A New Index for Tracking Trends in Household Economic Well-Being and Its Disparities Among Black, Hispanic, and White Americans

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Abstract

This policy brief presents the development of a new index of economic well-being, the EWB-I, that is derived on an annual basis from the data in Federal Reserve Board's annual Survey of Household Economic Decision-Making (SHED). Recent reports and articles have reported on trends in measures such as income, wages, and employment status, but have omitted a range of additional potentially relevant aspects of economic well-being that are included in the SHED surveys. By incorporating these additional items into a conceptually broader index, the EWB-I, and applying this index to 7 years of SHED data (from 2013 to 2019), we have examined a picture of economic progress during this period that appears to differ in important respects from much of the previous literature.

Our results suggest rather different pictures for the period 2013-2016 versus the period from 2016 to 2019. Specifically, it appears that the gains from economic progress in the 2013-2016 period were rapid and widely shared across income and racial/ethnic groupings, that the upward trend in these gains slowed after 2015, and that after 2016 the gains from economic progress did not accrue to all these groups. EWB-I index values after 2016 actually suggest a decline in economic well-being for lower income, Hispanic, and Black households. We also find that while prior analyses of longer-term trends have shown that Hispanic-White and Black-White disparities are persistent, the experience of the 2013-16 demonstrated that real short-term progress is possible. In the 3 years following 2019, however, most of the 2013-16 reduction in disparities was erased.

Introduction

A number of economic analysts have observed recently that our most widely-cited proxies for economic well-being – household income, unemployment, and wages - are seriously incomplete.[1] As a picture of your economic situation, income comes up short in various ways. It takes no account of assets (e.g., financial assets, human capital), debts, or the costs of earning income (e.g., commuting, child care) which can be substantial.[2] It also does not reflect the uncertainties and risks that individuals face, with the exception of risk premiums for health hazards and cyclical or seasonal job loss risks.[3] It also does not capture the value of non-cash fringe benefits, which account for a large share of employer-paid costs for employee compensation.[4] Average hourly or weekly wages have many of the same limitations as income, but also do not account for changes in hours worked or employment levels for all household members.

Unemployment merely indicates that you do not have a job and have spent some (unspecified) amount of time and effort looking for one. It lumps together people with a high reservation wage, because they can easily survive while looking for the "right" job, in the same category as persons desperate for any job to avoid being evicted from their homes. Moreover, it ignores those no longer looking who would still take the "right" job (or any job?), as well as ignoring those working in jobs who for various reasons (e.g., low pay, poor benefits, too-short hours, too-long hours, variable hours, risky working conditions, risk of job loss) are looking to change jobs or take on additional work.[5] It also does not reflect employment levels aggregated across all household members.

One suspects that income, unemployment and wages are so widely used as indicators of economic well-being because they are regularly presented in publicly-available BLS and Census Bureau data

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[1] See, for example, OECD (2013), "Economic well-being", in *OECD Framework for Statistics on the Distribution of Household Income, Consumption and Wealth*, OECD Publishing, Paris. DOI: https://doi.org/10.1787/9789264194830-5-en

[2]A recent estimate is that families with children under 5 spend 10% of their income on child care. See Malik R. (2019) "Working Families Are Spending Big Money on Child Care," Center for American Progress, June 20. A recent Census Bureau estimate of commuting expenses (i.e. not including time costs) for the "average American", $2,600 per year, was cited in Josephson A. (2018) "The Average Cost of an American Commute", *Smart Asset* (July 5).

[3] Topel R. (1984) "Equilibrium earnings, turnover, and unemployment: New evidence," *Journal of Labor Economics*, 4, 500-522; Viscusi K. (2018) *Pricing Lives*. Princeton: Princeton University Press. Chapter 1.

[4] All fringes account for more than 30% of employers' costs and non-cash fringes account foer moer than 20%. See Salkever D. (2020a) "Private-Sector Workers' Hourly Compensation in the Trump ERA: The Case of the Disappearing Rise in Real Pay Rates", Public Policy Brief, School of Public Policy, University of Maryland at Baltimore County; and (2020b)"Real pay data show Trump's 'blue collar boom' is more of a bust for U.S. workers, in 3 charts, *The Conversation* (February 8).

[5] Abraham KG, Haltiwanger JC, Rendell LE. (2020) "How Tight is the U.S. Labor Market?", Brookings Papers on Economic Activity, Conference Draft (March 19); Hornstein A, Kudlyak M. (2020) "Why is Current Unemployment Rate So Low?," Federal Reserve Bank of San Francisco Working Paper 2020-05 (February) https://www.frbsf.org/economic-research/publications/working-papers/2020/05/ .

from household surveys, and are produced on a fairly consistent basis over time. Like the story of the drunk looking for his lost keys under the street light, use of these data is somewhat defensible but does not preclude alternative approaches that are broader in scope.

The "SHED" from the "FED"

An alternative household-survey-based data source is, however, available: the Federal Reserve Board (FED) annual Survey of Household Decision-Making (SHED). This survey was first fielded in the last quarter of 2013 and has been continued at annually ever since. The respondents are a stratified sample of adults, one per household, with the weighted sample designed to be representative of the U.S. population of such adults. Every year, the FED makes the survey data available within 6 months after survey completion and also publishes an annual report on "Economic Well-Being of U.S. Households," that document the survey results and methods from that year's SHED survey.

A long series of detailed and specific questions are included in the SHED surveys. In the 2019 survey, these questions related to 8 different substantive categories defined in the report: employment, income, dealing with unexpected expenses, banking and credit, housing, higher education, student loans and other educational debt, and retirement.[6] The listing of categories, and topics covered in the surveys varied over the years but the principal question about overall economic well-being did not change substantially.

The FED's annual reports, however, rely only on the response to a single, purely subjective question for their "overall" assessment of each respondent household's economic well-being:

"Overall, which one of the following best describes how well you are managing financially these days?

4. Living comfortably
3. Doing okay
2. Just getting by
1. Finding it difficult to get by"

The FED interprets two responses to this question - "(d)oing okay" or (l)iving comfortably" - as indicating a positive outcome, and the remaining responses -"(j)ust getting by" or "(f)inding it difficult to get by" - as indicating a negative outcome. Accordingly, the first result highlighted in each of these annual reports[7] is the percentage of respondents with a positive outcome.

A clear problem with using the response to this single question to calibrate levels of well-being is the fact that the question itself is entirely subjective in nature in the sense that it does not relate specifically to any facts or events that are at least in principle observable. This contrasts with measures like

[6] Several other questions, pertaining to subjective economic well-being in the past and respondents' assessments of current conditions in the local and national economies, are also included in the surveys.

[7] Report on the Economic Well-Being of U.S. Households in 2019, Featuring Supplemental Data from April 2020
HTML

unemployment or level of income, where self-report survey responses are used in Federal Census and BLS statistics but they refer to observable facts that are at least not entirely subjective. [8]

A New Index of Economic Well-Being Based on SHED Data

A number of other detailed questions from the SHED do, however, relate to events or facts that are in principle observable. Responses to many of these questions could plausibly relate to the respondent's economic well-being, and therefore could be used as a less subjective basis for its measurement. Yet, as noted above, these questions range across a number of different substantive subject categories, so using only one of these questions and its responses would be as incomplete as using only income level or unemployment status. A regression analytic strategy for combining these individual items into a single index ameliorates this problem.

In this report, I propose using 17 different specific items from the SHED survey to construct the overall economic well-being index, henceforth designated as EWB-I. These specific items included the income category for the respondent's household income, and 16 binary (i.e., 0-1) indicators of potential economic stressors or vulnerabilities.

Using the data for each of these 17 items, I employ a survey-weighted logistic regression equation that relates these items to the FED's 0-1 outcome of subjective overall economic well-being of each individual. I denote this outcome, for the ith individual, as $EWBsubj_i$. The predicted probability that $EWBsubj_i = 1$ is used as the indicator of EWB for the ith individual.

I apply this approach to data from all respondents across all 7 years of the SHED surveys. Thus, the analysis is of necessity restricted to items that appear in essentially the same form in each of the survey years. The specific items are all defined as binary (0-1) indicators. All these binary items are coded so that a value of "0" corresponds, ceteris paribus, to an expectation of greater economic well-being (or financial strength) and a value of "1" corresponds to an expectation of lesser economic well-being (financial weakness). The a priori hypothesis is that for each of the 16 binary items, a value of "1" (rather than "0") implies a lower probability that $EWBsubj_i = 1$.

The items used in the analysis are described in Table 1. The specific rationales for inclusion vary among the items. For example, items 9, 11 and 12 pertain to debts the respondent may have, while items 5, 10 and 13 pertain to presence or absence of assets (including human capital), and item 16 relates to future asset accumulation through saving or income adequacy. Items 3 and 4 relate to the respondent's vulnerability to adverse future financial risks, items 6-8 pertain to the respondent's access problems in accessing financial services and credit. Item 1 reflects adequacy of resources to maintain health capital, and items 13, 14 and 17 relate to the respondent's current abilities or disabilities in generating income and commanding resources.

[8] While some other widely-used economic indicators are also entirely subjective, such as measures of consumer or business confidence, these are typically forward-looking forecasts of future conditions that are not in principle directly observable ex ante.

TABLE 1: DEFINITIONS OF INDICATOR COMPONENTS OF AN INDEX OF ECONOMIC WELL-BEING			
Item #	**SHED Category**	**Item Label**	**Item Definition**
1	Unexpected Expenses	Skip Health Care	=1 if any health services or drugs were needed in the past 12 months but not purchased because of cost; = 0 otherwise
2	Unexpected Expenses	Major Medical O-o-P Expenses in Past Yr.	=1 if any unexpected out-pf-pocket major medical expenses were (not fully covered by insurance) in past yr.; = 0 otherwise
3	Unexpected Expenses	Could not cover $400 Emergency	=1 if an unexpected $400 emergency expense could not be paid for without incurring any added debt; = 0 otherwise
4	Unexpected Expenses	No Emergency Fund Cover	=1 if you were unable to tap savings, borrow, or sell assets to cover expenses for 3 months if you lost your main income source;=0 otherwise
5	Retirement	No retirement funds	=1 for non-retired workers with no retirement savings; = 0 0therwise
6	Banking and Credit	Unbanked	=1 if no bank, savings, or money market account; = 0 otherwise
7	Banking and Credit	No Credit Card	=1 if respondent has no credit card; = 0 otherwise
8	Banking and Credit	Credit Problem in Past Yr.	=1 if requested credit denied or reduced in amount, or if not applied for because denial was expected; = 0 otherwise
9	Banking and Credit	Carried credit card debt in past yr.	=1 if any credit card balances were carried over; = 0 if all balances were paid in the months they were incurred
10	Housing	Does not own home	=1 if respondent does not own their residence; = 0 otherwise.
11	Housing	Mortgage Debt	=1 if respondent owes any mortgage debt;=0 otherwise
12	Student/Education Loan	Education Debt	=1 if respondent owes any education-related debt;=0 otherwise
13	Higher Education	No post-HS Ed	=1 if respondent has not post-high-school education; = 0 otherwise
14	Employment	Disabled	=1 if current employment status is "not working" and "disabled", = 0 otherwise
15	Employment	Unemployed / Laid-off	=1 if current employment status is "not working" and either "looking for work" or "on temporary layoff", = 0 otherwise
16	Income	Spent more than income	=1 if the respondent's spending in the past month exceeded their income; = 0 otherwise.
17	Income	HHInc	Coded in categories from 1 (household income in past year < $5,000) to 19 (income $175,000 or more)

Regression Results Used to Generate the EWB-I

As noted above, data for the 17 SHED items were used as regressors in a survey-weighted logistic multiple regression analysis. The outcome variable in the regression, $EWBsubj_i$, is defined as = 0 for individuals "finding it difficult" or "just getting by", and as =1 for individuals who reported that they were "doing okay" or "living comfortably").[9] The results of this regression analysis are shown in Table 2.

The estimated coefficients for these 17 items, combined with the data on the predictor variables, were used to calculate the predicted probability of a “0” or “1” value for $EWBsubj_i$ for each individual.[10] These predicted probabilities are each individual respondent’s input into our EWB-I estimates at the group level. Note that these estimates in effect combine the purely subjective data, from the $EWBsubj_i$, with the data on the predictor variables that relate to specific facts that are in principle observable. Averaging these results across individuals, and applying the FED’s sampling weights, yields a population-level predicted probability which is the value for EWB-I.[11]

Since a “1” response corresponds to “doing okay” or “living comfortably”, a negative coefficient in Table 2 for any predictor variable implies that the occurrence of that predictor, holding other predictor values constant, on average reduces (rather than increases) EWB. Because the HHInc predictor is categorical rather than binary, the coefficient interpretation is slightly different. Positive (negative) coefficients for an income category, however, only indicates that having that category of income reduces (increases) expected EWB relative to that of an otherwise identical person with less than $5,000 income (the reference category). Examination of the coefficient in Table 2 indicates that 13 of the 16 binary predictors have the expected positive signs and all but one (No post-HS Ed) are precisely estimated (relative to their estimated standard errors), while the remaining three (Unbanked, Does not own home, and Mortgage Debt) have negative estimated coefficients that are very small in magnitude and imprecisely estimated.[12]

The pattern of coefficient estimates for the 8 lowest income categories (excluding the refence group) is interesting in that the signs are unexpectedly positive in 7 of these categories but only one is large relative to its standard error. This suggests that $EWBsubj_i$ is not significantly higher on average for these categories than for the lowest-income (reference group) respondents. This might be explained by availability of income-conditioned supports and services for many of these lower-income households. Estimated coefficients for all of the 10 higher-income categories are negative (as expected) and precisely estimated.

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[9] The regression was estimated using Stata 16 software and the command svy:logit.

[10] In the case of HHInc, which is defined as 19 categories in ascending levels of income, there were 18 separate coefficient estimates (with the lowest income category as the reference group).

[11] The FED weights used were those for the U.S. adult population.

[12] These positive coefficients may reflect omitted variables. For example, persons who own homes with no mortgages may be living in homes that are considerably older on average but data on age of home are not available in the SHED data set.

TABLE 2: Logistic Regression Results for Outcome Variable of Finding it Difficult/ Just Getting By (=1)				
Predictor Variables	**Coeff.**	**Std.Err.**	**t**	**P>|t|**
Unbanked	0.0544	0.0748	0.73	0.467
Could not cover $400 Emergency	-0.85535	0.0408	-20.97	<0.0005
No Emergency Fund Cover	-1.01672	0.0396	-25.65	<0.0005
Carried credit card debt in past yr.	-0.47835	0.0393	-12.16	<0.0005
No retirement funds	-0.1972	0.0479	-4.11	<0.0005
No post-HS Ed	-0.04056	0.0393	-1.03	0.302
Credit Problem in Past Yr.	-0.31695	0.0483	-6.57	<0.0005
Major Medical O-o-P Expenses in Past Yr.	-0.21239	0.0403	-5.28	<0.0005
No Credit Card	-0.49141	0.0526	-9.34	<0.0005
Skip Health Care	-1.0018	0.0378	-26.52	<0.0005
Does not own home	0.0319	0.0449	0.71	0.477
Education Debt	-0.21358	0.0432	-4.94	<0.0005
Mortgage Debt	0.0679	0.0423	1.6	0.109
Spent more than income	-1.04788	0.0423	-24.79	<0.0005
Unemployed / Laid-off	-0.42817	0.0769	-5.57	<0.0005
Disabled	-0.371	0.068	-5.45	<0.0005
HHInc				
$5,000 to $7,499	-0.08703	0.1509	-0.58	0.564
$7,500 to $9,999	-0.20212	0.149	-1.36	0.175
$10,000 to $12,499	-0.37938	0.1245	-3.05	0.002
$12,500 to $14,999	-0.07296	0.1264	-0.58	0.564
$15,000 to $19,999	-0.14387	0.1131	-1.27	0.204
$20,000 to $24,999	-0.09507	0.1042	-0.91	0.361
$25,000 to $29,999	0.0502	0.1054	0.48	0.634
$30,000 to $34,999	-0.08924	0.1028	-0.87	0.385
$35,000 to $39,999	0.2168	0.1044	2.08	0.038
$40,000 to $49,999	0.2284	0.107	2.13	0.033
$50,000 to $59,999	0.3055	0.1083	2.82	0.005
$60,000 to $74,999	0.4241	0.1034	4.1	<0.0005
$75,000 to $84,999	0.6181	0.11	5.62	<0.0005
$85,000 to $99,999	0.5726	0.1113	5.14	<0.0005
$100,000 to $124,999	0.7912	0.1072	7.38	<0.0005
$125,000 to $149,999	0.9634	0.1273	7.57	<0.0005
$150,000 to $174,999	0.9442	0.144	6.56	<0.0005
$175,000 or more	1.4711	0.1349	10.91	<0.0005
Constant	2.3493	0.0992	23.68	<0.0005

The average marginal effect for each variable, based on the logistic regression, is shown in Table 3. Estimates for each of the 16 binary predictors are interpreted as indicating the average predicted magnitude (as well as direction) if the change in probability of a $EWBsubj_i = 1$ when the corresponding item takes on a value of 1 rather than 0 (holding all other items at their observed values). The estimated marginal effects for 12 of the 16 binary predictors are negative (as expected), relatively large in magnitude (ranging from -0.02756 to -0.15139), and large relative to their standard errors. Of these 13 predictors, 4 had average marginal effects that were particularly large. In descending order of effect magnitude, these 4 were: Spent more than income, No Emergency Fund Cover, Skip Health Care, and Could not cover $400 Emergency. Two of these four indicate lack of financial reserves to cover risk of adverse events, while the other two pertain to inadequate funds to meet perceived expenditure needs. Analogous marginal effect estimates for the 4 remaining binary predictors (Unbanked, No post-HS Ed, Does not own home, and Mortgage Debt) are very small in absolute magnitude (0.00406, 0.0069, -0.00519, and 0.00868) and not large relative to their standard errors.

Since the qualitative results, in terms of signs and significance for the marginal effects in Table 3, parallel the results for the coefficient estimates in Table 2, we again see unexpected signs and generally small and insignificant marginal effects for the 8 lowest income categories. For the 10 higher income categories, we see highly significant and relatively large positive marginal effects (as expected). Note also that, with one exception, the magnitude of these effects for the higher income categories increase with the level of income. This confirms the expected result that having more income does indeed increase one's level of economic well-being.

TABLE 3: Estimated Average Marginal Effects			
Predictor Variable	Marg.Eff.	Std.Err.	P
Unbanked	0.0069	0.0094	0.464
Could not cover $400 Emergency	-.012446	0.0066	<0.0005
No Emergency Fund Cover	-0.15101	0.0066	<0.0005
Carried credit card debt in past yr.	-0.06161	0.0051	<0.0005
No retirement funds	-0.02581	0.0064	<0.0005
No post-HS Ed	-0.00519	0.005	0.303
Credit Problem in Past Yr.	-0.04205	0.0066	<0.0005
Major Medical Out-of-Pocket Expenses in Past Yr.	-0.02756	0.0053	<0.0005
No Credit Card	-0.06652	0.0075	<0.0005
Skip Health Care	-0.14616	0.0061	<0.0005
Does not own home	0.00406	0.0057	0.476
Education Debt	-0.02768	0.0057	<0.0005
Mortgage Debt	0.00868	0.0054	0.109
Spent more than income	-0.15139	0.0067	<0.0005
Unemployed / Laid-off	-0.05730	0.0098	<0.0005
Disabled	-0.04949	0.0095	<0.0005
HHInc			
$5,000 to $7,499	-0.01333	0.0232	0.566
$7,500 to $9,999	-0.03132	0.0233	0.178
$10,000 to $12,499	-0.0598	0.0197	0.002
$12,500 to $14,999	-0.01116	0.0194	0.564
$15,000 to $19,999	-0.02217	0.0174	0.203
$20,000 to $24,999	-0.01458	0.0159	0.36
$25,000 to $29,999	0.00758	0.0159	0.634
$30,000 to $34,999	-0.01367	0.0157	0.383
$35,000 to $39,999	0.03214	0.0156	0.04
$40,000 to $49,999	0.03381	0.016	0.035
$50,000 to $59,999	0.04483	0.0161	0.005
$60,000 to $74,999	0.06138	0.0154	<0.0005
$75,000 to $84,999	0.08737	0.016	<0.0005
$85,000 to $99,999	0.08139	0.0162	<0.0005
$100,000 to $124,999	0.10939	0.0155	<0.0005
$125,000 to $149,999	0.1302	0.01739	<0.0005
$150,000 to $174,999	0.12795	0.0192	<0.0005
$175,000 or more	0.18506	0.017	<0.0005

Index Values for EWB Over Time: Aggregate and by Income Class

I calculated the EWB-I index for any individual respondent as their predicted probability of a good outcome in the regression (i.e., “doing okay” or “living comfortably”) which serves as our EWB index value for that person. The corresponding EWB-I value for a group of persons is simply the survey-weighted mean EWB-I value for all persons in that group.

Table 4 presents the overall EWB-I index value for all persons by year, as well as the corresponding values for 4 income groups and the three major racial-ethnic groups (non-Hispanic Whites, non-Hispanic Blacks, and Hispanics). The index increase for the 2013-19 period overall was 14.32%, but the difference in trends between the first half of the period (2013-2016) and the last half (2016-2019) are also striking. The first half showed a robust of increase (12.85%) compared with the minimal rise in the second half (1.32%). The fact that the economy was still coming out of the Great Recession in the 2013-2014 year explains part of this differential, but the increase from 2014 to 2016 was also fairly strong.

EWB index trends for the 4 income groups of respondents are shown in the second through fifth rows in Table 4. These data show interesting differences among the groups. In particular, for all 3 of the income groups with <$100,000 annual income, the highest EWB index value was reached in 2016, and was followed by a downward (albeit uneven) trend in 2017-2019. In contrast, households with more than $100,000 annual income showed an upward trend over the entire period (though their rate of increase over time slowed somewhat after 2016). Note also that the percentage gain for the lowest income group was the largest for the 2013-16 while the percentage loss for this group in the period from 2016 to 2019 was much larger than that of the other two lower income groups. I will explore the possible reasons for this differential in a subsequent report.

Table 4: Mean EWB Index Trends Over Time, 2013-2019, Overall and by Income Group										
	2013	2014	2015	2016	2017	2018	2019	%↑or↓ 2013 - 19	%↑or↓ 2013 - 16	%↑or↓ 2016 - 19
EWB- I (overall ave.)	0.6385787	0.6882932	0.7051118	0.7206227	0.7115698	0.7303436	0.7300302	14.32%	12.85%	1.32%
EWB- I (HHInc<$35K)	0.3990888	0.4686408	0.4835515	0.4912925	0.4592655	0.4875333	0.4560781	14.28%	23.10%	-7.12%
EWB-I (HHInc >$34999 & <$60K)	0.6170461	0.6516394	0.6686389	0.6680057	0.63760609	0.6602293	0.6576918	6.59%	8.26%	-1.51%
EWB-I (HHInc >$59999 & < $100K)	0.707249	0.7649215	0.7718239	0.7767302	0.7701778	0.7610629	0.7666567	8.40%	9.82%	-1.28%
EWB-I (HHInc > $100K)	0.8394635	0.8602016	0.8656431	0.8824742	0.8882559	0.8939269	0.8977822	6.95%	5.12%	1.73%
EWB-I non-Hispanic White	0.6756387	0.7236456	0.7374383	0.7499062	0.7509254	0.7703939	0.7737268	14.52%	9.90%	3.18%
EWB-I non-Hispanic Black	0.5061436	0.5723373	0.6126157	0.6199542	0.5698259	0.6096703	0.6044295	19.42%	18.36%	-2.50%
EWB-I Hispanic	0.5543215	0.5963225	0.6123282	0.6450889	0.6196154	0.6337203	0.6255026	12.84%	16.37%	-3.04%

Black vs. White EWB Levels and Disparities Over Time

During the recent pandemic months, as well as in the preceding year, economic reports in the press often focused on the economic hardships of Black Americans and the disparities between their situation and that of the White majority. These reports often take a longer historical perspective and document how disparities in income and wages have persisted over decades, and economic progress hs done little to ameliorate these disparities.

For policy-makers, however, a much shorter perspective can also be very relevant. Shorter-run questions of policy impacts and potential need for new directions can be overlooked when the context in which an issue is viewed spans 30 or 40 years. Because the data needed to generate EWB-I values are collected by the FED annually and are made available with a time lag of less than 6 months, the analysis of these data can be useful in discussions of consequences of changing economic conditions and policies in a shorter run context.

It is therefore of interest that when we apply the EWB-I index developed in this report to the SHED data on non-Hispanic White and non-Hispanic Black Americans, we observe some potentially significant differences in trends. As is shown in Tables 4 and 5, EWB-I values for both White and Black groups clearly rose over the 2013-2019 but the trajectories within the period were quite different. During the short 3-year period from 2013 to 2016, economic well-being increased more rapidly for Black Americans. Moreover, the White-Black disparity decreased steadily in each year and fell during the overall period by almost one-fourth. From 2016 to 2019, however, economic well-being continued to rise for Whites but at a slower pace than previously, while the EWB-I index for Blacks actually declined. The result was that the disparity in the index at the end of 2019 was back to the level observed in the late 2013 SHED data. Given the increase from 2013 to 2019 for both groups, however, the changes resulted in an increase in Black EWB-I relative to White EWB-I of 3.2 percentage points. This was the net result of the large 7.8 percentage-point increase from 2013 to 2016 and the subsequent 4.6 percentage point decline.

Trends in disparities were similar for Hispanics vs. Whites though 2013-2016 narrowing of disparities was smaller and the 2016-19 widening was larger so the 2013-19 was small widening rather than a small narrowing.

Table 5: Changes in Absolute and Relative EWB Disparities, 2013-2019, for Blacks Compared to Whites and Hispanics Compared to Whites

	Changes in Differences in EWB-I Levels VS. White			Change in EWB-I as % of White		
	2013 - 19	2013 - 16	2016 - 19	2013 - 19	2013 - 16	2016 - 19
Non-Hispanic Blacks	-0.02%	-3.95%	3.93%	0.032	0.078	-0.046
Hispanic	2.69%	-1.65%	4.34%	-0.012	0.04	-0.052

Comparisons of the EWB-I Model with Those Using Only Income or Income + Unemployment

It is interesting to compare our model, that adds additional EWB indicators, relative to models with only the "standard" income and unemployment predictors in terms of explanatory power. While numerous explanatory power measures have been suggested for the binary-outcome logistic model, Allison has persuasively argued for the use of an R-squared measure first proposed by Tjur in 2009.[13] This measure is calculated simply as the average value of the predicted probability of a "1" outcome for cases actually reporting that outcome, minus the average predicted probability of a "1" outcome for cases that actually reported a "0" outcome instead.

We therefore used Tjur's R-squared to examine the explanatory powers of the following models:

1) Our full model reported above with the 17 predictors;
2) A model that only includes the categorical income variable;
3) A model the only includes the income and out-of-work predictor variables;
4) Our full model but with income excluded; and
5) Our full model but with both income and the out-of-work variable excluded.

The results are reported in Table 6. These indicate that our full model yields a value for Tjur's R-square of 0.40. In comparison, a model that only include the income variables (with 19 categories) yields a corresponding value for Tjur's R-square of only 0.1454. Adding

[13] Allison P. (2013) "What's the Best R-Squared for Logistic Regression?", *Statistical Horizons*, Feb,. 13 https://statisticalhorizons.com/r2logistic.

The out-of-work indicator (which corresponds roughly to unemployment) only increases the Tjur's R-square to 0.152. The final two rows of Table 6 indicate that the 15 0-1 indicators from the SHED data, even when the commonly-used well-being proxies of income and unemployment are not included in the analysis, still yields a Tjur's R-square in excess of 0.38.

Another intuitively appealing fit measure uses the percent of "correct" predictions (defined as either an outcome=1 and a predicted probability >0.5 or an outcome=0 and a predicted probability <0.5). Subtracting this percentage from the fraction of outcomes =1, and dividing by (1- minus the fraction of outcomes=1) yields the excess of the correctly predicted fractions relative to the highest possible additional fraction predicted correctly. The denominator of this ratio corresponds to the idea of total variability above the mean and the numerator corresponds to the fraction of this total variability explained by the model.[14] Like Tjur's R-square, this measure shows that the inclusion of the 15 0-1 indicator variables adds far more to the fit of the model than do the standard income and unemployment predictors.

Table 6: Comparisons of Models in Terms of Tjur's R-Squred and % "Correct" Predictions

		Mean Predicted EBW for:		Tjur's R-Sq.	% Added Correct Predictions Above Ave.*
Row	**Predictor Variables**	**EBWsubj=1**	**EBWsubj=0**		
1	Full Model	0.8226	0.4200	0.4026	36.63%
2	Categorical Income Only	0.7184	0.5730	0.1454	8.82%
3	Categorical Income + Out of Work	0.7235	0.5715	0.1520	9.40%
4	Full Model w..o. Categorical Income	0.8289	0.4463	0.3825	34.61%
5	Full Model w..o. Cat. Inc. or Out of Work	0.8281	0.4467	0.3814	34.47%

*This % = (% correct predictions-.7041)/(1-.7041) were 70.41% of outcomes=1.

Discussion and Comments on Further Analyses

This development of the EWB-I and analysis of its overall trends and components points toward several important empirical conclusions. First, it provides evidence that a number of other factors besides current income, current employment, and current wages are important to economic well-being. These include liquid assets that provide insurance against uncertainty, maintaining financial access to health care and services, and access to credit. These are factors that have not been explicitly included in prior analyses that have focused on trends in income, wages, and employment.

[14] This measure of fit is a variant of one proposed by Kennedy P. (2008) *A Guide to Econometrics* (6th ed.), Chap. 16. Oxford: Blackwell Publishing.

Second, the data suggest that the gains from economic progress in the 2013-2016 period were rapid and widely shared across income and racial/ethnic groupings, that the upward trend in these gains slowed after 2015, and that after 2016 the gains from economic progress did not accrue to all these groups.

Third, while prior analyses of longer-term trends have shown that Black-White disparities are persistent, the experience of the 2013-16 demonstrated some short-term progress is possible. Similar comments apply to Hispanic-White disparities. The reasons why this progress was reversed after 2016 need further investigation. The dramatic changes in Federal economic policies relating to taxes and to economic assistance with the 2017 changes in administration coincided with this reversal but more detailed examination of that recent history is clearly needed.

Follow-up research on this analysis in the immediate future will look more closely at the changes in circumstances of the groups seem to have experienced economic well-being declines during the past several year, including lower-income and Black Americans. In a longer time frame, further work on testing the methods used in the EWB-I computations and possible modifications should be explored. The FED is continuing to add additional categories of items to the SHED and the possibility of incorporating some of these into future versions of the EWB-I is a useful next step in this work. As more experience is gained with some of these new items and the length time over which they are measured expands, the modification of the EWB-I to incorporate these items is a high priority.