Predicting Child Welfare Referrals Based on Caregiver Financial Instability

An Exploration to Inform Child Maltreatment Prevention Services

REPORT HIGHLIGHTS:

- **Financial shocks in earned income are strongly correlated with child welfare hotline referrals.**
- **Referrals to the child maltreatment hotline are correctly predicted for 10%-40% of caregivers who experienced financial instability, depending on the statistical model.**
- **One potential policy response is to develop and administer caregiver financial stability screenings where they place the least possible burden on caregivers and service providers, and where appropriate referrals to prevention services can be made based on the screening result.**
- **Several opportunities exist to incorporate screening questions into existing tools, including the Colorado Family Support Assessment (CFSA) 2.0 used by members of the Family Resource Center Association and the Universal Preschool (UPK) Colorado Application Portal.**

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Introduction

Colorado is working diligently to shift from a system that reacts to child maltreatment to one that prevents it. An important component of this effort is Colorado Community Response (CCR), an innovative, voluntary program to prevent child maltreatment and strengthen families by targeting the protective factors of concrete support and social connections. Primary caregivers are referred to CCR after being reported to the state's child abuse and neglect hotline and "screened out" by county child welfare staff because the allegations do not meet the statutory definition of abuse or neglect and/or the child is not at imminent risk of harm. The hallmarks of CCR are family-driven goal-setting and comprehensive, short-term (about 20 weeks) case management to help caregivers access formal and informal services and supports to meet their immediate concrete needs, create a foundation for long-term economic security, and build social capital for sustained well-being and connections. Individual caregivers are referred to CCR, but the benefits of participating accrue to whole families.

Unfortunately, by the time a primary caregiver is reported to the hotline and becomes eligible for referral to CCR, their risk for child abuse or neglect may have already escalated. The purpose of the research agenda under which this study was conducted is to explore indicators of economic insecurity that are visible through administrative data and may predict future child abuse and neglect before a caregiver is referred to the hotline. Leveraging such predictions to outreach *even earlier* with voluntary prevention programs like CCR could be a game changer for Colorado's child maltreatment prevention efforts.

> **This study serves as a model approach for using economic security indicators to identify actionable opportunities to prevent child maltreatment through a focus on family financial well-being. As an initial use case example, this report can:**
>
> - **Enhance referral processes for voluntary prevention programs like CCR, moving further upstream in outreach to families experiencing financial instability; and**
> - **Inform investments in policies and practices that target the financial well-being of families as a key strategy to prevent child maltreatment.**

Prior research demonstrates the link between economic insecurity—broadly defined —and child maltreatment.[1] The connection is particularly reliable for income losses (vs. material hardship) among recipients of public cash assistance programs (Aid to Families with Dependent Children or Temporary Assistance for Needy Families [TANF]).[2, 3, 4, 5, 6, 7, 8] This study examines the relationship between reductions in earned income and child welfare involvement for caregivers who are identified as having children based on their application to the state-subsidized childcare program, Colorado Child Care Assistance Program (CCCAP). This population includes higher income caregivers than prior studies since income eligibility requirements for CCCAP are higher than for TANF, and applicants need not have met CCCAP income eligibility requirements to be included. The study population excludes caregivers who are disabled enough that they cannot work for at least five consecutive quarters during the study period. Research is also underway examining the relationship between reductions in child support payments received and child welfare involvement for custodial parents to explore another potential early intervention point for preventing child maltreatment.

The underlying theory for this research agenda is the family stress model of economic hardship. When economic hardship occurs, like a reduction in earnings, the increased pressure on caregivers increases parenting stress which leads to depression, demoralization, and "disruptions in skillful parenting" that can lead to child maltreatment.[9] If we can identify and support caregivers experiencing these financial shocks quickly enough, we can interrupt the cycle and prevent child welfare involvement. The first step in applying this theory of change is confirming that our measure(s) of financial shocks are in fact predictive of future child welfare involvement.

Approach

> **Formally, the question of interest for this study is: What is the relationship between a substantial loss in earnings and CCR-eligible referrals to Colorado's child abuse and neglect hotline?**

We address this question with a sample of caregivers who were identified from CCCAP applications as having at least one child under the age of 13 at some point from 2014 to 2019.

Sample

To be included in the analytic sample, a primary caregiver of at least one child under the age of 13 must have had quarterly earnings at some point between 2014 and 2019. Figures 1a and 1b show how the sample inclusion criteria overlap to determine when a primary caregiver was included in the analysis. Figure 1a displays the example of a caregiver who was eligible for inclusion during the entire study period because they had both earnings data and a child under 13 at all points from 2014 to 2019. Figure 1b shows a caregiver who was eligible for inclusion in the study in 2017 and 2018 only. While they had earnings data starting in 2015, their first child was not born until 2017 and earnings data ended at the end of 2018.

Figure 1a. Sample Inclusion Criteria: Example of a Caregiver in the Sample for the Full Study Period

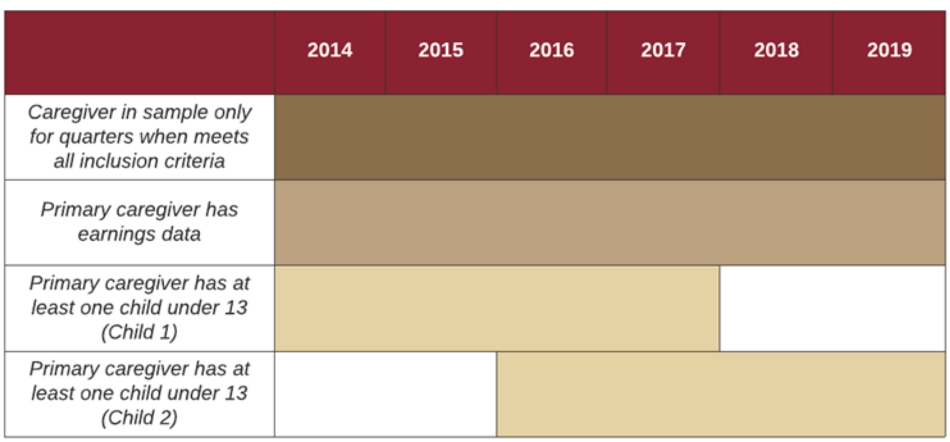
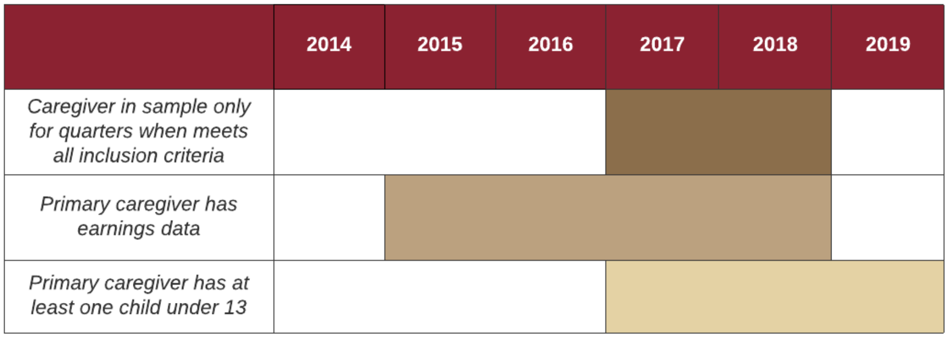


Figure 1b. Sample Inclusion Criteria: Example of a Caregiver in the Sample for a Portion of the Study Period



For more detail on how a primary caregiver is identified and how children are linked to caregivers, please see Appendix A.

Outcome

The outcome of interest is zero or one depending on whether a primary caregiver is referred to Colorado's child abuse and neglect hotline for a CCR-eligible reason within 6 months of experiencing a financial shock. To estimate the relationship between financial shocks and hotline referrals, all referrals meeting the CCR inclusion criteria (e.g., neglect, abuse, homelessness, lack of supervision) were included regardless of whether the referral was screened out or accepted for assessment, and regardless of whether an assessment became an open case. This is because earlier CCR involvement might have prevented a hotline referral from being made at all, or, if it was made, from being screened in. Referrals were excluded that included any CCR exclusion reasons like domestic violence, sexual abuse, child trafficking, or beyond control of parent.

CCR-eligible referral reasons *include* neglect, abuse, homelessness, and lack of supervision but *exclude* domestic violence, sexual abuse, child trafficking, and beyond control of parent.

Hotline referrals occur for many reasons, not all of which are related to a caregiver's economic security. We include all hotline referrals for a CCR-eligible reason in the analytic sample regardless of when they occurred. In the statistical models, we will estimate the strength of the relationship between experiencing a financial shock and a hotline referral. If there are a lot of hotline referrals that do not immediately follow a financial shock, the relationship between a financial shock and subsequent hotline referral will be weaker.

For more detail on how the outcome is defined, please see Appendix A.

Financial Shocks

We identify a financial shock, or a substantial drop in quarterly earnings, by comparing each quarter's earnings to the average of the prior four quarters for that same person. This accounts for the seasonality of earnings. We limit the financial shock calculation to instances when the average quarterly earnings over the prior four quarters was at least $300 (average of $100/month) and less than $14,120. Bounding on the low end avoids small dollar changes in income leading to large variability calculations just because the baseline level of earnings is so low. Bounding earnings on the high end avoids the inclusion of large dollar income swings among high income earners whose baseline income level is substantial enough that it is unlikely from a theoretical perspective to limit a caregiver's ability to provide basic material support for their children.

To determine whether a reduction in earnings is large enough to qualify as a "substantial drop," we compare it to the typical variability in earnings that occurred over the prior year for primary caregivers with a similar average income. This approach acknowledges that a given drop in earnings may not be meaningful for someone with a higher earnings level but may feel substantial for someone with a lower earnings level. Variability is measured using the standard deviation (S.D.) of quarterly mean earnings among all caregivers within the same decile of average income. We consider drops in quarterly earnings that are smaller than 1 S.D. "typical," and drops at least 1 S.D. in size "substantial."[10] To demonstrate how we apply this cutoff, consider a caregiver earning $5,000 per quarter on average over the prior year (about $20,000 annually). The relevant cutoff is 1 S.D. for all the caregivers in the decile in which the mean quarterly earnings of $5,000 falls, or $1,678. In practical terms, this means that it is typical (according to our definition) to see caregivers with earnings in one quarter of $3,500 offset by earnings of $6,500 in another quarter while the average remains $5,000. Therefore, a single quarter's earnings must be $3,322 ($5,000 minus $1,678) or lower to be considered a substantial drop for the purposes of this study.

As with the hotline referrals, we include all financial shocks in the analytic sample regardless of when they occurred (as long as the caregiver was eligible between Q1 2014 and Q2 2019). In the statistical models, we estimate the strength of the relationship between experiencing a financial shock and a hotline referral. If there are a lot of financial shocks that are not followed by a hotline referral, this relationship will be weaker. The frequency with which financial shocks are followed by hotline referrals in the full sample is described below.

For more detail on how financial shocks are defined, please see Appendix A.

Descriptive Statistics and Results

Logistic Regression

Before tackling the more complex analysis associating a particular hotline referral to a specific financial shock, we tested whether the probability of a hotline referral was higher among caregivers with generally less financial stability. For the purposes of this simple analysis, we consider caregivers experiencing at least one financial shock during the study period as susceptible to financial instability. The analytic sample contained one record for each primary caregiver, an indicator for whether they had at least one financial shock over the study period, and an indicator of whether they were involved in a hotline referral (regardless of timing).

Table 1 shows that in the sample of 88,222 primary caregivers, 78% experienced at least one financial shock. A simple comparison of means (34.9 vs. 29.1) indicates that 6 percentage points more caregivers with a financial shock had a hotline referral during the study period than those without a financial shock.

Table 1. Sample Descriptives

Caregiver Had a Financial Shock During Study Period	N (%)		
	No Hotline Referral (n=60,553)	Hotline Referral (n=27,669)	Total
No Financial Shock	17,736 (70.9)	6,372 (29.1)	24,108 (22.0)
Financial Shock	42,817 (65.1)	21,297 (34.9)	64,114 (78.0)

N=88,222 caregivers
Note: Percentages weighted for the number of quarters a caregiver was in the sample.

We estimated simple logistic regression models predicting the probability of a hotline referral based on whether a caregiver experienced at least one financial shock during the study period or not. The results were highly statistically significant and they are of substantial magnitude. In the preferred model, which is weighted to account for the number of quarters a caregiver appears in the data, a caregiver with at least one financial shock during the observation period was 30% more likely to have a hotline referral than a caregiver without a financial shock during the same period (Odds Ratio=1.30; p<0.001).[11]

While a financial shock is a strong predictor of a hotline referral, there were a large number of caregivers (42,817 or 65%) who experience at least one financial shock and were never referred to child welfare. In other words, having experienced at least one financial shock correctly predicts a child welfare referral 35 percent of the time. Thus, referring caregivers to CCR solely based on having experienced at least one financial shock over the prior 6 years will include a large number of caregivers who did not have a hotline referral during that same time period. Future research should examine the protective factors that prevent child maltreatment resulting from a financial shock.

A caregiver with at least one financial shock during the observation period is 30% more likely to have a hotline referral than a caregiver without a financial shock during the same period.

To try to address this problem, we also predict the probability of a hotline referral based on the number of financial shocks a caregiver experienced during the study period. Table 2 shows that 17% of caregivers experienced exactly one financial shock while 18% of caregivers experienced five or more. Depending on how many financial shocks a caregiver experienced during the study period, Table 2 also shows that the percent of caregivers with a hotline referral ranges from 30% (caregivers with one financial shock) to nearly 40% (caregivers with at least 5 financial shocks). The third column of Table 2 simultaneously answers the question of how many hotline referrals are correctly predicted solely based on information about the number of financial shocks experienced. With one shock, 30% of caregivers are correctly predicted to have a hotline referral, while the percent of caregivers with correctly predicted hotline referrals increases gradually to 40% for caregivers with 5 or more financial shocks. While 40% is substantially better than the 35% correctly predicted in Table 1, it is still substantially less than half the sample.

Table 2. All Caregivers and Caregivers with a Hotline Referral by Number of Financial Shocks

Number of Financial Shocks	N of Caregivers (%)	Caregivers with a Hotline Referral (%)
0	24,108 (22.0)	29.1
1	16,955 (17.3)	29.5
2	13,505 (15.7)	32.6
3	11,945 (15.0)	35.7
4	9,432 (12.6)	36.6
5+	12,277 (17.5)	40.1

N=88,222 caregivers
Note: Percentages weighted for the number of quarters a caregiver was in the sample.

We also explored whether the number of financial shocks per caregiver was statistically related to the odds of a hotline referral. Table 3 shows that the results of this analysis are highly statistically significant and of substantial magnitude. Compared to caregivers with no financial shocks, a caregiver was increasingly more likely to have a hotline referral with each additional financial shock beyond one (Odds Ratio=1.18 [two shocks vs. no shocks]; Odds Ratio=1.63 [five shocks or more vs. no shocks]. Therefore, a caregiver with two financial shocks was 18% more likely to have a hotline referral during the study period compared to a caregiver with no financial shocks. Similarly, a caregiver with five or more financial shocks was 63% more likely to have a hotline referral during the study period compared to a caregiver with no financial shocks. This result indicates that the number of financial shocks a caregiver experienced is more accurate at predicting which caregivers will experience a hotline referral than simply whether a caregiver experienced a financial shock. Thus, the number of financial shocks a caregiver experienced may be useful when deciding which caregivers to refer to CCR.

Table 3. Logistic Regression Model by Number of Financial Shocks Per Caregiver

Number of Shocks	Odds Ratio	Standard Error	P-value
1	1.02	0.025	0.380
2	1.18	0.029	<0.001
3	1.35	0.034	<0.001
4	1.41	0.038	<0.001
5+	1.63	0.040	<0.001

N=88,222 caregivers
Note: Model weighted for the number of quarters a caregiver was in the sample.

Table 4 shows that caregivers who are in the sample for longer are more likely to experience at least one financial shock. This is simply because we observe them longer and is why weighting is important in the statistical models. Indeed, 84% of those who appear in the data for the full study period experienced at least one financial shock. This is why it is important to weight individual observations by the length of time they were in the sample when conducting analyses.

Table 4. Eligible Earnings Quarters

	N Caregivers (%)	Mean Number of Quarters Appearing (S.D.)	Min	Max	N Caregivers with 26 Eligible Quarters (%)
No Financial Shock	24,108 (27.3)	15.3 (7.5)	4	26	4,167 (16.4)
Financial Shock	64,114 (72.7)	20.3 (6.1)	5	26	21,174 (83.6)

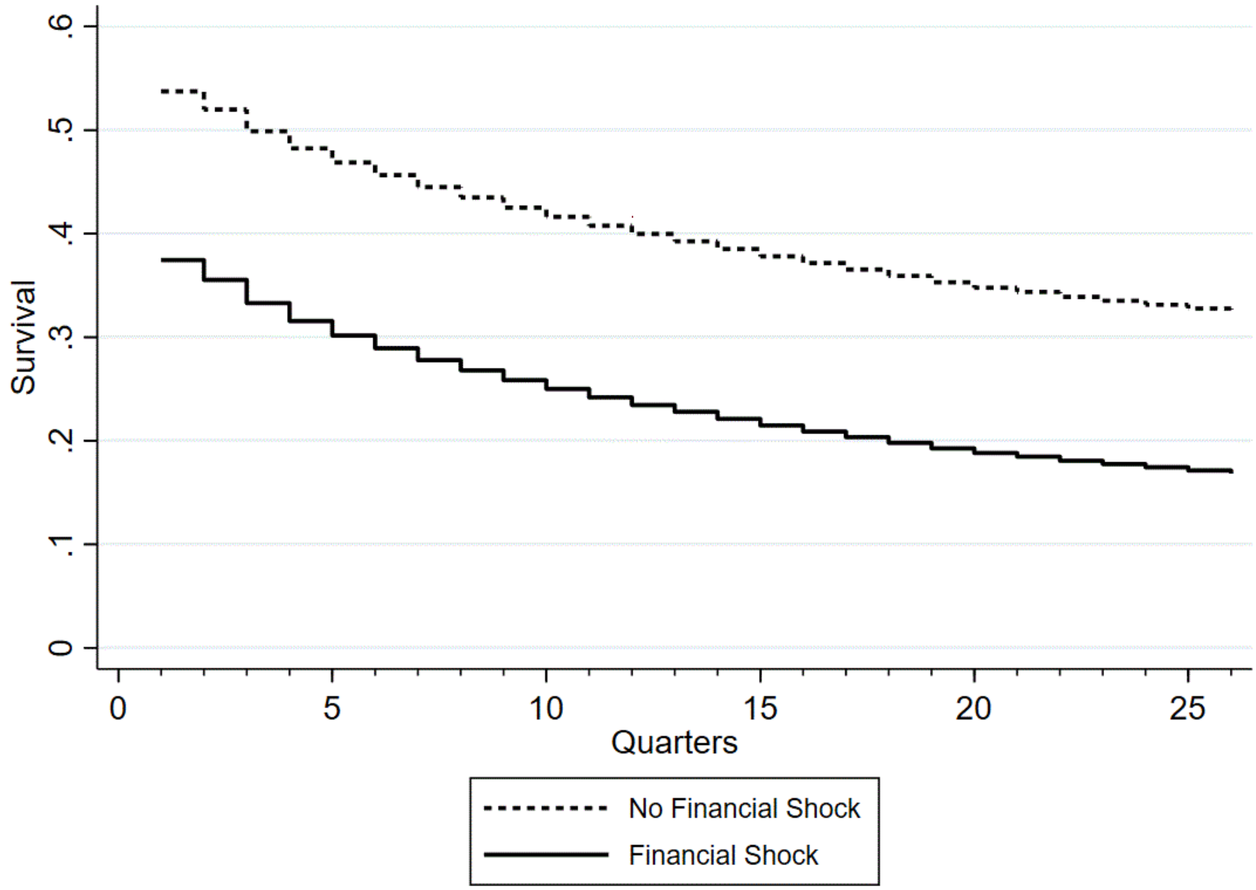
N=88,222 caregivers

Survival Analysis

Having established the general relationship between financial instability and hotline referrals, we move to a more sophisticated model to explore the predictive power of financial shocks for a subsequent hotline referral. We created a second analytic file containing all eligible quarterly earnings records, an indicator for a financial shock in each quarter, and an indicator for whether each quarter was followed by a hotline referral within 6 months.

We estimated the probability that a financial shock is associated with a subsequent hotline referral using a Cox proportional hazards model which accounts for the intertemporal dimension of the question. In the preferred weighted model, as in the logistic regression, the results are both statistically significant and of practically significant magnitude. Primary caregivers were more likely to have a hotline referral within 6 months of a financial shock compared to caregivers in the same quarter with no financial shock.

Figure 2. Estimated Survival* Among Caregivers with and without a Financial Shock



* Survival indicates the chance that a caregiver does not have a hotline referral.

We illustrate these findings in Figure 2 which shows the chance of survival (*not* having a hotline referral) across the 26 quarters observed by financial shock status. For caregivers with or without a financial shock, the chance of not having a hotline referral (survival) decreases over time at about the same rate as indicated by the relatively parallel lines. In other words, the probability of a hotline referral *increases* over time at about the same rate for both groups.

The probability of a hotline referral is approximately 16 percentage points higher among caregivers with a financial shock compared to those without a financial shock at a given point in time. To see this, at each timepoint, compare caregivers with and without a financial shock. The top dashed line indicates the chance of survival among caregivers without a financial shock. The solid line indicates the chance of survival among caregivers with a financial shock. At Quarter 12, the chance of survival is about 40% among caregivers without a financial shock (dashed line) but that chance drops to approximately 24% once a caregiver has a financial shock (solid line).

> The probability of a hotline referral is approximately 15 percentage points higher among caregivers with a financial shock compared to those without a financial shock at a given point in time.

Despite the magnitude of the relationship between financial shocks and subsequent hotline referrals, there is still the problem of correctly predicting a hotline referral for a given caregiver. Table 5 describes 190,463 financial shocks that occurred among the 88,222 caregivers in the sample. The same 73% of caregivers (N=64,114) as before experienced at least one financial shock. Only one in 10 of these financial shocks were followed by a CCR-eligible hotline referral (10.4%). With only 10% correctly predicted to have a subsequent hotline referral, information about a recent financial shock may not be as useful in identifying candidate caregivers for CCR as information about the number of financial shocks experienced over a broader time period as discussed in the previous section.

Table 5. Description of Financial Shocks

Description	N (%)
Total Financial Shocks	190,463
Caregivers with at least One Financial Shock	64,114 (72.7)
Shocks Followed by a Hotline Referral	19,850 (10.4)
Shocks Not Followed by a Hotline Referral	170,613 (89.6)

N=88,222 caregivers

Limitations

There are several limitations to this study.

1. The study sample is limited to caregivers with earnings within a specific range as described in Appendix A. Therefore, the study findings may not be relevant to the populations of caregivers with no earnings, very low earnings, or very high earnings. These populations provide opportunities for future research.

2. This study includes hotline referrals for reasons of abuse or neglect but specifically excludes referrals for reason of sexual abuse, beyond control of parent, and child trafficking. Although it is possible that the study findings would differ by the reason for referral if examined separately for abuse and neglect, in Colorado neglect is defined in statute as any reason for referral that is not physical or sexual abuse. Given this lack of nuance, it would not be informative for this study to decouple abuse from neglect as distinct outcomes.

3. The available wage data are reported quarterly which limits us to identifying financial shocks that occur between quarters. Ideally, we would examine financial shocks from one month to the next.

4. Because the purpose of this study is to inform future avenues for referral to prevention services like CCR, we keep the analytic model parsimonious and do not account for caregiver demographics such as age, gender, race, or relationship to child. Thus, we do not know whether the findings would differ by those characteristics.

5. This study does not account for all sources of income, and only considers the earnings of one caregiver per household. Although CCCAP application data identifies all earners in the household at the time of application, we do not know how household composition changes over time. Rather

than make assumptions about the stability of household composition, we consider only the earnings of the primary caregiver.

Recommendations

This study examines the relationship between variation in primary caregiver earnings and child welfare referrals based on the family stress model of economic hardship. Our approach considers financial shocks to be a proxy for material hardship (the inability to meet basic needs such as food, shelter, and medical care), which has been shown to be a better predictor of family well-being than just income levels.[12,13] We measure substantial reductions in earned income relative to a caregiver-specific historical norm that theory suggests is likely to cause stress.

We find that financial shocks in earned income are strongly correlated with child welfare referrals generally, and 33% of caregivers who experienced financial shocks were referred to child welfare during the study period. Similarly, individual financial shocks are associated with a subsequent child welfare hotline referral, but only 10% of financial shocks resulted in a hotline referral within 60 days. Overall financial instability as measured by repeated financial shocks is most strongly correlated with a child welfare referral while correctly predicting a referral to child welfare for the greatest number of caregivers, correctly predicting referral to child welfare for as much as 40% of caregivers.

Whether this level of accuracy is acceptable depends on the nature of the policy response. Using information about financial shocks to screen caregivers for prevention services is one response, in which case the acceptable level of accuracy depends on i) the societal cost of failing to intervene when a hotline referral would have happened in the absence of intervention, and ii) the cost of intervening when a hotline referral would not have happened in the absence of intervention. However, these findings can also inform policies that address structural changes to support families in absorbing financial shocks like the Earned Income Tax Credit, or revisions to the Children's Code determining when caregivers are reported to the state for neglect.

If using this information for screening, and the level of accuracy is acceptable, the next question is how to obtain information about caregivers' general financial instability so that prevention programs can be activated. Screenings should be administered where they place the least possible burden on caregivers and service providers, and where appropriate referrals can be made based on the screening result. For example, the Colorado Family Support Assessment (CFSA) 2.0 is used by members of the Family Resource Center Association's network to assess family strengths and needs. Among other things, the CFSA asks about current income levels, and these questions might be supplemented with questions about variability in income over time. The CFSA would provide a good starting place for developing and piloting financial instability screening questions since it is an existing, validated tool, the Family Resource Center Association has a demonstrated history of supporting research in this area, and the organizations administering the assessment are used to referring families to services that increase self-sufficiency and reduce the likelihood of child maltreatment based on screening results. Learnings from modifications to the CFSA could then be applied to other tools.

Programs like universal home visiting programs and universal preschool provide optimal screening opportunities because they are broad-based. The home visiting program Family Connects, which is expanding in Colorado, targets newborns and provides an entry point into families that may have older children as well. The strong relationships developed with caregivers through home visiting provides a foundation for honest reporting about financial instability should a screening tool be systematically deployed through that program. Work on the CFSA could inform development of a tool that fits the needs of this population.

The state's new Universal Preschool Program (UPK Colorado) targets families with 3- and 4-year-olds and intends for its app to ultimately be the single point of entry for all programs managed by the Colorado Department of Early Childhood. Administering a voluntary financial instability screening questionnaire through this app would be an efficient way to screen and refer caregivers across the income spectrum to services that prevent child maltreatment. This route would also facilitate low-cost linking of self-report and administrative data to support evaluation and continuous quality improvement for the screening tool and referred services. Caregivers could elect to opt in or not to completing the screening tool and, conditional on completing the screening, having their information used for evaluation purposes.

Federally Qualified Health Centers (FQHCs) are a potential place to screen families with 1- and 2-year-olds that aren't caught by home visiting or preschool screenings. As community-based health care providers targeting medically underserved areas, FQHCs serve a population that is likely to experience financial instability and thus could benefit from voluntary child maltreatment prevention services. However, any new screening tool should be embedded into existing FQHC screening efforts to minimize burden on all involved.

To identify additional potential screening and referral opportunities, the state might consider using the Health eMoms Survey to explore who moms tell when they experience a financial shock. For example, if moms share about their financial challenges with childcare providers or clergy, those community members may be potential partners for conducting screening and providing a warm handoff for support services. The Health eMoms Survey itself wouldn't be used for screening, but rather to identify additional community partners who can provide a warm handoff to prevention services should caregivers be experiencing financial instability.

In addition to identifying the right places to administer a financial instability screening, it is essential that the screening tool itself is valid. This means the caregiver's self-reported information on financial instability correlates strongly with the administrative data used here about financial shocks, and/or an analysis similar to the one conducted here shows a strong correlation between the self-reported data on financial instability and child welfare involvement. Given the importance of the number of financial shocks, the screening questionnaire might be designed similar to the Adverse Childhood Experiences (ACEs) Questionnaire. ACEs assigns a risk level for toxic stress that increases as the number of adverse childhood experiences goes up. This approach would be consistent with the theory that families generally have sufficient resources to withstand one financial shock but savings and social capital get depleted when multiple shocks accumulate, increasing the risk of child welfare involvement. The next step is to develop a screening questionnaire (or a couple of versions), pilot it with a sample of caregivers, and correlate the results with the administrative data. Given the large number of participants, the UPK Colorado Application Portal would provide the ideal environment for such pilot testing. Once the best wording has been identified, it would serve as the foundation for screening tools system wide.

Appendix A: Methodology

Data Preparation

We used CCCAP data to define the sample of financially vulnerable families who we then identified in the earnings data. CCCAP application data were used to identify the primary caregiver and the age of the child or children associated with that caregiver. We then linked the primary caregiver to state unemployment insurance earnings data to determine whether they experienced a financial shock during the study window, and to state child welfare data to determine whether they were the subject of a hotline referral.

CCCAP, earnings, and child welfare data went to LINC first for identity resolution. The LINC data scientist assigned each individual a unique LINC ID so that the same person could be identified across the different data sources as needed to answer the research questions while protecting privacy. Identifying information like names and social security numbers (SSNs) were removed and all dates, including dates of birth, were collapsed to month and year before the data were shared securely with the Colorado Evaluation and Action Lab (Colorado Lab) for subsequent cleaning and analysis.

CCCAP Data

We started with all CCCAP data on caregivers receiving CCCAP payments as of 2018 or who applied for CCCAP between January 2019 and October 2021. We excluded children born before April 2001 because they would have turned 13 years old before the end of March 2014 (Q1 2014) when we started looking for financial shocks in the earnings data. We excluded children born after June 2019 to allow us time to look for subsequent hotline referrals prior to the start of the COVID-19 pandemic.

Using the CCCAP data produced by the LINC data scientist, the Colorado Lab identified the primary caregiver in each case. The primary caregiver is the unit of analysis and the individual with whom financial shocks and hotline referrals are associated. In most cases, only one person was identified as the primary caregiver per case.[i] The CCCAP data includes a variable called ind_crtkr (individual caretaker) that generally uniquely identified the primary caregiver. In the few instances where more than one primary caretaker was identified or a child was accidentally identified as the primary caretaker. In these cases, we required that the primary caregiver be identified as both the primary caretaker (ind_crtkr=1) and as a head of household. The CCCAP data did not contain gender information, so it was not possible to use this information to identify primary caregivers.

Next, we identified all children associated with adults who were the primary caregiver across multiple cases. To determine the structure of the caregiver's household, we needed to know all children associated with a primary caregiver.[ii] This is because we only considered financial shocks for households containing a child under the age of 13. We used the dates of birth of the oldest and youngest child associated with

[i] The LINC data scientist identified each person as an adult or a child based on their date of birth, education level, marital status, role, and status (i.e., eligible or ineligible adult or child). Because of the wide range of time the data covers, it is also possible that a person could be a child in an early case but an adult in a later case. Adults can also be heads of household in one case but not in another.

[ii] All individuals associated with a case ID were kept, regardless of whether they were reported as "not requesting individual" in the CaseIndivList table. For the purpose of this project, all children associated with a primary caregiver were included even if those children were excluded from the calculations used to determine a household's CCCAP eligibility. This is because the CCCAP data are used only to identify caregivers with children; CCCAP program eligibility is irrelevant to the research question.

each primary caregiver to determine the earliest and latest quarter and year to include earnings data—the earliest year and quarter when the oldest child was born or when the primary caregiver turns 18 years old (whichever is later); the latest year and quarter is the quarter prior to the youngest child turning 13.[iii] We assumed that any child associated with a primary caregiver at the time of CCCAP application remained associated with that caregiver from the child's birth up to age 13. However, this may not be true for foster children or for other children living in the household (i.e., nieces, nephews, cousins, other unrelated persons).

Finally, we excluded any primary caregivers with a missing or unrealistic date of birth (i.e., born before 1920, born after June 2019, turned 18 after their oldest child turned 13). We did not exclude from the sample primary caregivers who were under age 18 when their youngest child was born although we did limit the time period for their earnings data such that the earliest year and quarter for their earnings data was during the year and quarter they turned 18 (as noted above) rather than in the year and quarter that their youngest child was born. This resulted in a total of 124,749 primary caregivers identified in the CCCAP data and for which we attempted to match to the earnings data.

Earnings Data

Employers report quarterly earnings data to the Colorado Department of Labor and Employment (CDLE) for state unemployment insurance purposes. These data exclude occupations that are not covered by the state unemployment insurance program, like the Army Reserve or National Guard. For this project, CDLE provided quarterly earnings records for Q1 2010 through Q4 2020 to LINC, in which the LINC data scientist used SSNs to associate earnings records for any member of a household identified in a CCCAP application. The LINC data scientist then removed all SSNs and assigned a unique LINC ID to each person to allow matching across other data sources used for this project.

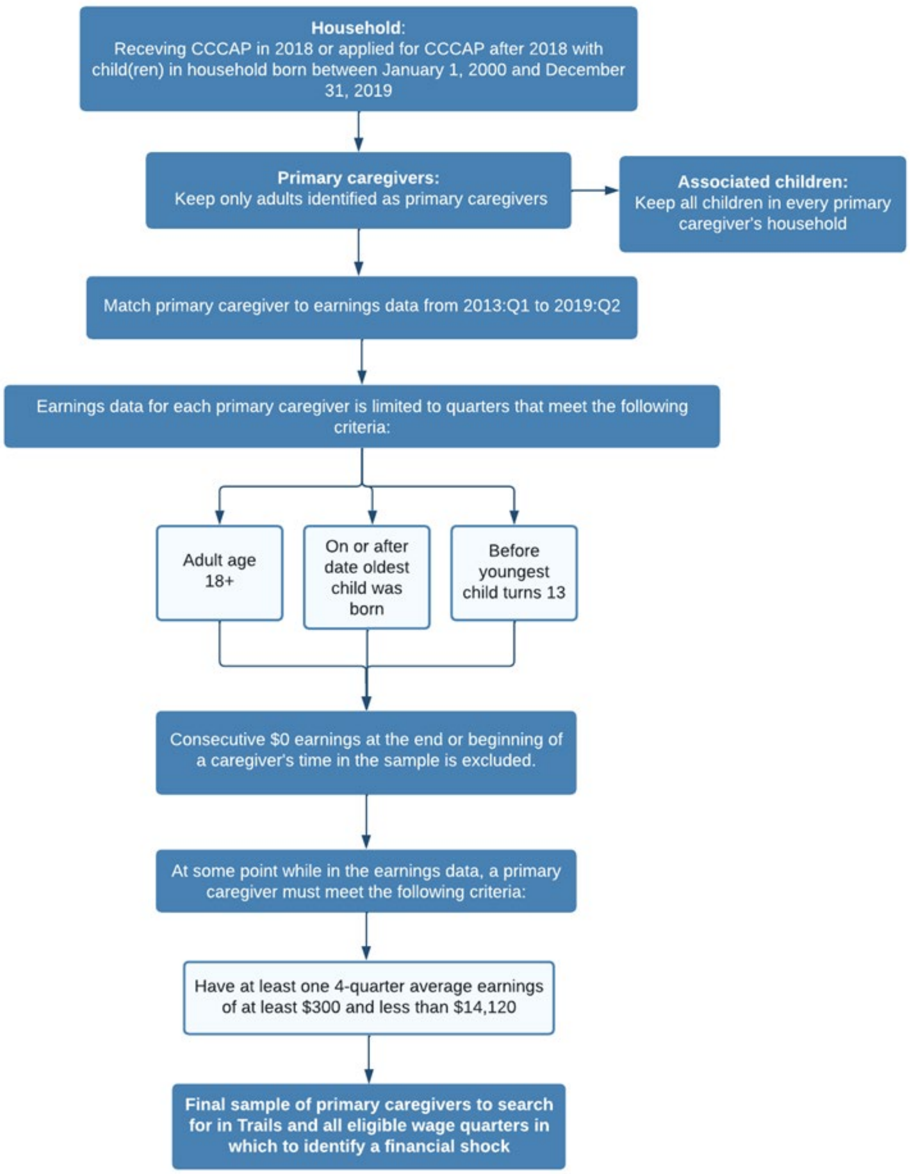
For the purpose of this project, we only included earnings data for primary caregivers as identified in the CCCAP dataset and defined above. We matched that CCCAP data with the LINC-processed earnings data which contained earnings records for 110,282 individuals. We exclude earnings records from Q3 2019 through Q4 2020 since they were outside the scope of this project. For individuals with more than one earnings record per quarter (i.e., for earnings reported by more than one employer in a quarter), we created a single record that contained the total earnings amount per person per quarter. These steps resulted in 1,675,093 earnings records for 106,902 unique individuals.

We created a dataset containing one record per quarter per person from Q1 2013 through Q2 2019 (26 records per person). When a person had no reported earnings for a given quarter, we assumed their earnings were $0 for that quarter. For all 106,902 primary caregivers in the earnings data, we filled in any missing quarters from Q1 2013 to Q2 2019 with a quarterly earnings amount of $0. Then, for each primary caregiver, we limited their records to only include the quarter when their oldest child was born or from when they turned 18 years old (whichever was later) to the quarter before their youngest child turned 13 years old. All earlier or later earnings records were excluded.

[iii] There were instances in which an adult was indicated as the primary caregiver in one case and not a primary caregiver in another case. Children in the latter type of cases are not attached to that primary caregiver. Individual children can appear in multiple households, which is not a problem because the primary caregiver is the unit of analysis. Cases without any associated children were excluded.

Finally, we limited each caregiver's records further so that consecutive $0 earnings quarters at the beginning or end of their eligible time in the sample were also excluded. For example, if a caregiver had earnings data for all quarters in 2017 and 2018 and had an eligible child starting in 2016 and continuing beyond 2019, we excluded the missing quarters of earnings data from 2016 and the first half of 2019. Therefore, this caregiver would be included in the sample only from Q1 2017 through Q4 2018. We did not exclude missing quarters of earnings data that occurred in the middle of a caregiver's time in the sample. Figure A1 maps out the process we followed to build the analytic sample in which we then searched for financial shocks and hotline referrals.

Figure A1. CCCAP/Earnings Sample Criteria



We excluded any earnings quarter in which a primary caregiver was not associated with a child under age 13. This affected 23 caregivers who had children in their household with at least a 13-year gap in time between the birth of one child and the birth of a subsequent child.

Child Welfare Data

We used the Colorado Department of Human Services' Trails data system to determine whether and when a primary caregiver from the CCCAP-based analytic sample described above experienced a hotline referral. The LINC identity resolution process between Trails and CCCAP was performed in three stages. Once an individual was matched, they were removed from the next matching stage. The first stage used exact matches of State Identification Module, the second stage used exact matches of SSNs, and the third stage used the Senzing identity resolution tool to match using a combination of name and date of birth, limited to people born before January 1, 2008.

Client records from Trails were only included if Involvement Role (role of client during a specific child welfare involvement) in the referral was reported as 'Of Interest,' 'Alleged Perpetrator,' 'Person Responsible for Care,' 'Parent/Adult,' 'Other Adult in Home,' or 'Non-Custodial Parent' in the Trails Involvement Clients table. Clients with any other Involvement Role were excluded. Referrals in which the client was involved with Colorado's Division of Youth Services (previously the Division of Youth Corrections (DYC)) were also excluded from the analytic file.[iv]

Before transferring data to the Colorado Lab, the LINC data scientist removed identifying information like names and SSNs from Trails and all dates, including dates of birth, were de-identified to month and year. The LINC data scientist assigned a unique identifier, a LINC ID, to each person in the Trails data. The LINC ID is consistent across all data sources used for this project so that the same person could be identified in the earnings data and in Trails as needed to answer the project's research questions. The LINC data scientist also assigned a unique identifier for each child welfare involvement.

For the purpose of this project, we identified people in the Involvements table from the LINC-processed Trails data who had a hotline referral with a "CCR eligible reason" and had no "CCR exclusion reasons." We focused only on involvements categorized as referrals and therefore excluded information about assessments and cases. We defined a CCR-eligible reason for a hotline referral as including any one of the following LINC-created categories (which may include multiple Trails referral reasons):

- Issue_Neglect
- Issue_Abuse
- Issue_Physical_Abuse
- Issue_Substance_Abuse
- Issue_Homelessness
- Issue_Lack_Supervision

We excluded hotline referrals that had any of the following "CCR exclusion reasons" listed:

- Issue_Domestic_Violence
- Issue_Sexual_Abuse
- Issue_PA4_BCOP (beyond control of parent)
- Issue_PA4_Placement_Eval (placement evaluation indicated as referral reason)

[iv] Cases with DYC involvement were excluded in two ways. Cases with child welfare involvement originating with DYC were excluded such that Invovlement_Type was reported as "Case - DYC" in the Trails Involvements table. Cases with "DYC" listed as the County_Agency (the county or agency responsible for the involvement) in the Trails Involvement Clients table were also excluded.

Since the outcome of interest is a hotline referral, all referrals meeting the inclusion criteria were included regardless of whether the referral was screened out or accepted for assessment, and regardless of whether an assessment became an open case.

For matching the Trails data with primary caregivers from the earnings data, we limited the Trails data to only keep referrals with an “open_date” between January 2014 and December 2019 which aligns with the earliest date a person could have a financial shock in the earnings data (Q1 2014) and the latest date we would look for a referral after a financial shock in the earnings data (December 2019, which is 6 months after the end of Q2 2019).

Defining a Financial Shock

We identified a financial shock, or a substantial drop in quarterly earnings, by comparing each quarter’s earnings to the average of the prior four quarters for that same person. This accounted for the seasonality of earnings. We limited the financial shock calculation to instances when the prior four-quarter average earnings amount was at least $300 (average of $100/month) and less than $14,120. Bounding on the low end avoids small dollar changes in income leading to large variability calculations just because the baseline level of earnings is so low. Bounding earnings on the high end avoids the inclusion of large dollar income swings among high income earners whose baseline income level is substantial enough that it is unlikely from a theoretical perspective to limit a caregiver’s ability to provide basic material support for their children. The maximum value is based on an income of $4,706.51/month or $56,478.12/year, the maximum monthly income criteria for CCCAP eligibility for a family of four (averaged over the 32 CCR counties, eligibility criteria effective date October 1, 2021) to focus the sample on caregivers who were more likely to be low income.

To determine whether a reduction in earnings was large enough to qualify as a “substantial drop,” we compared it to the typical variability in earnings that occurred over the prior year for primary caregivers with a similar average income. Variability is measured using the standard deviation of quarterly mean earnings among all caregivers within the same decile of average income. In the absence of a clear break in the data, we defined a substantial drop in earnings in two ways. For the first definition, we considered drops in quarterly earnings that were smaller than 1 S.D. “typical,” and drops at least 1 S.D. in size “substantial.”[v] In the second definition, we considered a drop in quarterly earnings that was smaller than 2 S.D. “typical,” and a drop of at least 2 S.D. in size “substantial.”

To demonstrate how we apply this 1 S.D. cutoff, consider a caregiver earning $5,000 per quarter on average over the prior year (~$20,000 annually). The relevant cutoff is 1 S.D. for all the caregivers in the decile in which the mean quarterly earnings of $5,000 falls: $1,847. In practical terms, this means that it is typical (according to our definition) to see caregivers with earnings in one quarter of $3,500 offset by earnings of $6,500 in another quarter while the average remains $5,000. A single quarter’s earnings must be $3,153 ($5,000 minus $1,847) or lower to be considered a substantial drop for the purposes of this study.

To demonstrate how we apply the 2 S.D. cutoff, consider the same caregiver described above earning $5,000 per quarter on average over the prior year. The relevant cutoff is 2 S.D. for all the caregivers in the decile in which the mean quarterly earnings of $5,000 falls: $3,694. In practical terms, this means that it is

[v] Typically, in statistics, a “1 S.D.” difference refers to half a standard deviation above the mean or half a standard deviation below the mean. In this case, however, we are referring to a full standard deviation below the mean.

typical (according to our definition) to see caregivers with earnings in one quarter of $1,500 offset by earnings of $8,500 in another quarter while the average remains $5000. A single quarter's earnings must be $1,306 ($5,000 minus $3,694) or lower to be considered a substantial drop for the purposes of this study.

As demonstrated by this example, these are practically meaningful drops in income. However, we still needed to confirm that our cutoff was stringent enough for statistical purposes. If our cutoff was too loose, it would result in caregivers regularly experiencing back-to-back financial shocks, which would not allow for meaningful prediction of correlated hotline referrals. Thus, we examined the time between each occurrence of a financial shock applying the criteria that the difference between the prior four quarters and the current quarter had to be at least 1 S.D. Table A1 shows the number of financial shocks experienced per caregiver between 2014 and 2019 among all primary caregivers.

Table A1. Number of Financial Shocks per Caregiver

Number of Financial Shocks	N of caregivers (%)	
	Earnings Drop of at Least 1 S.D.	Earnings Drop of at Least 2 S.D.
0	26,132 (29.0)	52,161 (57.8)
1	16,952 (18.8)	17,259 (19.1)
2	13,504 (15.0)	10,839 (12.0)
3	11,946 (13.2)	6,202 (6.9)
4	9,434 (10.5)	2,400 (2.7)
5	5,793 (6.4)	930 (1.0)
6	3,397 (3.8)	321 (0.4)
7*	1,784 (2.0)	137 (0.2)
8	840 (0.9)	n/a
9	318 (0.4)	n/a
10+	149 (0.2)	n/a

N=90,249 caregivers
* For an earnings drop of at least 2 S.D., the category of 7 financial shock includes caregivers with seven or more shocks because few caregivers had more than seven shocks.

In an attempt to identify fewer potentially eligible families for CCR, we used the definition of a financial shock as an earnings drop of at least 2 S.D.. However, using the 2 S.D. cutoff was not a useful way to identify families most in need of CCR services because we identified 38,000 potentially eligible caregivers with this method (Table A2).

Table A2. Sample Descriptives: Earnings Drop of at Least 2 Standard Deviations

Caregiver Had a Financial Shock During Study Period	N (%)		
	No Hotline Referral (n=60,553)	Hotline Referral (n=27,669)	Total
No Financial Shock	34,600 (69.0)	15,539 (31.0)	50,139 (56.8)
Financial Shock	25,953 (68.1)	12,130 (31.9)	38,083 (43.2)

N=88,222 caregivers

Additionally, in this study we define a financial shock as a drop in earnings of at least 1 S.D. because using a larger standard deviation only captures financial shocks among caregivers with higher earnings. Caregivers with the lowest earnings, specifically with four quarter average earnings that fall in the lowest three deciles of earnings, could not have a drop in earnings of at least 2 S.D. because their earnings were not high enough for that to be mathematically possible. For example, if a caregiver earns on average $1,500 per quarter, a drop in earnings of at least 2 S.D. would have to be at least $3,222 lower. This is not possible because $1,500 is the largest drop in earnings the caregiver could have in that quarter (e.g., a drop to $0 in quarterly earnings). Therefore, with the tighter criteria of a financial shock, we did not identify any financial shocks among families who were the most financially unstable.

Using the definition of a drop in earnings of at least 1 S.D., we wanted to understand the overlap of financial shocks for a caregiver (e.g., are shocks occurring one after another or is there significant time between each shock). In Table A3 we describe the time between financial shocks among caregivers with at least four financial shocks using the largest standard deviation definition we can. When a smaller standard deviation was used to define a financial shock, there were more financial shocks per caregiver and there was more overlap in financial shocks. Conversely, when a larger standard deviation was used to define a financial shock, there were fewer financial shocks and there was less overlap in shocks.

Table A3. Time Between First Four Financial Shocks*

Timing of Financial Shocks	Mean (Qtrs)	Median (Qtrs)	S.D. (Qtrs)	Range (Qtrs)	N Caregivers with only One Quarter between Shocks (%)
Between Shock 1 and 2	2.6	1	2.9	1 to 19	13,510 (62.2)
Between Shock 2 and 3	2.7	1	3.0	1 to 19	13,867 (63.9)
Between Shock 3 and 4	2.9	1	3.2	1 to 19	13,479 (62.1)

N=21,715. Table excludes caregivers with fewer than four financial shocks.
* A financial shock was defined as a drop in earnings of at least 1 S.D.

In the Cox Proportional Hazard Ratio model weighted for caregiver time in the sample, caregivers were 54% more likely to have a hotline referral within 6 months of a financial shock compared to caregivers in the same quarter with no financial shock (Hazard Ratio: 1.54; robust standard error: 0.009; p-value: <0.001).

Endnotes

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[10] Typically, in statistics, a “1 S.D.” difference refers to half a standard deviation above the mean or half a standard deviation below the mean. In this case, however, we are referring to a full standard deviation below the mean.

[11] Using inverse probability weights equal to the number of quarters a caregiver is eligible for inclusion in the sample (as represented by the first row in Figure 1) divided by 26, the maximum number of quarters possible.

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