86 percent of families were impacted in at least one of these dimensions, and 55 percent were impacted across multiple dimensions.

Put differently, the medical payment left a lasting imprint on families’ balance sheets. Comparing the peak in assets prior to the payment to a year later, families had depleted their liquid assets by \$1,329 and increased their revolving credit card debt by \$256, when faced with a \$2,089 medical payment.<sup>35</sup> Moreover, the persistent deterioration in not just the balance sheet picture but also income and non-medical expenses suggests that major medical payments were associated with lasting changes in families’ financial wellbeing.

# Implications

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In summary, we find that families across the income spectrum experienced high levels of expense volatility and income volatility. Monthly fluctuations in expenses were comparable in magnitude to typical monthly housing payments. Middle-income and older families were particularly vulnerable to large extraordinary payments related to medical services, auto repair, and taxes. While income volatility declined with age, expense volatility remained high, though the range in income and expense volatility was greater among older families.

Around the time of a major medical payment, we observed multiple changes across family income, non-medical expenses, assets, and liabilities. In particular, major medical payments coincided with increases in income and liquid assets, followed by long-lasting declines in income, non-medical expenses, and liquid assets and a rise in revolving credit card debt. These findings have important implications for the financial resilience of American families.

1. **Liquid assets play a critical role in managing expense spikes.** The high levels of expense and income volatility observed in our data underscore the difficulty with which families manage their day-to-day financial lives and the importance of short-term liquidity. While many families experienced an increase in income in the month in which they made a major medical payment, liquid assets were the primary source of funding to cover the medical payment. Families marshalled substantial liquid assets prior to the payment which they spent down to cover the payment. This highlights the central role short-term savings play in managing expense volatility and the need for policies and solutions to promote emergency savings.<sup>36</sup>
2. **Financial health and physical health are interrelated.** Our research underscores two important links between financial and physical health. First, there is a link between ability to pay and medical payments. We found evidence that medical payments were more likely to occur when families had higher income and liquid assets. This implies that families either delayed medical treatment until they were able to pay, which could be bad for their physical health, or they delayed payment until they were able to pay, which could be bad for their financial health. In either case, families make choices about the timing of their out-of-pocket healthcare expenditures, underscoring the need to better understand the connection between liquidity constraints and healthcare consumption.

The second link is that major medical payments were associated with lower incomes, non-medical expenses, and liquid assets and higher credit card debt a year later. Even over this timeframe of expanding health insurance coverage, families were not fully insured against the economic consequences of major health payments. Families are resourceful in that they made payments when they had more income and liquid assets and also increased credit card debt. Nonetheless, most families did not fully recover financially within 12 months of a major medical payment.

3. **Older families face a unique set of financial challenges that warrant more customized solutions.** The link between financial and physical health is even stronger for older families who spend a higher fraction of their budget on medical expenses and are more likely to make major medical payments. But older families are also distinct in a number of ways. Older families face a unique challenge of high expense volatility and low income volatility, but also a greater range of expense and income volatility. While older families experienced more volatility from discretionary expenses categories, over which they might have some control, they are also more likely to have made extraordinary payments that might be difficult to predict and plan for.

Thus, while we might expect older adults to have more predictable lives, expense volatility is something they continue to have to manage. As a result, seniors need access to liquidity reserves or investment portfolios that allow for liquidity without incurring major costs. They need better tax planning and tools to forecast medical expenses, including long-term care. In general, seniors stand to benefit from more customized financial and insurance solutions that are tailored to their individual expense profile and needs. Policymakers should also consider interventions to reduce this expense volatility for seniors, given their reliance on fixed incomes. In particular, medical expenses are a major source of this volatility and could be a fruitful area for helping seniors.

**4. Better solutions could help families mitigate and manage expense volatility.**

Having liquid savings, access to credit, and insurance are typical ways families manage their expenses. However, our research highlights categories such as auto expenses, home repair, and even tax payments that contribute significantly to expense volatility, for which there appear to be limited or incomplete solutions. There is more room to develop and scale emerging solutions that help families forecast and plan for expense spikes and measure financial resilience. A recent solution provides a mobile application that enables individuals to track mileage and costs and forecast tax obligations from work-related driving. More broadly, recently developed measures of financial well-being (Consumer Financial Protection Bureau, 2015) and financial health (Center for Financial Solutions Innovation, 2016) have included, appropriately, a family's ability to meet their obligations and manage these fluctuations.

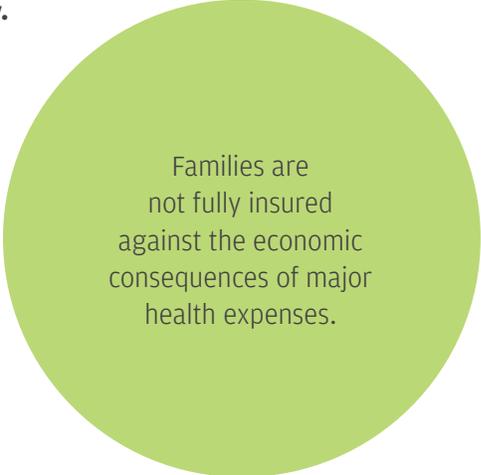
Families could also benefit from solutions that help families afford expense spikes.

As we saw, families are resourceful and use multiple strategies to manage expense spikes, including increasing their income, drawing down on liquid assets, and taking on credit card debt.

This suggests that better solutions could help families rely not only on their balance sheets (assets and liabilities) but also their income statements (income and expenses) to become more financially resilient. For example, one recent solution allows individuals to purchase a discounted monthly transit pass through weekly, adjustable payments that build a credit history. More broadly, employers could offer small-dollar loan and savings programs that operate through payroll deductions. Public policies and insurance programs, including the Affordable Care Act, also play a key role in helping families mitigate expense volatility.

- 5. Integrated, high-frequency data of income, expenses, assets and liabilities shed new light on financial behavior.** With the benefit of monthly data, we observed far greater expense volatility (29 percent monthly changes) than is evident with the typical year-over-year picture (15 percent annual changes). Moreover, observing income, expenses, liquid assets, and liabilities in tandem among the same families, indicated that major medical payments were indeed correlated with income increases over time. Whereas most scholars focus on the impact of income on expenses, our research points to the case for examining the opposite relationship as well—the impact of expenses on income.

Understanding the ways in which expenses fluctuate and how financial behavior changes with this volatility is critical to improving our understanding of, and efforts to strengthen, the financial resilience of American families.



Families are not fully insured against the economic consequences of major health expenses.

# Data Asset

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In this report, the JPMorgan Chase Institute assembled a de-identified data asset of over 250,000 core Chase customers between January 2013 and December 2015 to study how consumers' expenses vary over time and how their financial behavior changes when faced with extraordinary payments. This month-to-month panel of family finances provides a first ever look into the components of expense volatility based on real financial transactions and the changes to income, expenses, liquid assets and revolving credit card debt that coincide with extraordinary medical payments. In conducting this research we went to great lengths to ensure the privacy of customer data.

## Data Privacy

The JPMorgan Chase Institute has adopted rigorous security protocols and checks and balances to ensure all customer data are kept confidential and secure. Our strict protocols are informed by statistical standards employed by government agencies and our work with technology, data privacy, and security experts who are helping us maintain industry-leading standards.

There are several key steps the Institute takes to ensure customer data are safe, secure and anonymous:

- Before the Institute receives the data, all unique identifiable information—including names, account numbers, addresses, dates of birth, Social Security numbers, and Employer Identification Numbers (EIN)—is removed.
- The Institute has put in place privacy protocols for its researchers, including requiring them to undergo rigorous background checks and enter into strict confidentiality agreements. Researchers are contractually obligated to use the data solely for approved research and are contractually obligated not to re-identify any individual represented in the data.
- The Institute does not allow the publication of any information about an individual consumer or business. Any data point included in any publication based on the Institute's data may only reflect aggregate information.
- The data are stored on a secure server and can be accessed only under strict security procedures. The data cannot be exported outside of JPMorgan Chase's systems. The data are stored on systems that prevent them from being exported to other drives or sent to outside email addresses. These systems comply with all JPMorgan Chase Information Technology Risk Management requirements for the monitoring and security of data.

The Institute provides valuable insights to policy makers, businesses, and nonprofit leaders. But these insights cannot come at the expense of customer privacy. We take precautions to ensure the confidence and security of our account holders' private information.

## Assembling the sample

From a universe of 35 million checking account customers, we assembled a de-identified data asset comprised of roughly 250,000 core Chase customers for whom we could categorize at least 80 percent of expenses between January 2013 and December 2015. These families met the following five sampling criteria:

1. Had at least five outflows from personal checking account in every month
2. Had a credit bureau record on file
3. Used their debit or credit card at least once each month and have transacted at least once per month in the following categories: Grocery, Restaurant, Fuel or Transit, Clothing, Miscellaneous Retail, Drug Store, Home Supply or Improvement, and Entertainment.
4. Spent less than 20 percent of total expenses through channels that cannot be categorized, i.e. checks, cash, payments to unobserved credit cards, and other uncategorizable electronic channels.
5. Made at least one housing payment in each year. These include payments made both electronically as well as via paper check. We describe the algorithm built to identify housing related payments via paper check below.

Our sample differs from the nationally representative census sample in a number of ways. Figure 22 shows the joint distribution of age and income in JPMorgan Chase Institute sample compared to the Census Bureau's American Community Survey (ACS) 2014 1-Year Estimates. For the purposes of weighting, family income is assessed based on an annual pre-tax income estimate for 2014 ascertained by JPMorgan Chase based on individual, third-party, and zip code-level data. Figure 22 indicates that the sample over-represented younger families and middle-income families and underrepresented families in the first and fifth income quintiles as well as older families.

**Figure 22: Age and income joint distribution in JPMorgan Chase Institute sample prior to re-weighting versus national population**

	Age	Income					Total
		1st Quintile (< \$20,000)	2nd Quintile (\$20,001 - \$38,800)	3rd Quintile (\$38,801 - \$63,000)	4th Quintile (\$63,001 - \$104,600)	5th Quintile (> \$104,601)	
JPMorgan Chase Institute sample prior to re-weighting	19-29	1.8%	11.3%	11.4%	4.9%	1.6%	31.0%
	30-39	0.6%	5.8%	11.0%	7.7%	4.2%	29.4%
	40-49	0.3%	2.9%	6.0%	5.2%	4.0%	18.4%
	50-64	0.5%	2.9%	5.5%	4.4%	3.4%	16.7%
	65+	0.4%	1.3%	1.6%	0.8%	0.5%	4.5%
	Total	3.6%	24.2%	23.0%	23.0%	13.7%	100%
U.S. Adult Population*	19-29	4.9%	2.7%	2.3%	3.8%	3.8%	17.5%
	30-39	3.7%	2.9%	2.5%	3.8%	4.5%	17.3%
	40-49	3.8%	3.6%	3.2%	4.9%	4.2%	19.6%
	50-64	3.8%	4.2%	4.2%	6.2%	3.6%	21.8%
	65+	3.5%	4.1%	5.3%	7.7%	3.2%	23.7%
	Total	19.6%	17.4%	17.5%	26.4%	19.1%	100%

\* National estimates come from the Census Bureau's American Community Survey (ACS) 2014 1-year estimates. Cut-points for the income quintiles are computed using ACS family income in order to more closely match family income estimates of the JPMorgan Chase Institute sample. Age distributions are calculated at the individual level based on ACS data. Differences in the composition of families by income levels may explain why the total number of families within each income quintile band does not reflect exactly 20 percent of the population.

To make our sample representative of the U.S. population in terms of age and income, we assigned weights to each family in our sample. Weights were calculated by dividing the proportion of people in each age-income bin in the ACS by the corresponding age-income bin in the sample. Figure 23 depicts the sample weights computed for families in different age and income bins.

**Figure 23: Sample weights applied to achieve national representativeness in terms of income and age**

Weights	1st Quintile (< \$20,000)	2nd Quintile (\$20,001 - \$38,800)	3rd Quintile (\$38,801 - \$63,000)	4th Quintile (\$63,001 - \$104,600)	5th Quintile (> \$104,601)
19-29	2.6	0.2	0.2	0.8	2.3
30-39	6.2	0.5	0.2	0.5	1.1
40-49	11.1	1.2	0.5	1.0	1.1
50-64	8.1	1.5	0.8	1.4	1.1
65+	9.3	3.2	3.4	9.3	6.5

The resulting weighted sample was representative of the nation in terms of age and income distributions but still biased in favor of men as well as families in the West, and individuals who transact using card-based and electronic channels. Payment instrument usage is an important consideration, since previous research has shown strong correlations between use of electronic payment instruments with not only age (negative correlation) and income, which we account for, but also education, race (higher usage among white individuals), and marital status (higher usage among married individuals) (Connolly and Stavins, 2015). Thus even after weighting our sample to reflect the age and income distribution of the nation, our sample might still favor individuals who are more highly educated, white, or married.

**Figure 24: Gender and Geographical coverage in JPMorgan Chase Institute Sample versus the national population**

	US Adult Population*	JPMorgan Chase Institute Sample (N=249,667)
Men (%)	49%	56%
Women (%)	51%	44%
Northeast (%)	18%	14%
Midwest (%)	21%	23%
South (%)	38%	29%
West (%)	24%	34%
Percent of payments using paper instruments**	34%	8%

\* Unless otherwise noted, national estimates come from the Census Bureau's American Community Survey 2014 One Year Estimates. Regional distribution sums to greater than 100 percent due to rounding.

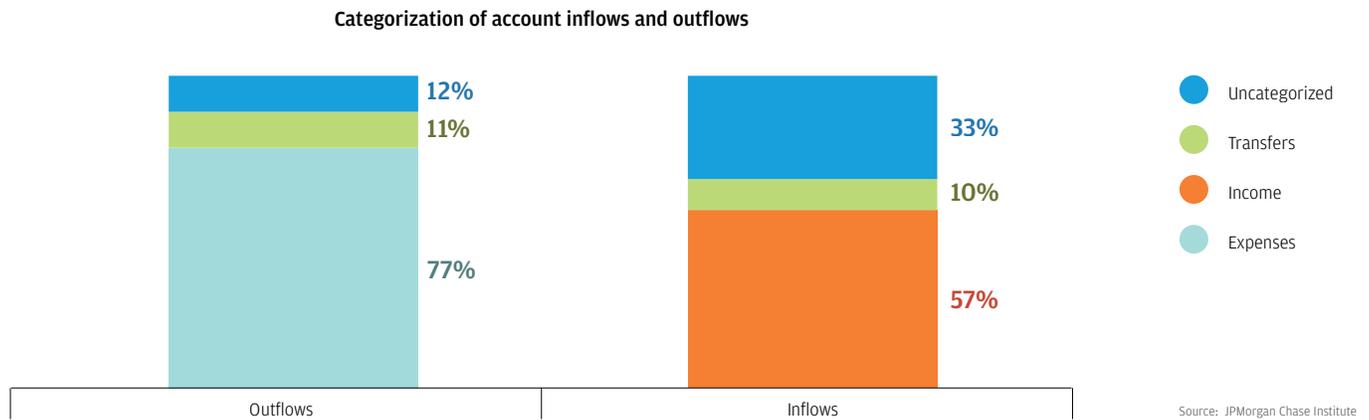
\*\* Paper instruments include paper checks, money orders and cash. US estimate based on the 2014 Survey of Consumer Payment Choice as reported in Greene et al (2016). JPMorgan Chase Institute estimate of the percent of payments using paper instruments is biased downwards due to the fact that we observe the number of ATM withdrawals and not cash payments.

## Categorizing expenses and income

Expenses include all outflows out of checking accounts that have been categorized as expenses, including all debit and credit card transactions as well as all checks, cash withdrawals, and online bill payments. It does not include outflows categorized as transfers to other financial institutions and other electronic or wire transfers that were unable to be categorized. All told, 88 percent of outflows were categorized including 77 percent as expenses and 11 percent as financial transfers (Figure 25).

Income includes all payroll related direct deposit, tax refunds, government income, capital income, and other income, which mostly represents paper checks. It does not include inflows that represent transfers from other financial institutions or electronic transactions that could not be categorized. Two-thirds of inflow dollars were categorized, including 57 percent as income and 10 percent as transfers.

Figure 25: We were able to categorize 88 percent of expenses within our sample



Within income and expenses, sub-categories are ascertained based on a number of techniques depending on the transaction channel. For all credit and debit card transactions we infer the expense category based on the merchant category code, which is known for all card transactions. In the case of electronic transactions, the expense or income category was inferred by analyzing the text description associated with the transaction. For outgoing paper checks, we developed an algorithm to identify check payments for tax, rent, or mortgages (described below). The resulting distribution of expenses closely mirrored key categories of expenses within the Consumer Expenditure Survey (Figure 26).

Figure 26: Composition of expenses in JPMC Institute sample compared to the Consumer Expenditure Survey

Percent of total expenses*	U.S. Adult Population**	JPMorgan Chase Institute Sample (N=249,667)
Housing	20%	22%
Food at home	7%	10%
Utilities	7%	7%
Fuel	4%	4%
Restaurant and Entertainment	9%	7%
Other unknown	N/A	12%

\* Values do not sum to 100 percent because not all expenses categories could be neatly cross-referenced to categories listed within the Consumer Expenditure Survey.

\*\*Estimates reflect averages based on the 2013-2015 Consumer Expenditure Surveys. Housing includes shelter only, i.e. excludes utilities, household operations, furnishings and equipment. Fuel represents gasoline and motor oil. Restaurant and entertainment includes food away from home, fees and admissions, and audio and visual equipment and services.

In evaluating expense volatility an important distinction is whether the expenses represent non-discretionary expenses (everyday necessities such as groceries, housing, and bills) or discretionary expenses (one-time durable purchases and leisure expenses). Figure 27 displays the sub-categories included within discretionary and non-discretionary expenses and descriptions for each.

**Figure 27: Sub-components of expense**

Category	Sub-category	Examples
Discretionary	Restaurant / Entertainment	Restaurants, bars, movies, tourist attractions
	Non-durable Retail	Clothing stores, department stores, office supplies
	Other Services	Personal professional services, membership dues
	Durable Retail	Home repair, furniture, electronics, and appliance stores
	Automobiles	Auto dealers, auto parts manufacturers, auto repair
	Travel and Hotel	Airlines, car rental, hotels, cruises, travel agencies
	School	Tuition payments and educational services
Non-Discretionary	Grocery	Grocery stores
	Utilities	Phone, cable, electricity, gas
	Fuel	Gas stations
	Auto Loans	Auto loan payments
	Student Loans	Student loan payments
	Insurance (Non-health)	Car insurance, home insurance
	Housing	Rent, mortgage payments
	Other Debt	Finance charges, escrow, home equity loan payments
	Drugstore Retail*	Drugstores
	Discount Store	Wholesale clubs and off-price retailers
	Medical*	Doctors visits, hospitals, dental, optical, medical equipment, specialty drugstores
	Transit	Taxi, commuter subway or rail, bus, tolls, parking
Tax	Tax payments	
Other / Unknown	Checks	Outgoing checks
	Cash Withdrawals	Cash withdrawals at ATMs or tellers
	Non-Chase Credit Card Payments	Payments made to pay off non-Chase credit cards
	Other Electronic Bills	Other bills paid online

\* Purchases at major drugstores that were increments of five dollars were assumed to be prescription drug co-payments and included as part of Medical.

This categorization necessarily required judgment calls. One challenge is that for all debit and credit card expenses, categories of expenses are based on merchant category codes assigned at the merchant level (e.g. discount store). Since we did not have itemized receipt-level information, everything purchased at a given merchant had to be categorized uniformly. This is an easy task for specialized merchants, but more difficult in cases such as discount stores, which sell many different types of goods, including groceries (a non-discretionary purchase) and furniture (a discretionary purchase). As indicated in Figure 27, we chose to consider all discount store expenses as non-discretionary, for example.

A second challenge is that individual circumstances dictate whether a purchase is truly discretionary or not. We considered all automobile-related expenses as discretionary on the grounds that vehicles are a durable expense. In reality an automobile repair could be a real necessity if it would otherwise prevent an individual from being able to go to work.

## Classifying paper checks

In order to develop a better window into the composition of expenses, we developed an algorithm to estimate the economic purpose of certain paper check transactions. Paper check withdrawals represented 25 percent of total expenses within our sample, but the expense category associated with each paper check transaction was unknown. We adopted a machine learning framework to impute four different categories of payment for paper checks: tax, rent, mortgage payments, and other. We targeted tax, rent, and mortgage payments because they capture large payments often made using paper checks. For example, 42 percent of US households pay rent using checks, and 27 percent of US households pay their mortgage using checks (Zhang, 2016). As a result, when we relied exclusively on categorized electronic payments, we estimated roughly half the amount of housing expenses reported in the Consumer Expenditure Survey.

We used samples of ACH transactions that had been already categorized as rent, mortgage, tax, or other to develop an algorithm to classify paper checks that relied only on attributes observable for check-based transactions. This procedure involved three key steps. First, we selected a list of variables that could potentially best distinguish the expense categories from one another based on information available for paper check transactions. These variables included attributes at the transaction, family and neighborhood levels.<sup>37</sup> Second, we trained an algorithm using training and testing samples of categorized ACH transactions as “truth sets.” We applied the parameters of the algorithm that resulted in the smallest error rate in the testing sample (i.e. the out-of-sample error). We were able to achieve nearly 80 percent out-of-sample accuracy using the trained algorithm. Third, we applied the algorithm to each paper check transaction to predict the category of payment and the confidence probability of this categorization. We further refined the results by only accepting paper check payments categorized as tax payment in April.<sup>38</sup> Additionally, we established the constraint that no family could make more than two payments (electronic or paper-check) within a category per month.<sup>39</sup>

Figure 28 compares aggregate statistics on transactions categorized as taxes, rents and mortgages that are ACH transactions versus paper check transactions. The aggregate statistics are quite similar for both ACH and classified checks for the three categories. Mean transaction values were nearly identical between ACH and check transactions identified as tax, rent, or mortgage payments. Median transaction values differed somewhat, however, suggesting differences in the distributions of values between ACH and check-based payments. In addition, in the case of tax and rent payments, a higher number of payments per month was identified as made with checks rather than ACH. This is consistent with other evidence that check payments are more common than ACH payments for rent (Zhang, 2016).

**Figure 28: Descriptive statistics of electronic payments align well with those of paper check payments**

	Tax		Rent		Mortgage	
	ACH	Check*	ACH	Check	ACH	Check
Mean transaction value	\$ 1,811	\$1,794	\$ 1,145	\$1,131	\$ 1,387	\$ 1,362
Median transaction value	\$ 200	\$254	\$ 944	\$ 577	\$ 1,139	\$ 701
Mean number of transactions per month	1.3	1.6	1.1	1.4	1.3	1.3

\* Tax checks were identified only in the month of April.

## Adjusting for secular trends

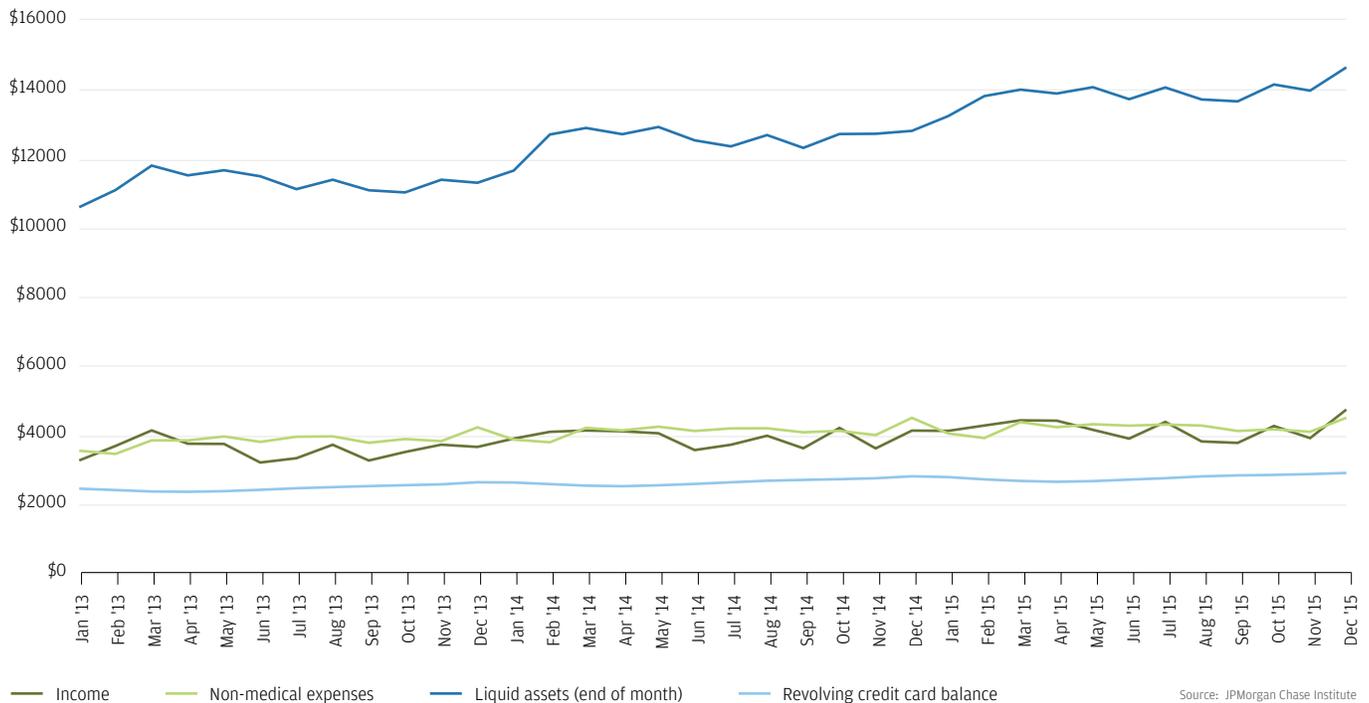
In evaluating the path of income, non-medical expenses, liquid assets and revolving credit card debt around a medical payment, we observed upward trends in these variables (Figure 29). These upward trends—8 percent per year for income, 5 percent per year for non-medical expenses, 11 percent per year for liquid assets, and 6 percent per year for revolving credit card balance—could be due to economic growth, growth in uptake of Chase products, and the well-documented national growth in the use of electronic payment instruments (Greene et al, 2016). In order not to overstate the path of recovery, we needed to account for these secular trends. To estimate the path of recovery after a medical payment, we adjusted each variable  $y$  for family  $i$  in month  $t$  as:

$$y_{it} = y_{it,raw} - (\bar{y}_t - \bar{y})$$

where  $y_{it,raw}$  are the original data,  $\bar{y}_t$  is the mean of the variable across the entire population in time  $t$  and  $\bar{y}$  is the grand mean of the variable across all time periods. This adjustment procedure implicitly establishes the entire population of roughly 250,000 families as a comparison group for the subset of roughly 54,000 families we examine who made exactly one major medical payment between 2013 and 2015.

We assembled a sample of roughly 250,000 families for whom we could categorize at least 80 percent of expenses.

**Figure 29: Trends in income, non-medical expenses, liquid assets, revolving credit card balance among all families**



Source: JPMorgan Chase Institute

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# Endnotes

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- 1 For example, Dynan et al. (2012), using the Panel Study of Income Dynamics, found that the percentage of people experiencing a 25 percent or more decline in income over a two-year period increased from 16 percent in the early 1970s to over 20 percent in the 2000s. Similar patterns have been documented by Gottschalk and Moffitt (2009) and Hardy and Ziliak (2014). Gorbachev (2011) and Dogra and Gorbachev (2016) find that food consumption volatility increased by around 19 percent between 1980 and 2004, while income volatility increased by 44 percent.
- 2 See Jappelli and Pistaferri (2010) for a survey of this literature. More recent studies using financial transaction data reveal that expenses are highly sensitive to transitory income shocks such as the 2008 government stimulus payments (Parker, 2015) and the 2013 government shutdown (Gelman et al., 2015).
- 3 Ibid. In addition, see Kaplan et al. (2014) for a discussion of liquidity constraints among wealthier households.
- 4 Similarly, Lusardi, Schneider, and Tufano (2011) find that among a survey of roughly 2,000 U.S. participants, 50 percent responded that they “probably” or “certainly” could not meet an unexpected need of \$2,000 in the next month.
- 5 We describe our sampling criteria, sample attributes, and methodology in more detail in the Data Asset section.
- 6 Among our sample 67 percent of accounts had multiple authorized users on the account, and 33 percent of primary account holders were individual account holders. The mean number of authorized users per account is 1.66, lower than the national household size of 2.65 in the 2014 American Community Survey (ACS), due to the fact that authorized users are typically adults whereas ACS household size would include children. It may also be the case that some families have multiple accounts with different individuals listed as the primary account holder. In addition, we refer to expenses and payments interchangeably. Our lens on expenses reflects payments made at the time of payment. For debit card and electronic transfers these payments result in a debit to the payer’s account. For credit card transactions they do not.
- 7 Previous work on consumption volatility has relied on survey instruments which are limited in frequency, duration, or categories of expenses. The Panel Study of Income Dynamics, used by Dogra and Gorbachev (2016), provides a biennial (annual between 1968 and 1997) measure of food and shelter consumption. The Consumer Expenditure Survey, used by Davis and Kahn (2008), provides quarterly data on a more comprehensive range of expense categories, but the same household is only observed for four quarters at a time. More recently the U.S. Financial Diaries project collected detailed financial diaries every two to four weeks from 235 low- and moderate-income households over the course of a year between 2012 and 2013 (Morduch and Schneider, 2013).
- 8 These estimates reflect the median value of the mean month-to-month or year-to-year change in family expenditure. Throughout this report medians are calculated as the mean of the ten median observations in order to meet minimum aggregation standards.
- 9 Throughout Findings 1 and 2, we estimate the symmetric percent change between observations A and B, calculated as  $(B-A)/(0.5 \times (A+B))$ . Symmetric percent change has the benefit of allowing for positive and negative changes to be represented symmetrically and also for changes from zero to be calculable.
- 10 Others have documented evidence of greater volatility in discretionary expenses, such as durable goods purchases, on a year-to-year basis (Black and Cusbert, 2010; Luengo-Prado, 2006).
- 11 Figure 27 in the Data Asset section lists detailed descriptions of each expense category.
- 12 This might also reflect some measurement error in categorizing rent and mortgage payments made via paper check. See the Data Asset section for a discussion of this methodology and error rate.
- 13 Each dot in Figures 5, 6, and 7 represents a group of families in order to adhere to privacy protocols.
- 14 The result that income is as volatile as expenses differs from Weathering Volatility in which we estimated that expenses were more volatile than income on a month-to-month basis. We believe the difference in the result stems from a difference in sampling requirements. In the sample for Weathering Volatility, we required families to have a minimum of \$500 in inflows into and five outflows out of their checking account every month. For the purposes of this report, we removed this sampling criterion on inflows, which resulted in higher income volatility within this sample. Other more stringent sampling criteria applied in this report to ensure a more complete and granular view on expenses, however, may have yielded lower expense volatility.

- 15 Some income volatility among older families may stem from retirement distributions which may be withdrawn annually or periodically throughout the year.
- 16 We used \$400 as a minimum threshold in order to provide some comparability between our measure of extraordinary payments and the 2015 Survey of Household Economic Decisionmaking. We allowed for this minimum threshold to scale with income in order to account for higher costs of services typically consumed by high-income families as well as to ensure that we were examining an extraordinary payment that would be material in magnitude across the income spectrum. In aggregate, extraordinary medical payment dollars were comprised of 19 percent doctors visits, 13 percent ambulance and hospital, 36 percent dental, 8 percent optical, 7 percent medical equipment, 15 percent other medical services, and 1 percent prescription drugs. Extraordinary auto repair payments included only payments to auto repair shops, a subset of total automobile spending (as shown in Figure 27). Tax payments excluded tax refunds. The standard deviation was calculated using all 36 months, including months with zero payment.
- 17 After the medical payment the family might also receive reimbursement from insurance.
- 18 The Survey of Household Economic Decisionmaking estimated that 24 percent of respondents in 2014 and 18 percent in 2015 experienced some form of financial hardship (either income or expense related). In 2015 the most commonly cited source of economic hardship (36 percent) was a health emergency. Pew Charitable Trusts (2015) estimated that 60 percent of households experienced a financial shock (either income or expense related) in the past 12 months with a median value of \$2,000. This includes 30 percent who paid for a major car repair, 24 percent who experienced a trip to the hospital, 24 percent who paid for a major home repair, and 24 percent who experienced a pay cut.
- 19 Incidence of extraordinary payments among low-income families was sensitive to the definition of an extraordinary payment. When we removed the \$400 minimum threshold, we found that the incidence of major payments was highest among low-income families.
- 20 As illustrated above, they were more common and larger in magnitude than extraordinary auto repair payments. In addition, health events can occur for anyone, whereas auto repair expense only applies to families who own a vehicle.
- 21 As described in the Data Asset section, we observed secular increases in income between 2013 and 2015, which have been removed from each of the income categories in Figure 16 in order not to overstate the path of recovery twelve months after the medical payment.
- 22 During tax time more than 70 percent of tax filers typically receive a federal tax refund (efile.com, 2016).
- 23 Among these families, in the month during which the medical payment occurred, 95 percent of other income came in the form of paper checks deposited, which could represent tax refunds or transfers from friends and family. Based on federal tax return data, between 2013 and 2015, roughly 73 percent of tax filers received a federal tax refund, of which 29 percent—roughly 25 million tax filers—received their federal tax refund via paper check (efile.com, 2016). Additional families may receive state tax refunds via paper check. According to the 2015 Survey of Household Decisionmaking, borrowing from friends and family was the third most common way individuals would cover a \$400 emergency expense (28 percent), after putting it on a credit card (38 percent) and delaying the expense (31 percent).
- 24 Dobkin et al. (2016) similarly find that incomes drop by 17 percent following hospital visits and remain permanently lower.
- 25 For example, see Shaefer et al. (2013) and Mendenhall et al. (2012)
- 26 Johnson et al. (2006) found that healthcare consumption increased significantly after receipt of tax rebates in 2001. Parker et al. (2013) examine the impacts of the 2008 Economic Stimulus Payment on healthcare consumption and find a very low marginal propensity to consume healthcare services (less than 3 cents for every dollar of stimulus). Gross and Tobacman (2014) provide evidence, however, that the Economic Stimulus Payment induced riskier behavior that resulted in a higher incidence of drug- and alcohol-related hospital visits.
- 27 See, for example, Allin et al (2009) and Chen and Escarce (2004).
- 28 Dobkin et al. (2016) find no evidence that spouses increase labor supply when an individual experiences a hospital visit. More broadly, previous research on the “added-worker effect” has documented that family members do insure against each others’ income shocks, but that this effect has been decreasing over time as women’s labor force participation and the correlation between spousal income shocks has increased (Gorbachev 2016; Juhn and Potter 2007). Instead families are increasingly mitigating income volatility through transfer income.
- 29 Our own work on the Online Platform Economy (Farrell and Greig 2016a, 2016b) and Katz and Krueger (2016) have documented the rise of contingent work.

- 30 Liquid assets include the deposits and cash equivalents in checking, savings, and Certificate of Deposit (CD) accounts but not brokerage accounts. Observed credit card accounts include most Chase credit card accounts, excluding certain credit cards offered in partnership with other entities. Between 2013 and 2015, income, non-medical expenses, end-of-month liquid assets, and revolving balance on credit cards increased considerably (8 percent per year for income, 5 percent per year for non-medical expenses, 11 percent per year for liquid assets, and 6 percent per year for revolving credit card balance). To account for this growth, we removed these secular trends from these time series. See the Data Asset section for a description of this process.
- 31 As shown in Figure 18, liquid assets fell precipitously between the month prior to the medical payment and two months after the medical payment. Among families who made the medical payment with a credit card, the impact on liquid assets might have only appeared when they made a payment towards their credit card balance. The prevalence of short-term savings horizons, particularly among low- and moderate-income households has also been documented by Morduch and Schneider (2015) based on the U.S. Financial Diaries.
- 32 For this analysis we segmented families into terciles of assets based on an estimate of total liquid financial assets, not exclusively liquid assets in observed Chase accounts. This total liquid asset estimate is ascertained by JPMorgan Chase based on individual level proprietary data and third-party data and includes deposits, other liquid assets and cash equivalents, stocks, bonds, mutual funds, and treasury notes. It does not include balances from retirement and other tax-qualified accounts of the customer (e.g. 401k or 529 plan balances) or other non-liquid assets such as home equity.
- 33 Notably, among families in the lowest asset tercile, extraordinary medical payments were associated with a larger increase in income and expenses prior to and during the major medical payment compared to families with higher estimated total liquid assets. In fact, families in the bottom tercile of total liquid assets were more likely to experience a major medical payment during March or April when they received a tax refund. Twenty-five percent of families who experienced a major medical payment in March are in the bottom tercile of financial assets, compared to just 20 percent among families who experienced a major medical payment in January.
- 34 The magnitude of the medical payment was larger for families with more total liquid assets. The mean magnitude of the medical payment was \$1,285 for families in the lowest tercile of liquid assets, \$1,447 for families in the middle tercile, and \$2,415 for families in the highest tercile of liquid assets.
- 35 Here we have subtracted the dollar change in pre-payment behavior from the dollar change in the one year post payment behavior listed in Figure 19, to reflect the total change in liquid assets ( $-\$1,329 = -\$410 - \$919$ ) and revolving credit card balance ( $\$256 = \$217 - -\$39$ ).
- 36 See JPMorgan Chase & Co. (2017) for a synthesis of insights about opportunities to increase emergency savings.
- 37 For example, we factored in the timing of the payment within the month, whether the family had an open mortgage, and demographic variables shown by others to be correlated with payment instrument choices according to the federal Survey of Consumer Payment Choice (Connolly and Stavins, 2015; Zhang, 2016).
- 38 Twenty-five percent of tax payments are made in April alone due to tax filing deadline. Although many people make tax payments in other months, the attributes of these tax payments are less distinct from all other bill payments or check-based payments, so we had less confidence in the ability of the algorithm to single out tax payments in other months.
- 39 We chose this constraint because more than 95 percent of people made at most two tax, rent, or mortgage payments in a given month in our ACH data. In cases where our algorithm classified more than two paper check payments into a single category, we selected the appropriate number of classified checks (zero, one or two) based on the number of ACH transactions already classified into that same category. We chose the paper check transactions with the highest confidence probability.

## Suggested Citation

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