Understanding and Measuring Income Shocks as Precursors to Poverty

Rediet Abebe, [1] **Jon Kleinberg,** [2] **Andrew Wang** [1]

[1]Harvard University
[2]Cornell University

Abstract

Poverty and economic hardship are multi-faceted and dynamic phenomena impacting over 50 million people in the United States and billions of people world-wide. Despite the prevalence of poverty, there remains much to be understood about what makes families susceptible to experiencing economic distress and what interventions many be effective and for which families. An important set of questions is related to the role of *income shocks*. Shocks may constitute unexpected expenses such as a medical bill or a parking ticket or interruptions to one's income flow, such as a delayed paycheck or loss of public benefits. Recently these phenomena have garnered increased attention, with a growing body of empirical and computational work showing their impact on various measures of socioeconomic welfare.

We present a computational study of a large survey-based longitudinal data-set to understand the role of shocks on poverty. We ask whether and which shocks hold predictive power in identifying families that will experience poverty, and whether there exist differences between different demographic groups. We then examine what relationships exist between different types of shocks themselves, showing that certain shocks may make families susceptible to experiencing further shocks. E.g., families that experience a medical shock are nearly four times more likely to experience another medical shock and nearly twice as likely to experience an income decrease within three months. We further reveal that the co-occurrence of shocks can yield insights about which families are likely to experience poverty. Synthesizing these results as well as numerous conversations with researchers and practitioners from the Poverty Tracker study, we present a discussion of how such computational techniques can inform poverty-alleviation programs and social work practice.

Introduction

Poverty and economic hardship are multi-faceted and dynamic phenomena, extending beyond static measurements of income or wealth (Alkire and Foster 2011; Anand and Sen 1997; Atkinson 2003; Grusky 2018; Council et al. 2011; Yapa 1996). Despite the prevalence of poverty – which impacts over 50 million people in the United States alone and billions of people world-wide – there remains a lot to be understood about the causes, characteristics, and consequences of poverty. This severely limits our ability to design and implement poverty-alleviation programs.

In recent years, there has been increased focus on *income shocks*, which are known to capture a number of mechanisms via which economic hardship may manifest in families' lives. Empirical work has explored what role such shocks may play in triggering or perpetuating cycles of poverty (Lens et al. 2016; Wimer et al. 2014a, 2016a, 2014b, 2016b). These shocks may constitute experiences including unexpected medical expenses, loss of public benefits, being a victim of a crime, and end of romantic relationships. There is a rich body of social scientific work that empirically explore the adverse impact of different types of shocks on housing, education, health, and other important measurements of socioeconomic welfare. There has also been interest in modeling shocks and examining algorithmic questions related to allocating interventions to mitigate their impact (Abebe, Kleinberg, and Weinberg 2020; Kube, Das, and Fowler 2018).

In this present work, we investigate what role computational techniques can play in shedding light on the complex nature of shocks, with an eye towards bridging these empirical and algorithmic lines of work. We use data from the Poverty Tracker Study – a large, survey-based longitudinal data-set from the Columbia Population Research Center and the Robin Hood Foundation covering 2,228 families in New York City – to examine the relationship between shocks and poverty. This data-set includes welfare measurements such as poverty status, material hardship, health, as well as experiences with a number of different types of shocks over a period of 24 months.

The Poverty Tracker data-set represents a massive undertaking spanning a range of several years and the painstaking collection of detailed information about hard-to-reach populations. At the same time, the retrospective nature of the data and the scale it reached is not necessarily sufficient to quantify the causal effect of specific shocks on various outcomes. This leads to an important challenge for computational approaches on such a data-set: given the limitations that exist even at this scale of data collection, what types of computational explorations of the data hold the most potential for producing insights that can leverage the rich structure of the data, with the potential to inform policy and social work practice? This is a crucial problem — stakeholders such as social workers or policy-makers stand to benefit from even coarse-grained insights based on the data, but without reasonable computational approaches we are essentially leaving these insights untapped in the data.

Computational Explorations via Prediction. We approach this question in a sequence of steps. We begin by formulating a set of prediction tasks on the data, asking to what extent and with which combinations of features we can forecast poverty outcomes. This is a first step toward obtaining computational insights about the power of different sources of information in the data, and it also has natural policy links, in that poverty is a domain where prediction itself — of future hardship and needs for future assistance — can be a crucial step in the policy process, in targeting interventions as accurately as possible. Such *prediction policy problems* (Kleinberg et al. 2015) have been proposed as an important component in the allocation of societal resources. And the prediction output itself is only one of the goals; such prediction tasks can also help policy-makers and practitioners develop hypotheses more efficiently, and they can inform future data collection.

For assessing computational insights into life outcomes, however, absolute prediction performance is inherently limited, as highlighted in recent work. For example, research on the Fragile Families data-set — another longitudinal, survey-based data-set with nearly 17,000 variables – has shown that predicting life outcomes like poverty status using machine-learning methods on these variables fails to outperform or at times even match the performance of simple techniques such as logistic regression over a small set of features selected by domain experts (Salganik et al. 2020).

As a result, we approach the underlying prediction questions in primarily a comparative sense rather than an absolute one: given the features in the data, we investigate the relative predictive performance of different subsets of features. This is an inherently combinatorial activity in which we enumerate a large collection of subsets of features, guided toward the sets that have relatively higher prediction performance. In a sense, this combinatorial enumeration of feature subsets can be viewed as setting an upper bound on the power of *any* theory of poverty and economic hardship that draws on the information collected by studies like the Poverty Tracker project, since our enumeration is essentially finding the limit of predictability from the available information. This approach to evaluating the *completeness* of theories in the social sciences — via the limit of their predictive accuracy — has proven to be useful in settings where the available features are amenable to this kind of combinatorial enumeration (Kleinberg, Liang, and Mullainathan 2017; Fudenberg et al. 2019).

Within this framework, we look at three main sets of questions:

Predicting Poverty. A key part in our enumeration of features is to treat types of shocks as features, and to ask whether different types of shocks can help us better predict poverty status across our population. We investigate what differences exist across different demographic groups. i.e., do certain types of shocks hold more explanatory power in predicting poverty for male respondents versus female respondents?

Relationship of Shocks. We next examine the prevalence and relationship between different types of shocks. For example, we can explore natural pattern discovery and *motif-finding* questions by asking whether certain combinations or sequences of shocks are more likely than others. Moreover, we ask whether the prevalence of these patterns differ by demographic groups.

Informing Interventions. By combining insights from the above two sets of inquiries, we ask whether uncovering these relationships improves our ability to predict poverty status. In doing so, we make progress towards measuring the impact of a specific type of shock on poverty.

Poverty Tracker Data

Our data-set comes from the Poverty Tracker study, a survey-based longitudinal data-set from the Columbia Population Research Center and the Robin Hood Foundation (Wimer et al. 2014a, 2016a). The original panel study followed 2,228 New York City residents for a period of 24 months between 2012 and 2014 by collecting survey data at a 3-month interval. The original data-set was constructed via a combination of random dialing and sampling of clients from social service agencies funded by the Robin Hood Foundation, a charitable organization working to alleviate the consequences of poverty in New York City. These extensive surveys were conducted mostly face-to-face for the annual surveys and primarily over the phone for interim surveys. Due to the well-documented phenomena of low-response rates among low-income families, the study oversampled from this population, but it also includes some middle and high-income families.

Three of the total of nine surveys — a baseline survey, 1-year survey, and 2-year survey — were conducted at the one year mark. These annual surveys contain demographic information, such as the respondents' age, gender, education status, immigration status, and other indicators, as well as various economic and quality-of-life benchmarks. These benchmarks include income, material hardship, and health measurements. These annual surveys also include whether the individuals' are above or below the Official Poverty Measurement (OPM) and the Supplemental Poverty Measurement (SPM). Since government assistance programs primarily use the OPM threshold to determine eligibility, we also use it as an indicator of poverty status and say that a family is in poverty if their income falls below the OPM threshold. Note, 718 individuals were above the poverty threshold for all three annual surveys and 98 were below. The remaining either dropped out of the study or experienced going in or out of poverty during the span of the study. Overall, we consider 23 features from the baseline survey in our study, including this poverty indicator. Further details about the annual surveys are included in the supplemental section.

This data-set also included quarterly surveys containing details about various shocks that could adversely affect families. These shocks are: major decrease in income,

Input Dataset	Random Forests	Logistic Regressions	Naive Bayes	KNN (K=5)	MLP (15, 5)	# of Samples
Income (Imputed)	0.771	0.78	0.749	0.766	**0.766**	1326
Demographics	0.742	0.751	0.715	0.712	0.713	1324
Hardship	0.752	0.755	0.738	0.731	0.737	1296
Health	0.744	0.741	0.717	0.704	0.709	1307
OPM/SPM	0.767	0.771	0.734	0.755	0.754	1326
Binary OPM	0.774	0.774	**0.774**	0.745	0.774	1328
All Baseline	**0.776**	**0.779**	0.745	0.77	0.749	1274
All Baseline & Shocks	0.774	0.775	0.736	**0.782**	0.721	886
OPM, hardship, health, & shocks	0.766	0.775	0.73	0.764	0.736	888

Table 1: Prediction of one-year poverty status among full population. Baseline includes OPM status, hardship measures, health measures, demographics, and income. We use k-fold cross-validation mean scores for $k = 5$. See Supplementary section for full details.

major unanticipated expenses, loss of public benefits, end of a romantic relationship, being the victim of a crime, loss or damage to valuable property, experiencing an accident/illness/injury, getting stopped by police, or getting arrested.[1] Each of these shocks have been extensively documented as creating disruptions in families' lives. Combined, these quarterly surveys present a clearer view of how unplanned factors, beyond simple indicators of income or wealth, may impact the dynamics of economic hardship.

There are several hundred questions aggregated across the nine surveys. We pruned the data-set to include only information that could be relevant to poverty and hardship for our purposes. Before making predictions, we combined the baseline survey and the first three quarterly surveys (at 3, 6, and 9 months) into a Pandas data-frame, dropped several parameters with a lot of missing data as well as erroneous entries. Details can be found in the supplemental section. We focus primarily on the first 12 months of the survey as the subsequent year saw a drop in participation, especially among individuals with the lowest income.

Overall, we have 23 features from the baseline survey as well as a combined set of 27 features indicating experiences with shocks from the interim surveys. We use these to predict poverty status at the one or two-year mark. In the supplemental section, we also predict other indicators of material hardship — such as running out of money or inability to pay rent — or poor health to check for robustness of our results. We include these results as well as further summary statistics about the individuals included in the data-set we consider in the supplemental section.

Measuring the Effect of Shocks on Poverty

We first consider a set of prediction tasks to investigate whether we can accurately forecast which families will fall below the poverty threshold at the one-year survey. It is a notoriously challenging problem in the social sciences to predict life-outcomes such as poverty, eviction, and material hardship. Recent work by Salganik et al. (2020) presents a detailed discussion and provides compelling evidence that this problem cannot be overcome by collecting thousands of additional variables or using state-of-the-art machine learning methods. In fact, Salganik et al. (2020) find that these approaches perform comparably and at times worse than simply using logistic regression with a handful of features selected by domain experts.

Our goal here is therefore to examine whether shocks hold any predictive power, even despite these challenges, and what qualitative insights about the impact of shocks on poverty we can extract from approaching this problem in a comparable rather than absolute sense. Specifically, we focus on which shocks appear to hold the most predictive power and whether there are meaningful differences across different demographic groups. We examine differences by gender, race, education, and immigration status. Focusing on the dynamics of poverty, we also study the role of different types of shocks for families who experience a persistent poverty status (i.e., are either above or below the poverty threshold at the annual surveys) or those who experience a change in their poverty status. By dis-aggregating the population in this way, we are able to isolate families who are near the poverty threshold and for whom assistance programs may have the greatest impact.

Table 1 shows the results of our predictions. Note, 74% of the population is above the poverty threshold at the one year survey, so even using all baseline and shock variables does not significantly improve above this simple benchmark as the best accuracy is 78.2%.[2] Our study therefore provides further evidence that accurate predictions of life-outcomes may be beyond reach in such studies.

However, we find that we can use such prediction tasks as a means to extracting qualitative insights about the impact of different types of shocks. We focus first on relative

[1]Note, there were only a few entries for whether people got arrested, in large part due to missing values. We drop this shock variable and instead consider a variable indicating whether the individual experienced by other major changes.

[2]We find notable differences in our ability to predict outcomes by different demographic groups. e.g., our prediction accuracy is typically higher for male respondents than female respondents for different outcomes of interest. These details are included in the supplemental section.

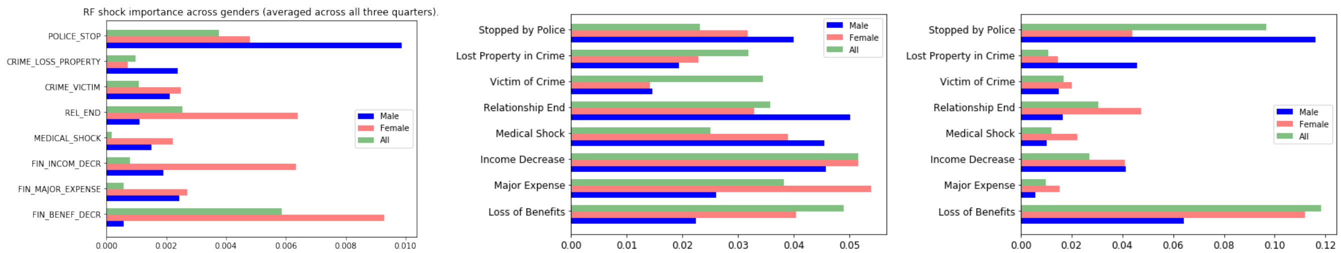

Figure 1: Relative feature importance between male and female respondents for (left) all respondents, (middle) respondents whose poverty status did not change between the base-line and 1-year surveys, and (right) families whose poverty status changes between the baseline and 1-year survey.

feature importance: i.e., which features appear to hold the most explanatory power? We examine this for a classifier that is trained using only shock features then running random forests. Figure 1 shows that benefit decrease has the highest feature importance among the full population as well as among female respondents. On the other hand, police stop is the most important feature for male respondents.[3] Note, 18.22% of the male respondents and 11.79% of the female respondents reported being stopped by the police. While the experience of this shock is not evenly distributed across these two demographic groups, the proportions indicate that these differences in relative feature importance cannot be exclusively explained by the shock being experienced by one group more than the other. Further, we note differences in feature importance even among shocks that are experienced in relatively even proportions among the two demographic groups, such as relationship ending. This feature is the second most important one among female respondents but one of the least important ones among male respondents when considering the full population.

We find evidence that the relative importance of shocks can vary by whether the families' experiences with poverty are persistent or dynamic. Specifically, we focus on two groups: (a) families whose poverty status does not change between the baseline and the one-year survey and (b) families whose poverty status does change between these two surveys. Figure 1 shows the relative feature importance among these groups. We identify some notable differences: for instance, being stopped by the police drops in feature importance among male respondents for those whose poverty status does not change, but rises among female respondents among the population that does experience a change in poverty status. This highlights the potential for experiences with the criminal justice system to lead to poverty among those who are near the poverty threshold. Likewise, end of a romantic relationship rises to be the most important feature among male respondents in the group that does not experience a change in poverty status, whereas it was the second least important feature for male respondents when considering the full population.

We re-run these analyses using material hardship and certain measures of health as the outcomes of interest. The feature importance for these largely mirrors our findings above. We also include further comparative insights between different demographic groups such as by age, immigration status, and education levels, and provide a discussion of the corresponding social work insights in the supplemental section.

To verify these insights, we conduct numerous robustness checks about the relative importance of features including, for instance, adding random noise to specific features to examine whether prediction accuracy drops. Embedded methods can also help determine feature importance in the context of a specific model. For instance, we can use the LASSO linear regression model, which includes a regularization term to implicitly limit the magnitude of the regression coefficients. LASSO fitted for one-year OPM status using only the shocks selects financial benefit loss, income decrease, police encounters, and relationship endings as the most important shocks as we increase the L1 regularization penalty. This further corroborates the above findings. Details on these as well as other robustness checks can be found in the supplemental section.

Uncovering Relationships between Shocks

We next focus on the space of shocks itself, which shows a rich set of interactions.[4] We are first interested in whether certain combinations or sequences of shocks are more-likely to occur. An analysis on which pairs or triplets of shocks are more likely to occur over the three interim surveys from the first year reveals that families are more likely to experience a persistence of the same shock: for instance, experiencing a major expense at each of the three interim surveys is the most frequent triplet, after normalizing for the prevalence of this shock. Similarly, experiencing a benefit decrease at the 6 and 9 month interim surveys is the most prevalent pair. (Details in the supplementary section.)

To gain further insight into the relationship between shocks, we approach the enumeration task in the following combinatorial manner: consider a given shock, such as loss of benefits. Given that an individual experienced this shock at 3 months, we ask what is the likelihood that they experience a given shock, such as a major expense, at 6 months or at 9 months. We normalize this value by the prevalence

[3] Among our 2,228 respondents, 812 of them are male and 1416 of them are female.

[4] The supplementary section includes summary statistics about the prevalence of shocks among different demographic groups.

	6-month given LB3	9-month given LB3	6-month ratio	9-month ratio
Loss of Benefits	28.7	37.2	5.1	4.2
Major Expense	35.1	26.6	1.7	1.5
Income Decrease	28.7	28.7	1.8	1.5
Relationship End	18.1	12.8	2.3	1.8
Medical Shock	19.1	17.0	1.4	1.3
Victim of Crime	6.4	5.3	1.4	1.8
Lost Property in Crime	13.8	13.8	1.7	1.8
Stopped by Police	11.7	23.4	1.8	1.8

Table 2: Proportion of people who faced a given shock, shown in percentage points, given that they faced a certain shock in the first quarter (LB3 = Loss of Benefits at 3 months). Column four (resp. five) normalizes column two (resp. three) by the prevalence of the given shock.

of the second shock under consideration (in this case, a major expense). This analysis allows us to consider how much more likely an individual is to experience a specific shock at the 6 and 9 month surveys given that they experienced loss of benefits at the 3 month survey.

Table 2 presents the results for experiencing loss of benefits at 3 months. This analysis presents numerous insights: individuals who experience loss of benefits at three months are over 5 times more likely to experience loss of benefits at 6 months and 4 times more likely to 9 months, again corroborating the insight on the persistence of shocks. This impact extends beyond loss of benefits. For instance, these same families are over twice as likely to experience a relationship ending and 1.8 times more likely to experience being stopped by the police at the 6 month survey. Typically, this effect dissipates over time, as can be seen by comparing the last two columns of Table 2. We provide further evidence of this in the supplementary section by considering subsequent interim surveys.

We similarly investigate the role of medical shocks at the 3 months survey: i.e., whether "someone had an accident, injury or illness that interfered with work or life." This shock is rather prevalent, with 27.2% of those who responded to all three interim surveys experiencing it at one point. We examine whether this shock appears to co-occur or appear in a sequence with certain types of shocks. We find that experiencing a medical shock at the 3 month survey increased the respondent's likelihood of experiencing a medical shock by 140% at 6 months and by 90% at 9 months, showing a persistence of this shock. This shock also shows a relationship with decrease in income, where experiencing a medical shock at the 3 month survey increased the likelihood of experiencing decrease in income by 40% and 30% at the 6 and 9 month surveys. Perhaps surprisingly, this shock has little impact in predicting whether respondents were able to pay for medical care. In the supplementary section, we dis-aggregating these results by the different demographic groups. Note, such insights can help with hypothesis generation or otherwise indicating causal relationships that may exist between different types of shocks.

Impact of Shocks on Poverty

We combine insights from the previous two sections to further isolate the impact of specific shocks on poverty outcomes. Rather than considering the full set of shock features, we focus on the following four based on their prevalence and feature importance from our analysis thus far:

1. Income decrease (s_1)
2. Benefit loss (s_2)
3. Police encounter (s_3)
4. Relationship end (s_4)

We consider a setting where the family's state is their poverty status, which we set to be 0 or 1, corresponding to whether they are above or below the poverty threshold. Focusing only on the first two shocks – income decrease and benefit loss – during the interim period, they might face one of four possibilities: experiencing both, neither, or exactly one of the shocks s_1 or s_2 at some point among the three quarterly surveys. Note, we aggregate the shocks in this way to minimize the set of possibilities and due to the sparsity of shocks. At the one year survey, they may end up either above or below the poverty threshold, with varying probabilities based on their initial starting point and what shocks they experienced in between.[5]

Table 3 identifies the distribution of interim shocks that families face and the probabilities of transitioning to a specific outcome. We see that a majority of households who are initially below the poverty line (upper panel) face an income decrease or a loss of benefits during the first year, with 18.7% facing both shocks. Those who do not experience either shock, however, are just as likely to be below the poverty line after one year, indicating that the likelihood of transitioning out of poverty may be relatively independent from income shocks and benefit losses. In other words, those who transition from state 0 to state 1 have a roughly 33% chance of doing so regardless of whether they experience these shocks.

[5]Note, unlike an Markov Decision Process, the actions here are not taken by the designer but rather supplied by nature, so this departs from a typical MDP formulation.

	(s_1, s_2)	# of respondents	# who end up **above** poverty at one-year
Below poverty at baseline:	00	81 (43.3%)	27 (33.3%)
	01	52 (27.8%)	19 (36.5%)
	10	19 (10.2%)	6 (31.6%)
	11	35 (18.7%)	13 (37.1%)
	(s_1, s_2)	# of respondents	# who end up above poverty at one-year
Above poverty at baseline:	00	497 (67.7%)	415 (83.5%)
	01	149 (20.3%)	121 (81.2%)
	10	31 (4.2%)	25 (80.6%)
	11	57 (7.8%)	33 (57.9%)

Table 3: Number of respondents who experienced an income decrease and/or benefit loss (the two shocks with highest feature importance) *at some point* during the first year, split by whether they are above or below the poverty line at baseline. Among the respondents who responded to all first-year surveys, there are 187 respondents below the poverty line and 734 above it at baseline.

In contrast, among the households who are initially above the poverty line (lower panel), the majority face neither shock and only 57 households (7.8%) face both shocks. Experiencing both shocks, however, more than doubles the proportion of cases in which the household dips below the poverty line (from $< 20\%$ to 42%). This suggests that providing extra support to families who were initially above the poverty line, but experience both an income shock and a loss of benefits can reduce the probability of transitioning into poverty.

We can extend this to a larger space of shocks. Adding shock s_3 (police encounters) to our interventions, we find that people who experience all three shocks are less likely to be above the poverty line at the one-year point. (Table included in the appendix.) Surprisingly, people who were in poverty at baseline and experience shocks do not seem to be necessarily worse off than those who did not experience any shocks. In particular, individuals who experience only income decreases and benefit losses or only benefit losses and police encounters appear to rise out of poverty at higher rates than their counterparts. In contrast, those who experience those same sets of shocks but were originally above the poverty threshold seem to drop below the threshold more often. In essence, these combinations of shocks are experienced more by those whose poverty status changes between the baseline and one year surveys.

We can also look at the most common shocks (major experience, income decrease, medical shock) or highly uncorrelated shocks (benefit loss, medical shock, and police encounter), shown in the supplementary section. Some broad themes emerge from these analyses: respondents who are initially above the poverty threshold but experience a shock are less likely to remain above the poverty threshold by around 10-20 percentage points. In contrast, respondents who are initially below the poverty threshold are just as likely to rise above the threshold regardless of whether they experience a shock, in line with what we observed in Table 3. However, this does not hold true for police encounters: only 27% of respondents who were in state 0 and were stopped by police transitioned out of poverty, compared with 37% among those who were not stopped.

Further Related Work

Studies of poverty and economic hardship have a long history in the economics, sociology, and public policy literature (Atkinson 2015; Grusky 2018; Grusky and Ku 2008; Grusky and Weeden 2016; Piketty 2015; Sen 1976; Sen, Foster et al. 1997). A key set of questions in the study of poverty is identifying measurements that more-accurately capture experiences with hardship and predicting which families may experience economic distress. These questions require investigations that account for the full complexity of hardship while preserving enough simplicity and tractability to inform policy and program design.

This work focuses specifically on the role of income shocks. There is a long-line of mostly empirical work investigating the complex interaction between shocks and issues including housing instability, job loss, and poor health or education outcomes (Atake 2018; Björkman-Nyqvist 2013; Desmond 2012, 2015, 2016; Desmond and Gershenson 2016; Desmond and Shollenberger 2015; Dinkelman, Lam, and Leibbrandt 2008; Giesbert and Schindler 2012; Jarosch 2015; Kijima, Matsumoto, and Yamano 2006; Kochar 1995, 1999; Morduch 1994; O'Flaherty 2009; Shapiro et al. 2004). Despite this extensive study, experiences with income shocks are not sufficiently accounted for in the design and implementation of social assistance programs. Recent studies, and most notably the Poverty Tracker study, have been documenting experiences with income shocks. See reports (Wimer et al. 2014a, 2016a, 2014b, 2016b; Lens et al. 2016). Several panel surveys, such as the Survey of Income and Program Participation, the Panel Study of Income Dynamics, and the Fragile Families and Child Well-being Survey, also collect data regarding household economic welfare and material hardship (Czajka, Jacobson, and Cody 2003; Salganik et al. 2020), although the Poverty Tracker study differs in it's specific focus on income shocks.

Our work is inspired by research from the Columbia Population Research Center, whose analysis of the Poverty Tracker data serves as an important backdrop to the line of work we present here (Wimer et al. 2014a, 2016a). For instance, in their 2018 study, they use the longitudinal nature of the surveys to study the dynamics of hardship and poverty for different demographic groups. Among their findings, they see that ”the most persistently disadvantaged New Yorkers are beset by repeated shocks to their finances and well-being” (Wimer et al. 2014a). Note, however, these reports primarily present summary statistics on the data, including experiences with different types of shocks, and do not include a deep-dive uncovering the types of relationships between shocks and poverty we explore here.

There are recent lines algorithmic inquiries on modeling shocks and hardship, which complement our work (Abebe, Kleinberg, and Weinberg 2020; Kube, Das, and Fowler 2018). These papers are specifically focused on evaluating the efficacy of difference assistance programs. For instance, Abebe, Kleinberg, and Weinberg (2020) ask questions about optimal design of government subsidy allocations in the presence of income shocks. While this work is also focused on income shocks, it crucially differs from the present work in two ways: this work presents a computational investigation using a data-set capturing real-world experiences, rather than designing theoretical algorithms. Further, our work explores the role of different types of shocks whereas shocks in Abebe, Kleinberg, and Weinberg (2020) are identifies solely by their frequency and magnitude. Similarly, Kube, Das, and Fowler (2018) focus on modeling treatment effects of different interventions targeted at families experiencing housing instability and homelessness. Using these insights, they ask questions around how to optimally allocate different types of resources to minimize the number of families that experience chronic homelessness. Despite this similarity, this work is not focused on shocks. Similar to our study, however, they use real-world data-sets to understand and measure the experiences of vulnerable families. Unlike these two studies, our work is not focused on designing optimal allocation polices but rather on gleaning insights on the impact of shocks on poverty, despite the aforementioned limitations of prediction and other machine learning based techniques.

Our focus on the combinatorial enumeration of subsets of features, corresponding to types of shocks and other related measures, connects to several lines of work. In the practice of data mining, it is a type of pattern discovering or motif finfing (Tan, Steinbach, and Kumar 2016). And recent work at the boundary of machine learning and the social sciences has argued for this approach as a way of assessing the *completeness* of social-science theories — the limit of their ability to make predictions (Kleinberg, Liang, and Mullainathan 2017; Fudenberg et al. 2019).

We view these above works, as well as this present work, as belonging to an emerging area of computational investigations of poverty that have the potential to bridge theoretical studies on the design of optimal policies and empirical work measuring treatment effects of different hardships or assistance programs.

Discussion and Conclusion

In this work, we consider what computational techniques we can leverage to glean insights into the relationship between shocks and poverty, as well as between shocks themselves. This work appears with two key challenges in the backdrop: first, predicting life outcomes with high accuracy, even using state-of-the-art machine learning techniques, is notoriously difficult on such data-sets. Second, we are limited in our ability to extract causal relationships due to sparsity of responses and relative size of survey-based data-sets. At the same time, such data-sets are painstakingly collected and tend to contain rich information on hard-to-reach and vulnerable populations. There is, therefore, a high cost to leaving possible findings unexplored. In this work, we find that despite these limitations, carefully-formulated prediction tasks present a rich set of possibilities for computational exploration.

Through our analyses based on predicting poverty outcomes, we identify what features appear to be the most important and for which demographic groups. Certain features do not hold much predictive power or yield interesting relationships with other features. Given the labor- and time-intensive nature of such data collection, we may consider eliminating these features in future. Further, insights about the relative importance of different features among different demographic groups can suggest that finer-grained data collection for certain groups may be fruitful. e.g., being stopped by the police holds significant predictive power among male respondents. Therefore, encoding the frequency, rather than simply collecting binary information, or capturing the nature of the interactions with the police may be useful.

By approaching our analyses of feature importance in a comparative, rather than absolute, manner, we also learn about the impact of different types of shocks on different groups. Insights obtained by comparing respondents whose poverty status is static versus dynamic – i.e., individuals whose poverty status changes over the course of the annual surveys or remains the same – especially hold great potential in informing targeted interventions. While it is known that there are many families who live on the verge of poverty, there remains a lot to be understood about what experiences tip the scale to start an upward or downward spiral for these families. Gaining further understanding of this group – e.g., such as that interactions with the police may play a role in starting a cycle of poverty – may suggest where social work or policy-based interventions may have the most impact.

There are many limitations to this study, which are further explained in the supplementary section. Two key ones are: data collection of such survey data can be prone to errors due to sensitivity of some questions and other biases. It is important to consider the possibility of such errors in interpreting results. Further, while we do not attempt to make causal claims in our work, certain results may be interpreted as such. We reiterate that insights from this work are intended to extract only prediction insights and potentially generate hypotheses.

Despite these limitations, there remain many opportunities to explore interventions: namely, the final analysis presents an opportunity to formulate a set of optimization problems where we can envision that there are different costs to interventions on different experiences with shocks. We can examine the impact of intervening on a fixed set of shocks, all shocks, or only once a family has fallen below the poverty threshold, then compare outcomes. Such insights can suggest whether certain types of social services may be effective at preventing poverty before families experience it.

Ethics Statement

This work uses a survey-based, longitudinal data-set on New York City residents. Many of these families are low-income or otherwise vulnerable populations. The data was obtained courtesy of the Poverty Tracker study. Our particular study was found to be IRB exempt. but we have the data in a secure manner compliant with non-exempt studies.

To ensure fairness considerations, throughout our analyses, we consider questions by dis-aggregating by different demographic groups. We aim to ensure that insights about one demographic group are not drowned out by others. The analyses in this study are conducted with an eye towards understanding the experiences of families in economic distress. This work entailed numerous conversations with domain experts, including social workers and any future work intended to support or suggest interventions will include conversations with a broader set of stakeholders.

Overall, we examine the ways in which computational techniques can help complement and add to empirical and theoretical studies to help identify and improve poverty-alleviation opportunities. We view our work as belonging to this emerging area and has the potential to amplify the social impact of AI techniques when used in harmony with insights from the social sciences.

References

Abebe, R.; Kleinberg, J.; and Weinberg, S. M. 2020. Subsidy Allocations in the Presence of Income Shocks. In *34th AAAI Conference on Artificial Intelligence*.

Alkire, S.; and Foster, J. 2011. Counting and multidimensional poverty measurement. *Journal of public economics* 95(7): 476–487.

Anand, S.; and Sen, A. 1997. Concepts or Human Development and Poverty! A Multidimensional Perspective. *United Nations Development Programme, Poverty and human development: Human development papers* 1–20.

Atake, E.-H. 2018. Health shocks in sub-Saharan Africa: are the poor and uninsured households more vulnerable? *Health economics review* 8(1): 26.

Atkinson, A. B. 2003. Multidimensional deprivation: contrasting social welfare and counting approaches. *The Journal of Economic Inequality* 1(1): 51–65.

Atkinson, A. B. 2015. *Inequality*. Harvard University Press.

Björkman-Nyqvist, M. 2013. Income shocks and gender gaps in education: Evidence from Uganda. *Journal of Development Economics* 105: 237–253.

Council, N. R.; et al. 2011. *Toward an Integrated Science of Research on Families: Workshop Report*. National Academies Press.

Czajka, J. L.; Jacobson, J. E.; and Cody, S. 2003. Survey estimates of wealth: A comparative analysis and review of the Survey of Income and Program Participation. *Soc. Sec. Bull.* 65: 63.

Desmond, M. 2012. Eviction and the reproduction of urban poverty. *American Journal of Sociology* 118(1): 88–133.

Desmond, M. 2015. Unaffordable America: Poverty, housing, and eviction. *Fast Focus: Institute for Research on Poverty* 22(22): 1–6.

Desmond, M. 2016. *Evicted: Poverty and profit in the American city*. Broadway Books.

Desmond, M.; and Gershenson, C. 2016. Housing and employment insecurity among the working poor. *Social Problems* 63(1): 46–67.

Desmond, M.; and Shollenberger, T. 2015. Forced displacement from rental housing: Prevalence and neighborhood consequences. *Demography* 52(5): 1751–1772.

Dinkelman, T.; Lam, D.; and Leibbrandt, M. 2008. Linking poverty and income shocks to risky sexual behaviour: evidence from a panel study of young adults in Cape Town. *South African Journal of Economics* 76: S52–S74.

Fudenberg, D.; Kleinberg, J.; Liang, A.; and Mullainathan, S. 2019. Measuring the completeness of theories .

Giesbert, L.; and Schindler, K. 2012. Assets, shocks, and poverty traps in rural Mozambique. *World Development* 40(8): 1594–1609.

Grusky, D. B. 2018. *Social stratification: Class, race, and gender in sociological perspective*. Routledge.

Grusky, D. B.; and Ku, M. C. 2008. Gloom, doom, and inequality. *Social stratification: Class, race, and gender in sociological perspective* 3: 2–28.

Grusky, D. B.; and Weeden, K. A. 2016. Do Disciplinary Boundaries Keep Us from Asking the Right Questions about Inequality?

Jarosch, G. 2015. Searching for job security and the consequences of job loss. *manuscript, Stanford University* .

Kijima, Y.; Matsumoto, T.; and Yamano, T. 2006. Nonfarm employment, agricultural shocks, and poverty dynamics: evidence from rural Uganda. *Agricultural Economics* 35: 459–467.

Kleinberg, J.; Liang, A.; and Mullainathan, S. 2017. The theory is predictive, but is it complete? an application to human perception of randomness. In *Proceedings of the 2017 ACM Conference on Economics and Computation*, 125–126.

Kleinberg, J.; Ludwig, J.; Mullainathan, S.; and Obermeyer, Z. 2015. Prediction policy problems. *American Economic Review* 105(5): 491–95.

Kochar, A. 1995. Explaining household vulnerability to idiosyncratic income shocks. *The American Economic Review* 85(2): 159–164.

Kochar, A. 1999. Smoothing consumption by smoothing income: hours-of-work responses to idiosyncratic agricultural shocks in rural India. *Review of Economics and Statistics* 81(1): 50–61.

Kube, A. R.; Das, S.; and Fowler, P. J. 2018. Allocating Interventions Based on Counterfactual Predictions: A Case Study on Homelessness Services .

Lens, V.; Nugent, M.; Wimer, C.; and Pavlenko, A. 2016. Poverty Tracker – Monitoring Poverty and Well-being in

NYC: Report 5. Technical report, Columbia Population Research Center and Robin Hood.

Morduch, J. 1994. Poverty and vulnerability. *The American Economic Review* 84(2): 221–225.

O'Flaherty, B. 2009. What shocks precipitate homelessness. *Unpublished manuscript. New York: Columbia University* .

Piketty, T. 2015. *The economics of inequality*. Harvard University Press.

Salganik, M. J.; Lundberg, I.; Kindel, A. T.; Ahearn, C. E.; Al-Ghoneim, K.; Almaatouq, A.; Altschul, D. M.; Brand, J. E.; Carnegie, N. B.; Compton, R. J.; et al. 2020. Measuring the predictability of life outcomes with a scientific mass collaboration. *Proceedings of the National Academy of Sciences* 117(15): 8398–8403.

Sen, A. 1976. Poverty: an ordinal approach to measurement. *Econometrica: Journal of the Econometric Society* 219–231.

Sen, A.; Foster, J. E.; et al. 1997. *On economic inequality*. Oxford University Press.

Shapiro, T. M.; et al. 2004. *The hidden cost of being African American: How wealth perpetuates inequality*. Oxford University Press, USA.

Tan, P.-N.; Steinbach, M.; and Kumar, V. 2016. *Introduction to data mining*. Pearson Education India.

Wimer, C.; Bannerman, C.; Garfinkel, I.; and Neckerman, K. 2014a. Poverty Tracker – Monitoring Poverty and Well-being in NYC: Report 2. Technical report, Columbia Population Research Center and Robin Hood.

Wimer, C.; Collyer, S.; Garfinkel, I.; Maury, M.; Neckerman, K.; Teitler, J.; Waldfogel, J.; and Wutchiett, D. 2016a. Poverty Tracker – Monitoring Poverty and Well-being in NYC: Report 4. Technical report, Columbia Population Research Center and Robin Hoods.

Wimer, C.; Garfinkel, I.; Gelblum, M.; Lasala, N.; Phillips, S.; Si, Y.; Teitler, J.; and Waldfogel, J. 2014b. Poverty Tracker – Monitoring Poverty and Well-being in NYC: Report 1. Technical report, Columbia Population Research Center and Robin Hood.

Wimer, C.; Garfinkel, I.; Maury, M.; Neckerman, K.; Phillips, S.; Teitler, J.; Waldfogel, J.; and Wutchiett, D. 2016b. Poverty Tracker – Monitoring Poverty and Well-being in NYC: Report 3. Technical report, Columbia Population Research Center and Robin Hood.

Yapa, L. 1996. What causes poverty?: A postmodern view. *Annals of the Association of American Geographers* 86(4): 707–728.