SOCIAL MOBILITY AND WELFARE

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1. INTRODUCTION AND BACKGROUND

Social welfare programs are among the most contentious public programs in industrialized society. Their design and implementation is costly, complicated, and often unpopular. Public opinion reflects skepticism towards government aid, with a 2014 Pew Research survey reporting 48% of U.S. adults believe government aid to the poor does more harm than good [1]. While data-driven conclusions about the optimal welfare configuration may be unattainable due to the complexity of social and economic systems, this paper adds value ongoing welfare configuration debate by addressing it using multiple regression and machine learning techniques.

Myriad theoretical analyses have been conducted both to justify and dispute the welfare state. This section summarizes the common arguments. After summarizing the extant literature, we present numerical analyses exploring the relationship between welfare policy and social mobility.

1.1. The Philosophy of Welfare

The philosophical debate over welfare services often centers on the relationship between individuals and social structures. Proponents believe out of respect for the dignity of the poor, wealthy societies should redistribute wealth to alleviate financial burden. Opponents claim out of respect for the autonomy of the poor and aversion to systems that foster dependency, the welfare state should be minimal. [2]

The proponent assumes a modern egalitarian stance – in his view equality of opportunity is a highly desirable social goal. To achieve this goal, welfare policy ought to maximize social mobility (a measure of the difference in socioeconomic status between parents and offspring) and minimize income inequality. [3] Accordingly, a perfectly egalitarian society would observe no significant relationship between the socioeconomic status of parents with their children.

The opponent prefers a Hobbsian, individualist perspective in which autonomy and accountability are supreme aspirations. To this end, social policy should be formulated with the goal of maximizing individual freedom. Welfare programs that create dependency may compromise the autonomy of the individual and ought to be avoided. The individualist sees a trivial welfare state as the configuration that maximizes social good, which may seem paradoxical when juxtaposed with the egalitarian stance.

1.2. The Economics of Welfare

Viewing the social welfare problem from an economic lens adds to the discussion. Extensive welfare programs require large amounts of taxpayer money. A common conservative position views social welfare programs as predatory, enrolling impoverished families without emboldening them to seek improved employment opportunities. The result of these systems is inter-generational poverty which creates severe economic strain. The progressive voice often heralds welfare programs as an essential feature of modern society. Providing childcare benefits to parents allows them to better provide for their children who in turn grow up to contribute economically. Similarly, unemployment checks help bridge the gap between jobs for the recently unemployed, giving workers more flexibility.

While both parties conjecture economic arguments, limited quantitative analysis has been conducted broadly assessing the economic effects of welfare. This analysis considers one dimension of economic freedom – social mobility – and attempts to explain it with welfare indicators.

2. DATA

Data were collected and compiled from multiple sources.

2.1. Social Mobility Data

Social mobility mobility data was scraped from Wikipedia but was originally published by the world economic forum in January 2020 as part of the *The Global Social Mobility Report* [4]. Social mobility is a complex and multi-dimensional construct that takes into account measurements such as intergenerational class mobility, occupational mobility, and earnings mobility [5]. The index provided by the World Economic Forum measures performance across five pillars: healthcare, education, technology access, working conditions, and social protection.

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2.2. Social Policy Indicators

The social policy indicators (SPIN) are collected by Stockholm University. SPIN data have been collected since 1990 for comparative analyses. Data is organized into modules covering different dimensions of social policy. Three modules were chosen for this analysis. Each dataset was subset to include only the most recent year and variables with no missing values.

2.2.1. Child Benefit Data -

The cleaned child benefit data (CBD) contained 6 variables with information about the generosity of child benefits in 33 countries. Children are a significant and sometimes unanticipated expense, and being born into poverty makes escape challenging. Child benefit programs are targeted towards impoverished families, so residents of countries that provide generous child financial support may enjoy enhanced mobility when compared to residents of welfare-deficient countries.

2.2.2. Social Assistance and Minimum Income Protection Data -

The cleaned social assistance and minimum income protection (SAIMP) data contained 19 variables with information about social assistance in 33 countries.

2.2.3. Out of Work Benefits Data -

The cleaned out of work benefits dataset (OUTWB) contained 37 observations of 78 variables. Out of work benefits variables may be highly correlated with social assistance variables, but they were included in this analysis to capture dimensions of income replacement that are not part of the social assistance dataset.

3. ANALYSIS

In this analysis, we present models explaining the relationship between indicators of social welfare policy and social mobility. We expect to see higher levels of social mobility in countries with more generous welfare systems.

3.1. Social Mobility and Child Benefits

The first analysis explored the relationship between social mobility and child benefits. The child-welfare policy data contained 7 predictor variables for 34 countries. An OLS model was fit to the data using all predictors and observations. This model had two significant predictors at $\alpha = 0.05$. Table 1 provides coefficient estimates and p-values.

Interestingly, these two variables capture the exact same information with the latter a linear transformation of the former (the correlation between the two variables is high, $r = 0.9998$). The model also had a high MSE considering the range of the response variable, $y \in [59.8, 85.2]$. To explore the relationship further and visualize the distribution of the data, a scatter plot was produced with total net child benefit on the x-axis and social mobility on the y-axis (fig. 1).

Variable	$\hat{\beta}$	p-value
Net APW Family	-0.0004	0.0235
Net APW Family (*0.5)	0.0007	0.0251

Table 1: *The two significant predictors have estimates for $\hat{\beta}_i$ that are remarkably small (MSE $= 30.188$). Given these data contain identical information, the opposing signs provide evidence of a bad model.*

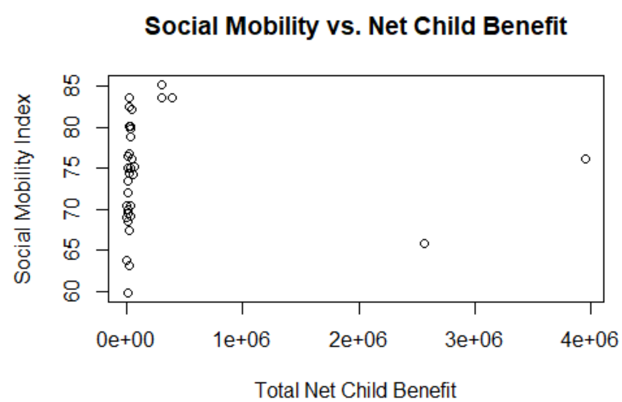

Fig. 1: *Two leverage points may be confusing the model.*

Using the plot, two points were identified as high leverage. These points belonged to countries Japan and Hungary. Research revealed these countries underwent significant child benefit welfare reform between 2010 and 2011. Due to the complex nature of social welfare systems, significant reform could result in unstable measurements during the transitional period. Thus, these points were dropped from the dataset.

A new OLS model was trained on the modified dataset. This model had zero significant predictors, but visually inspecting a scatterplot of the new data hinted at correlation (fig. 2). The plot shows three additional points with high leverage. These three points points belonged to Denmark, Sweeden, and Norway

In an attempt to account for the (potentially) undue influence of these three countries, robust models were fit to the data. Table 2 provides a summary including the MSE and number of significant predictors in each model.

GAM models were also fit to improve performance. The first model uses smoothing splines to explain the relationship between the child benefit data and social mobility. Figure 3 visualizes the predicted values computed by the spline model

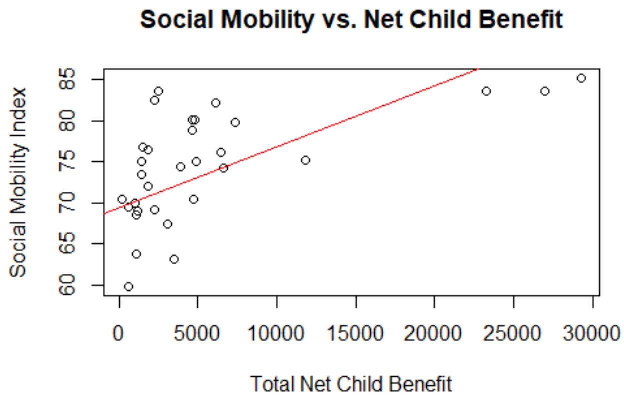

Fig. 2: *The OLS trend-line is given in red. Though the predictor is insignificant, the plot provides evidence of some relationship between the variables.*

Model	MSE	# Sig. Predictors
OLS (Subsetted Data)	26.86	0
MM-Estimator	26.87	1
LTS-Regression	26.86	0
PCR	27.70	NA

Table 2: *These models have lower MSE than the model trained on data with Hungary and Japan, but robust methods don't perform better than OLS.*

using the variable, "Total Net Child Benefit" for visualization. While the relationship between social mobility index and total child benefits appears to be better explained by this more flexible model, the absence of testing data still complicates inference. Without testing data the results of the model must be considered cautiously.

Additional GAM models are summarized in table 3. Using flexible models with limited data makes overfitting likely – the eighth degree polynomial spline is clearly overfit – but cursory models could inform future analyses.

Model	MSE
Cubic Splining	8.34
P-Spline	16.77
Thin Plate Regression Spline	19.69
Polynomial Spline (df=3)	24.37
Polynomial Spline (df=8)	5.16

Table 3: *Model choice can yield vastly different performance measurements. Such variability makes it difficult to draw conclusions about ostensible relationships.*

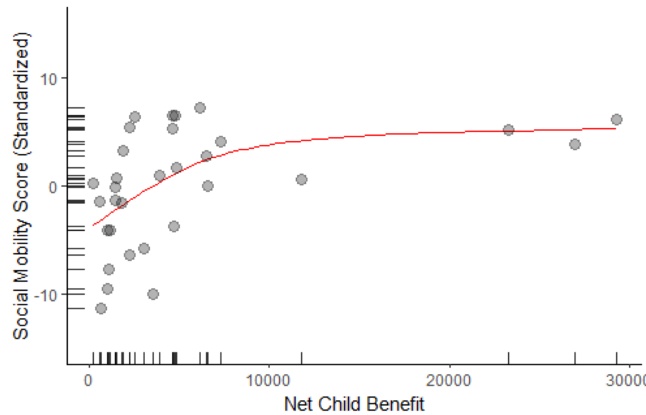

Fig. 3: *Smoothing spline model with default parameters. Denmark, Norway, and Sweeden still dominate the model, but without theoretical justification for removal they must remain in the dataset.*

3.2. Social Mobility and Social Assistance

An OLS model was fit to the data using all predictors. The OLS algorithm was unable to estimate 10 variable coefficients due to singularities. This suggests hypercolinearity in the predictor set. Principal components analysis (PCA) was performed on the data to assess the degree of multicolinearity in the data. Table 4 summarizes the principle components analysis.

Component	% Var. Explained	Cumulative Variance
PC1	99.83%	99.83%
PC2	0.13%	99.93%
PC3	.047%	99.8%

Table 4: *A single principal component explains nearly all the variability in a 19-factor predictor set.*

Two regularized models were fit to the SAIMP data, one using the L1-norm penalty and the other using L2. Performance metrics for the regularized models are given in table 5. As a baseline for comparison, the OLS model is summarized as well. Cross validation was used to find the optimal lambda value; however, the lambda value that was chosen algorithmically shrunk each coefficient estimate to zero. A model that uses mean social mobility to predict social mobility isn't useful, so lambda values were chosen using trace plots. A trace plot visualizing estimates of $\hat{\beta}$ for the ridge regression model is given in figure 4.

Model	Penalty	MSE
OLS	none	28.24
LASSO	$\lambda = 0.005$	42.85
Ridge Regression	$\lambda = 0.001$	42.92

Table 5: *Regularized models don't seem to accurately fit the data.*

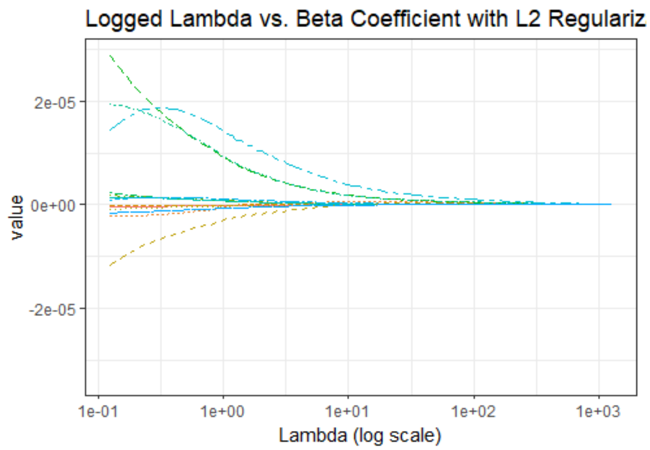

Fig. 4: *While three variables are chosen to stay in the model longer than others (all measuring minimum income protection for a two-parent family but on different scales), we cant necessarily conclude that the choice was non-arbitrary.*

3.3. Social Mobility and Unemployment

Multicolinearity continued to complicate analysis. The first OLS model trained on the OUTWB data failed to produce a coefficient estimate for more than half the predictors due to singularities. To better understand these relationships, a random selection of 5 covariates was chosen and a correlation plot was produced (figure 5).

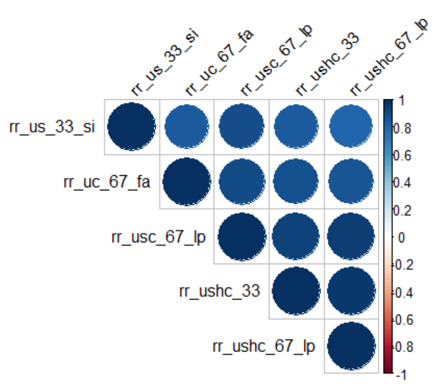

Fig. 5: *Predictors are highly correlated with one another. Between these variables, the lowest correlation value was 0.80.*

To further assess variable significance, 78 simple univariate OLS models were fit to predict social mobility using individual variables. 16 out of 78 models had significant p-values at the 0.05 level. The most significant model used a variable measuring the total unemployment benefits received by a single person making 33% of an average wage. A plot of the data with its estimated regression line is given in figure 6.

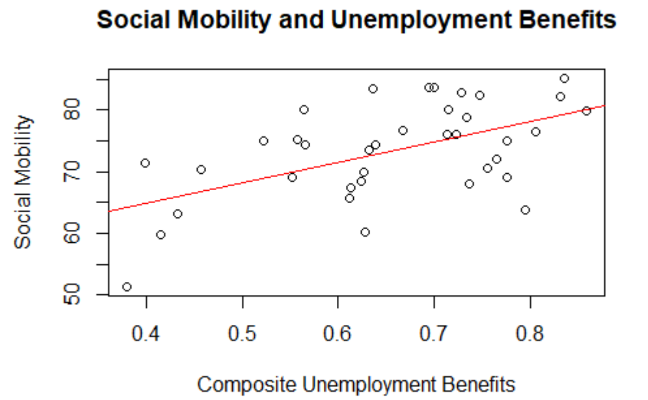

Fig. 6: *With a 78-variable predictor set, spurious significance is likely. A visual assessment does not corroborate the statistical test – the relationship appears weak at best.*

3.4. Final Model

Using the single most significant predictor from each of the prior analyses, a final model was produced. This model performed no better than the others (MSE = 29.98). A summary of the model is given in table 6.

Varialbe	$\hat{\beta}$	p-value
Child Benefit	-0.0026	0.673
Social Assistance	-0.0000	0.235
Unemployment	2.747	0.005

Table 6: *Though each predictor is significant in isolation, when combined into one model only unemployment remains statistically significant at the 0.05 level. Is the variable choice arbitrary?*

4. CONCLUSION

The analyses presented in this experiment fail to establish a statistically significant relationship between social mobility and welfare policy. Insufficient data gave the study low statistical power. Many models were constructed and most failed to make reasonably accurate predictions. Those that had low MSE (polynomial splining, etc.) were almost certainly overfit to the training data. Additionally, the lack of validation data makes thorough model evaluation impossible.

Though statistically significant models were difficult due to limited data, this project provides a cursory exploration of the relationship between social mobility and welfare policy using a model-oriented approach. This work highlights the need for better data designed for comparative analysis. Future work should consider numerous dimensions of welfare spending and control for country features like wealth and literacy rate. While we do not have evidence that the SPIN database can explain variability in social mobility, there is adequate theoretical justification to get better data and continue the analytical exploration.

Social systems are naturally complex and difficult to model well. In some cases statistical analysis of social systems can provide quantitative insight, but there may not be an underlying mapping from the space of social policy to the space of social mobility. This study fails to answer its research question but opens the door for further exploration.

5. REFERENCES

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