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Economic Activity by Race

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Economic Activity by Race

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Abstract

We observe empirical differences between races across various macroeconomic variables for the White, Black, Asian, and Hispanic populations in the U.S. For instance, the Black unemployment rate in the U.S. is more often than not double the White unemployment rate. In this paper, I treat nine macroeconomic variables as noisy indicators of economic activity and estimate an index that measures the economic activity of racial demographic groups in the U.S., called Economic Activity by Race (EAR). The noise of the indicators motivates the use of Kalman filter estimation to extract a common component from the noisy indicator variables. My index suggests that there are empirical differences between Black and White economic activity in the U.S., supporting the disparities found between races in racial stratification literature. Further, my results suggest that a structural shock to White economic activity is more persistent than a structural shock to Black, Asian, or Hispanic economic activity due to more heterogeneous sensitivity to various measures of economic well-being.

JEL Classification Codes: E37, E01, C22, J15

Keywords: racial stratification, economic activity, racial disparities, unemployment rate, macroeconomic forecasting, macroeconomic data, Kalman filter

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1 Introduction

We often see headlines that say the Black unemployment rate is higher than the national average and the White unemployment rate. In January 2022, the Bureau of Labor Statistics (BLS) reported that the unemployment rates for December 2021 were 3.2% for White people, 3.8% for Asian people, 4.9% for Latino or Hispanic people, and 7.1% for Black people. The Black unemployment rate in the U.S. is more often than not double the White unemployment rate, even during periods of strong labor market conditions. Over the years, many policymakers have become more concerned about the economic disparities between demographic groups in the U.S. In the aftermath of the death of George Floyd and COVID-19 especially, many corporations have sought to become more equitable toward and inclusive of women, people of color, and LGBTQ+ people. Indeed, many analysts have also become more concerned about measuring economic disparities between demographic groups in the U.S. We can think of disparities between races, genders, and age groups for starters. Though many measures of economic well-being exist, such as employment and income, we lack a timely, more encompassing measure of economic activity, such as national GDP, for demographic groups.

Currently, U.S. government statistical agencies do not produce a measure for GDP by race. However, many macroeconomic variables are available by race. There is substantial economic literature that explores at length the disparities between races in the U.S. for any given macroeconomic variable. Ritter and Taylor [2011] and Charron-Chénier et al. [2017], for example, study the racial disparities in unemployment and household spending, respectively. Many agencies, such as the BLS and the Federal Reserve Board, produce data and surveys that measure specific components of economic well-being for races, but few if any produce a well-rounded timely measure of economic activity for any given demographic group. In addition, we know that the National Bureau of Economic Research (NBER) will not announce a recession solely based on consecutive negative GDP growth; several other economic indicators must also show negative growth. Against this background, I propose an index of economic activity for different races and ethnicities in the U.S. My index has three key components that are somewhat similar to that of the Philadelphia Fed's Aruoba-Diebold-Scotti business conditions index (ADS) model (Aruoba et al. [2009]) for national conditions.

First, like the ADS model, I work with a dynamic factor model in which I treat my index as a latent variable related to several observed indicators. Looking at average hours worked weekly, number of people employed, the unemployment rate, median weekly wages, assets, percent of total population in poverty, median annual income, net worth, and consumer expenditures for the White, Black, Asian, and Hispanic U.S. populations, we can see differences across races and ethnicities in recoveries from recessions and within recessions. These variables are noisy but may be good signaling indicators for the U.S. economy. It's especially important that these variables are available by race and ethnicity and not only as an aggregate of the U.S. population.

Second, also similar to the ADS model, I use mixed observation frequency data. I have monthly, quarterly, annual, and triennial indicators in my model. Despite the variation of the frequencies, I produce an index that may be updated monthly based on frequent and less frequent indicators.

Last and most important, my index measures the economic well-being not just for the U.S. but also for the White, Black, Hispanic\Latino, and Asian populations in the U.S.

In this paper, I use the Kalman filter to extract a common component from nine variables: average hours worked weekly, number of people employed, the unemployment rate, median weekly wages, assets, percent of total population in poverty, median annual income, net worth, and consumer expenditures. The existence of noisy indicators motivates the use of the Kalman filter method to estimate the common factor within all series. The common component is my index for EAR, comparable to what GDP by race and ethnicity might look like.

As mentioned, since the signaling indicators used to produce EAR are of different frequencies, an advantage to using the Kalman filter model is that I am able to produce a timely monthly index based on the mixed observation frequency data. If we are able to measure EAR, we can get a timelier sense of what kind of policies need to be put in place, to eliminate racial economic disparities. If we see that EAR for all races has decreased, that should signal that more aggressive policy is needed. On the other hand, if the EAR for some races has decreased while others are doing relatively well, that may call for less aggressive but more targeted policies.

When focusing on White, Black, Hispanic or Latino, and Asian U.S. populations during the 1980-2022 period, my results suggest that differences between races in the aforementioned indicators do in fact produce different measures of EAR. When compared to real GDP, my own measure of EAR for the national economic activity suggests that EAR is a good proxy for U.S. economic health, further suggesting that my estimated levels of White and Black EAR are robust. Indeed, my results suggest there are disparities among the racial groups in the U.S., and a structural shock to White economic activity is more persistent than a structural shock to Black economic activity for reasons we will discuss later in the paper.

This paper proceeds as follows: Section 2 provides a literature review of papers that provide context for economic racial disparities, section 3 describes the data and its limitations, section 4 describes my empirical model, section 5 describes my econometric results, and section 6 concludes.

2 Literature Review

Drawing on racial stratification research (Darity [2005]; Darity et al. [2015]), it is not surprising that I find racial and ethnic disparities in economic activity in the U.S. Researchers unanimously find persistent wealth gaps between Black and White populations in the U.S. Asian income and wealth levels are often similar to White levels, while Black and Hispanic levels are generally lower. Such racial disparities in income and wealth in turn affect access to investment and consumption for the disadvantaged demographic groups.

As mentioned, I base my index on data from the BLS, the U.S. Census Bureau, and the Board of Governors over the time period 1980-2022. There have been many contributions to the literature that highlight racial disparities based on data from the same sources I've used in this paper. McIntosh et al. [2020] examined the Black-White wealth gap and found staggering racial disparities using the Board's Survey of Consumer Finance (SCF) data. The results from the most recent SCF survey, in 2019, show that the median net worth of a White family was $188,000 while the median net worth of a Black family was $24,100. The median net worth for Hispanic families was $36,100 while Other families, a diverse group that includes those of Asian descent and Pacific Islanders, have lower median wealth than White families but higher median wealth than Black and Hispanic families (Bhutta et al. [2020]). Using data from the BLS's Consumer Expenditure Survey, Charron-Chénier et al. [2017] find not only that Black households consume less than White households but also that there are racial inequalities in access to goods and services.[1] Further, many studies similar to that of Bertrand and Mullainathan [2004] find that Black job candidates face differential treatment.[2] These papers examine the callback rate for fictitious resumes that imply racial characteristics.

Using other sources of data, researchers continue to find disparities between races in the U.S. Indeed, a quick Google search demonstrates that this problem has been a long-standing one in the U.S. For example, Marshall [1974] finds that the neoclassical theory is inadequate for modeling discrimination when examining economic models that would help shed light on racial discrimination. Darity [1998] finds strong evidence of intergroup discriminatory differentials when examining the empirical records in social science and argues that to "... adopt the principle of color-blindness in policymaking when race has such strong

[1]The authors discuss the lack of equity in access to credit; retail deserts, which have limited access to businesses such as grocery stores, banks, and pharmacies; and the biased treatment of non-White customers in retail and non-service settings.

[2]They study race in the labor market by sending fictitious resumes in response to help-wanted ads in Boston and Chicago newspapers. To manipulate perceived race, resumes are randomly assigned African-American- or White-sounding names.

and lasting intergenerational effects is perverse." Altonji and Blank [1999] find that Black men earn substantially less than White men with similar levels of schooling, a phenomenon that continues today. Chetty et al. [2020], using decennial and American Community Surveys (ACS) data, find that Black people and American Indians have the lowest rates of upward mobility and the highest rates of downward mobility. Collins and Wanamaker [2022] use Occupational Changes in Generational data (OCG) and the National Longitudinal Survey of Youth 1979 data (NLSY79) in their analyses to show also that Black men have less upward mobility and lower average income than White men.

Kuka and Stuart [2022] use the Survey of Income and Program Participation (SIPP) to examine unemployment insurance and receipts and find a 50 percent racial gap in UI receipt and a 30 percent racial gap in UI "take up". Ganong et al. [2020] find the consumption of Black and Hispanic households is 50 percent and 20 percent, respectively, more sensitive to similar sized income shocks than that of White households based on data from JPMorgan Chase and voter registration files. Looking closely at the effects of the Great Recession, Rugh and Massey [2010] use RealtyTrac data to show that Black people are more likely than White people to rely on subprime lenders. Akee et al. [2019] use restricted IRS tax data and Census data to show that the White and Asian groups have more income than any other racial group at every point of the income distribution.

Examining how monetary policy affects racial demographics, researchers find heterogeneous effects for races in the U.S. Using state-level panel data, Seguino and Heintz [2012] conclude that the effects of tightening monetary policy are not race neutral. Bartscher et al. [2021] suggest that monetary policy, as it operates under current conditions, may not be able to achieve racial equity, and their analysis finds a persistent and wide racial wealth gap. In fact, they find that accommodative monetary shocks exacerbate the difference between Black and White wealth, similar to Seguino and Heintz [2012]. The reasoning for the exacerbated effects is discussed by many researchers who study racial wealth and income dynamics. Looking closely at the SCF data, Bartscher et al. [2021] point to strong portfolio heterogeneity between White and Black wealth. The authors point out that many Black households do not have financial assets, therefore they can't benefit from increases in asset prices. White households in general have more to gain during periods of economic expansion since they hold more assets sensitive to interest rates.

Looking at recessions, the literature suggests that the recoveries after recessions are racially disparate and that the impacts are more strongly felt by Black and Hispanic workers. Addo and Darity [2021] investigate the wealth holdings of Black, White, and Latino workers from 2010 to 2019 and find that in terms of wealth, fewer Black households benefited from the economic recovery. Unsurprisingly, Hoynes et al. [2012] also find the impacts of the Great Recession have been felt more strongly for Black and Hispanic workers. Paying close attention to the housing bubble, Wolff [2016] and Kuhn et al. [2020] find that the collapse of housing prices widened the wealth gap. Further, as mentioned before, low income groups and minorities were targeted by subprime lenders and were subject to higher interest rate terms in comparison to their White counterparts (Young [2010] and Henry et al. [2013]). Szymborska [2019] uses the SCF to examine wealth structures and income distribution of U.S. households before and after the Great Recession, finding that Black and Latina women experience less positive effects after the Great Recession in comparison to their White counterparts. We continue to see that the literature finds that the differences in asset portfolios held by each demographic group perpetuate the racial disparities we observe in the various economic measures.

Darrick Hamilton and William Darity, among others, have many papers that dispute the notions that racial disparities are caused by differences in human capital and that the U.S. has transcended the racial divide. Hamilton and Darity [2010] discuss conventional explanations of racial disparity as a backdrop to their proposed baby bonds policy that would decrease the racial wealth gap. Zaw et al. [2016] discuss how the Black incarceration rate was still higher than the White incarceration rate at every level of wealth. Darity et al. [2022] show that there are no differences in the amount of effort that Black and White Americans show in the workplace.

The aforementioned papers and thousands of others, thoroughly show that racial disparities exist and are persistent. The ever growing literature on racial disparities also shows that the differences are not because the disadvantaged populations are any less capable but in fact arise because of the lack of equity in access to the social systems that serve them.

I add to the literature on racial stratification economics by providing a timely measure for analysts to use as a current pulse on racial economic activity in the U.S. The measure is based upon an amalgamation of variables and surveys and provides an inclusive outlook of economic activity for racial demographic groups in the U.S.

3 Data

I extract a common signal about economic activity from nine variables of varying observation frequency for the White, Black, Asian, and Hispanic U.S. population. I use monthly average weekly hours, employment, and the unemployment rate from the BLS; quarterly median weekly wages (BLS) and assets (Board's Distributional Financial Accounts (DFA)); annual percent of total population in poverty (Census), median annual income (Census), and total average expenditures or consumer expenditures (BLS); and triennial net worth (SCF). I focus on the sample period 1980-2019 for all parameter estimates.

Since all of the variables used in my index come from different statistical agencies and surveys, the definition of a race category may differ slightly across variables. For example, there are times when statistical agencies include an "other" category when measuring the White or Asian races. Consequently, the current model on occasion incorporates these more ambiguous aggregate measures for some indicators. White consumer expenditure and Asian assets and net worth are the only variables that include an "other" demographic group in the aggregate measure. For computational ease, I assume that the aggregate measure for race generally measures the same demographic group in the U.S. Appendix 7.1 has more details about variable and race/ethnicity definitions.

I begin with a quick inspection of the qualitative differences in economic activity between White, Black, Asian, and Hispanic for all variables. In figures 1 to 3, I show the time trends of all races combined, and of White, Black, Hispanic, and Asian for the monthly, quarterly, annual and triennial variables. Graphically, the data suggest that the economic activity for each race differs while trending similarly.

Since I use variables that trend upward over time, I transformed and standardized the data in order to estimate robust parameters for the Kalman filter model. For employment, hours worked, wages, assets, income, consumer expenditures, and net worth, I take period-over-period growth rates.[3] For unemployment and the poverty rate, I transform the data by taking first differences. All variables are standardized after their respective transformations. Figures 4 to 6 provide the graphs after transformations and standardization.

Taken together, figures 1 to 6 suggest that the time series for all races and ethnicities in the U.S. trend similarly but do differ from one period to the next and during recessions and expansions. These differences between periods reflect idiosyncratic movements, or noise, within each variable. My empirical methodology constructs an index that finds the commonality across all variables by extracting a strong signal and eliminating the noise.

To be specific, I model these variables as having two components, the idiosyncratic noise and systematic signal. The idiosyncratic noise is the random movement we see specific to each variable. Each variable in my model is a different macroeconomic variable, so each will have movements over the sample period that are unique. These unique movements give rise to the differences we see between the variables within each period. On the other hand, a systematic signal is a movement that is seen (and common) across the variables in my model.

[3]Estimation follows several procedures to ensure extreme values due to the COVID-19 recession do not adversely affect parameter estimation. I seasonally adjust hours, wages, and assets over the entire sample period January 1980-January 2023, including the extreme COVID-19 values. For the variables wages, assets, consumer expenditures and net worth I divide by CPI (all items excluding food and energy). When standardizing the data, I compute the mean and variance of the data only over the pre-COVID-19 period (1980-2019). Similarly, the state space model estimates only cover the pre-COVID-19 period (1980-2019) when estimating the model's parameters.

A close look at the shaded areas in figures 1 to 6, which indicate recessions, reveals that most variables move similarly, suggesting negative economic activity during recessions. Over the entire sample period there is similar systematic variation. Such variation represents the commonality across variables and is in fact the common component that I seek to extract for each race. Using the Kalman filter, I produce a monthly time series of the common component for each race named EAR, or economic activity by race. Tables 1-3 provide summary statistics of the data after they are transformed but before they are standardized.

4 The Empirical Framework

I propose a dynamic factor model at monthly frequency. Of the nine variables, only three are of monthly frequency, while the others are quarterly, annual, or triennial. Therefore, similar to the Philadelphia Fed's ADS (Aruoba et al. [2009] and Doelp and Stark [2021]), I obtain the measurement equations for the observed nine variables through explicit treatment of missing data and temporal aggregation given the mixed observation frequencies.

Not all variables in my model are available monthly. For any non-monthly variable, we must arrange the source data with missing values on any month that is not the last month of the period. For each non-monthly variable I define $\widetilde{Y}_t = Y_t$ on the last month of the indicator's observation period, and missing for all other months.

To extract the common component from the nine variables (hours worked, employment, unemployment rate, wages, assets, poverty, income, consumer expenditures, and net worth) I model the monthly EAR, C_t,[4] for each racial group as an autoregressive model of order two

$$C_t = \rho_1 C_{t-1} + \rho_2 C_{t-2} + \eta_t, \tag{1}$$

where the observed variables are a function of the common component and are modeled as

$$Y_t^M = \gamma^j C_t + \phi_1^j Y_{t-1}^M + \phi_2^j Y_{t-2}^M + e_{jt}^M \tag{2}$$

[4]See the appendix for a detailed model.

$$\widetilde{Y_t^Q} = \gamma^j C_t^{(Q)} + \phi_1^j \widetilde{Y_{t-3}^Q} + \phi_2^j \widetilde{Y_{t-6}^Q} + e_{jt}^Q \tag{3}$$

$$\widetilde{Y_t^A} = \gamma^j C_t^{(A)} + \phi_1^j \widetilde{Y_{t-12}^A} + \phi_2^j \widetilde{Y_{t-24}^A} + e_{jt}^A \tag{4}$$

$$\widetilde{Y_t^{3A}} = \gamma^j C_t^{(3A)} + \phi_1^j \widetilde{Y_{t-36}^{3A}} + \phi_2^j \widetilde{Y_{t-72}^{3A}} + e_{jt}^{3A} \tag{5}$$

for the monthly, quarterly, annual, and triennial indicators, respectively, and all

$$e_{jt} \overset{iid}{\sim} (0, \sigma_j^2); \quad j = 1, 2 ... 9. \tag{6}$$

In equations 3-5, $C_t^{(Q)}$, ($C_t^{(A)}$), and ($C_t^{(3A)}$) are the cumulative sums of the monthly EAR values over the quarter, year, and three years, respectively. These equations relate the indicator variables to their own lagged values and to the EAR.

Using the Kalman filter framework, my model finds a commonality across nine variables and extracts a strong signal, C_t, for each race. As a result I have a measure of economic activity for each race, EAR $\equiv C_t$, at a monthly frequency.

5 Results

I begin by comparing my EAR index to the Bureau of Economic Analysis' real GDP. In figures 7 and 8, I graph national EAR and real GDP with the NBER recessions shaded.[5] The results suggest that my index moves closely with real GDP. Though the two measures move closely, there is divergence in the magnitude of economic activity. EAR generally measures stronger negative and positive growth throughout. We also see that EAR suggests a deeper Great Recession (December 2007-June 2009) but more prominent rebound, the same can be said for the COVID-19 Recession (February 2020-April 2020). Notably, my index does not suggest consecutive negative growth in the second half of 2022, despite general economic sentiment, high inflation and decreasing real GDP growth during that time.

Given that national EAR trends similarly to real GDP and coheres generally with NBER business cycle chronology, my estimated EAR model appears to be a good proxy for economic activity in the U.S. Therefore I expect similar results for the EAR index for all racial groups.

[5] I use national measures for the nine indicators when producing EAR for all races combined.

Similar to the national measure of EAR, figure 9 shows that the EAR indexes for White, Black, Hispanic, and Asian also cohere to NBER chronology. In figure 10, I graph EAR for each race with real GDP and national EAR, focusing on the COVID-19 Recession. Like national EAR, the EAR for each race also trends closely to real GDP yet coheres to NBER chronology rather than economic sentiment as a result of the diverse indicators inherent in the model.

Turning to the estimation results, tables 4-8 also suggest that EAR differs across races and ethniticies in the U.S. In each table, the first two estimates are the coefficients for my autoregressive model (ρ_1 and ρ_2) of the index. Given the disparities we see between White and Black indicators of the model, it is not surprising to see that the estimate of White ρ_1 is double that of Black ρ_1.

Recall that the indicators are modeled as a function of the common component. The estimates for the coefficient γ^j in rows 3-11 of tables 4-8 relay the relationship between the common component and the indicators. Since all data have been standardized, all γ^j coefficients are comparable across variables and races. The coefficients that are statistically significant and non-zero provide signal content for economic activity. We see stronger signal content across all races for labor force indicators. Employment, the unemployment rate, poverty rate, and annual income all prove to be significant indicators for all races. Looking closely at White and Black Kalman filter estimation tables, we see stronger labor force signal content for the Black population. Assets are significant only in measuring economic activity for the White and Asian populations, as suggested by other literature in the economic stratification. For all races, wages is not a significant measure for EAR.

Overall my index suggests that Black economic activity is more sensitive than White economic activity when based on labor market conditions. Though, the impulse response functions of EAR in figure 11 show that economic shocks to the White population are more persistent than for all other races. The higher persistence of economic shocks for the White population may not seem intuitive given the disparities we observe in the indicators. The results suggest that along with larger negative shocks White people may experience large positive shocks as well. In studies that highlight racial disparities, this phenomenon is explained by the heterogeneity in asset portfolios. White people have more of a cushion to fall on, and in turn experience greater growth, or economic activity, when the tides turn. In regards to EAR, we can extend the notion of heterogeneity to economic activity. White people, in comparison to other races, have a more heterogeneous economic portfolio, which equates to the nine variables in this paper. For the White population eight of the nine variables are significant in measuring economic activity. The same can not be said for the other races and ethnicities, according to my results.

6 Conclusion

In the U.S., we observe empirical differences between races when looking at weekly average hours, employment, the unemployment rate, median wages, assets, percent of total population in poverty, median annual income, net worth, and consumer expenditures for the White, Black, Asian, and Hispanic populations in the U.S. In this paper, I use these nine variables to serve as noisy indicator variables for estimating Economic Activity by Race (EAR) in the U.S. economy. The noise in the indicators motivates the use of Kalman filter estimation to extract a common component across the noisy indicators. I find there are empirical differences between the Black and the White EAR in the U.S., supporting the disparities found between races in racial stratification literature. Further, my results suggest that a structural shock to White economic activity is more persistent than a structural shock to Black economic activity due to a heterogeneous sensitivity to various measures of economic well-being.

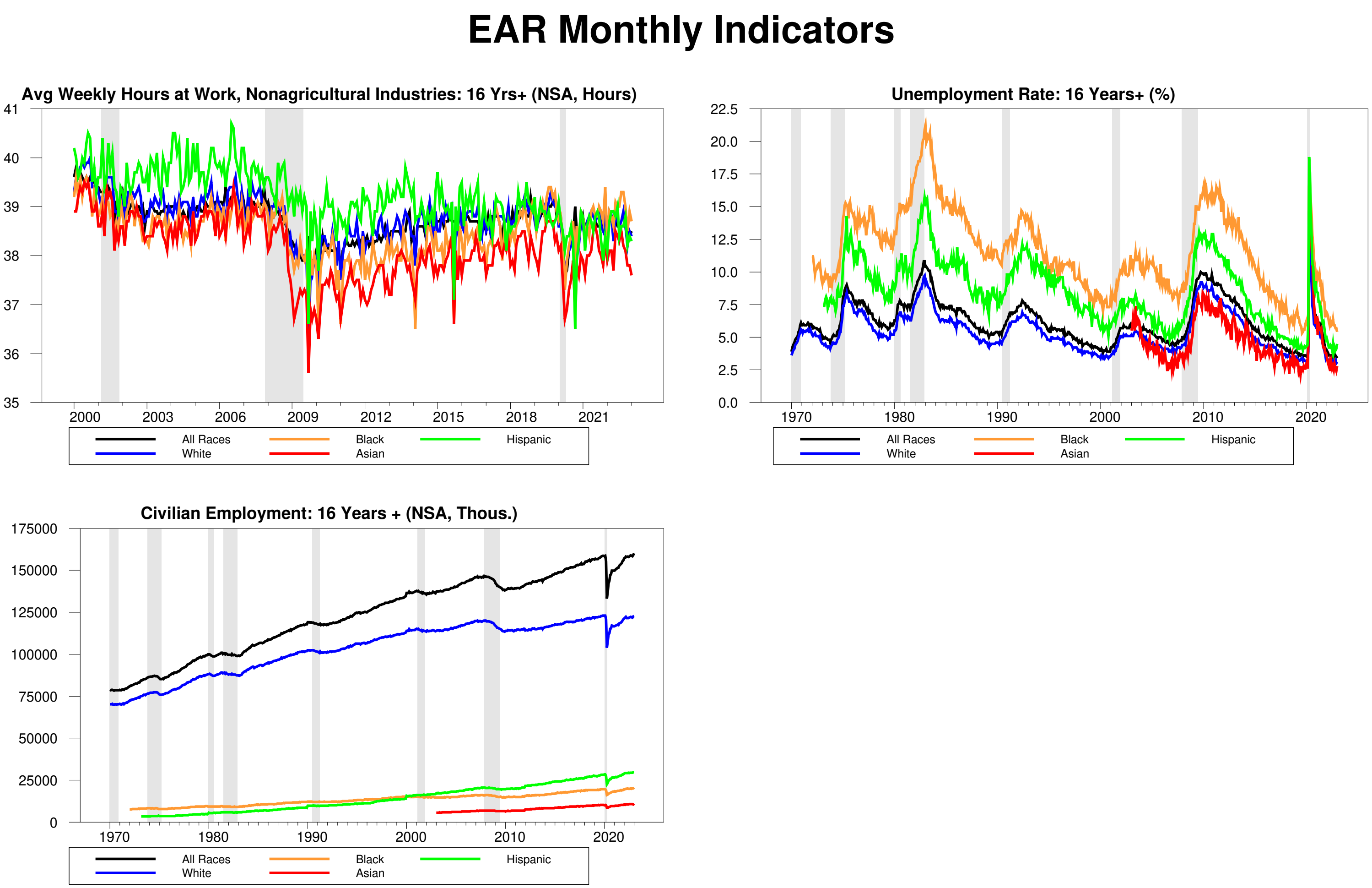

Figure 1: Monthly Indicator Variables

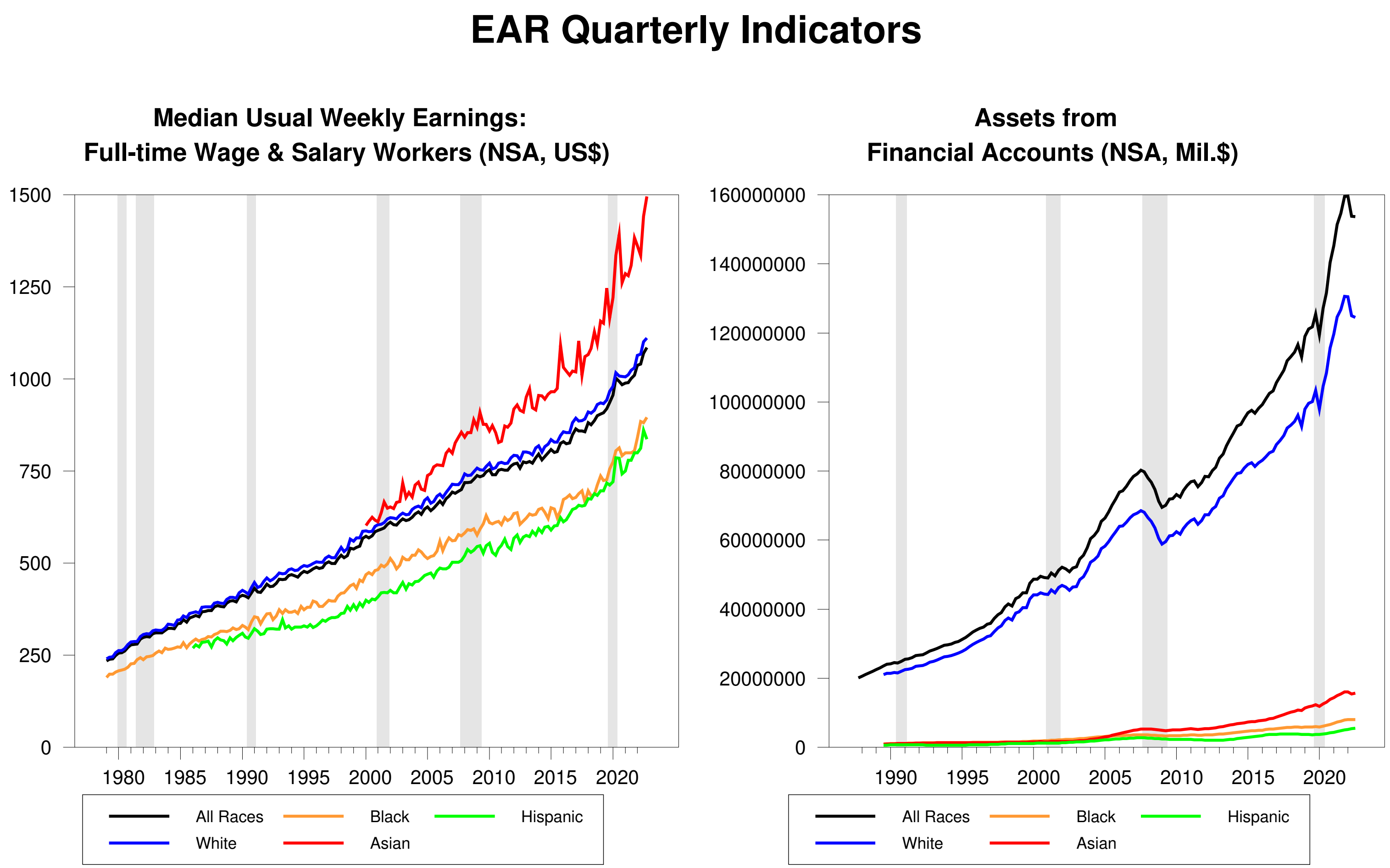

Figure 2: Quarterly Indicator Variables

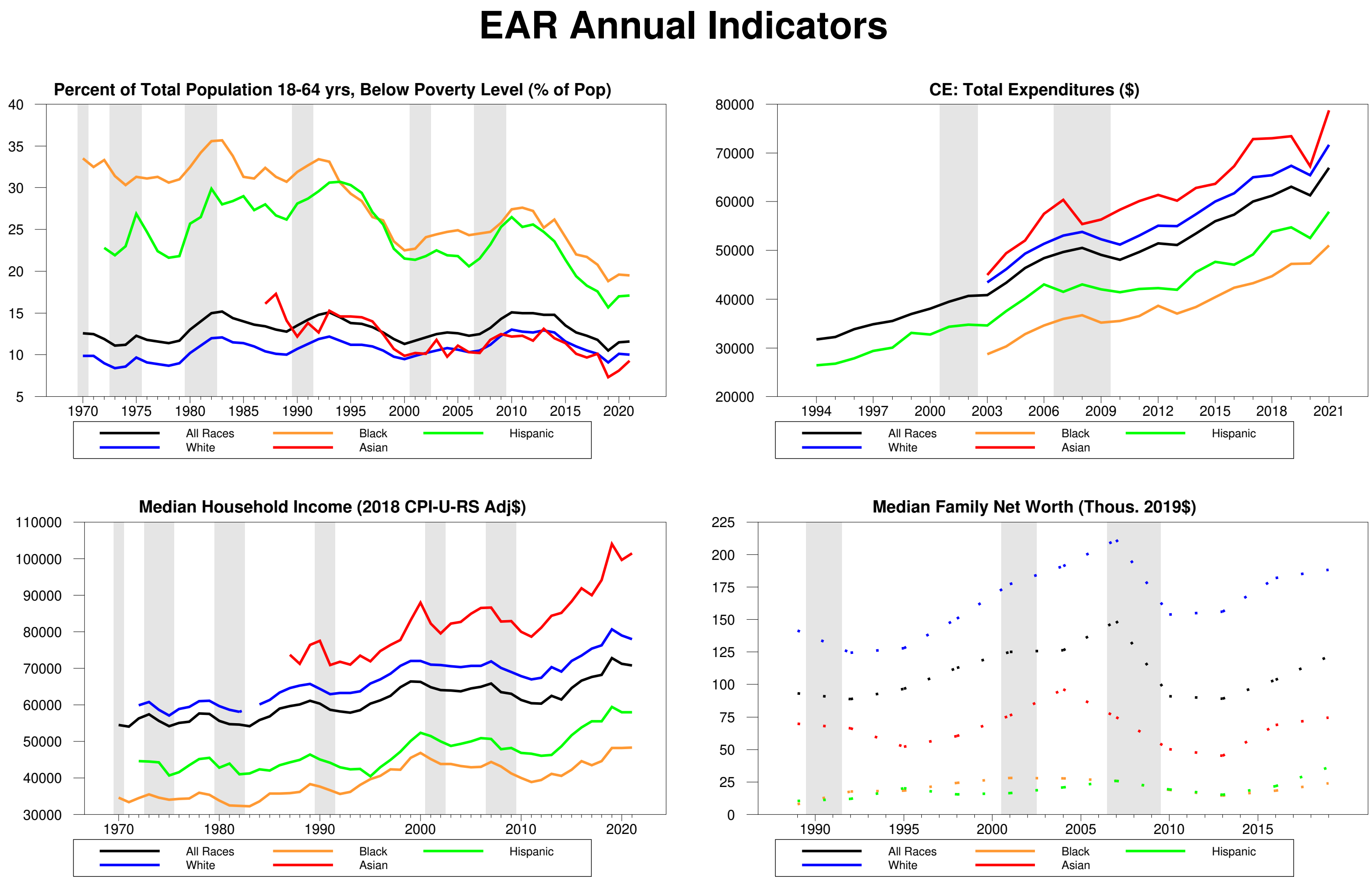

Figure 3: Annual and Triennial Indicator Variables

Figure 4: Monthly Standardized Indicator Variables

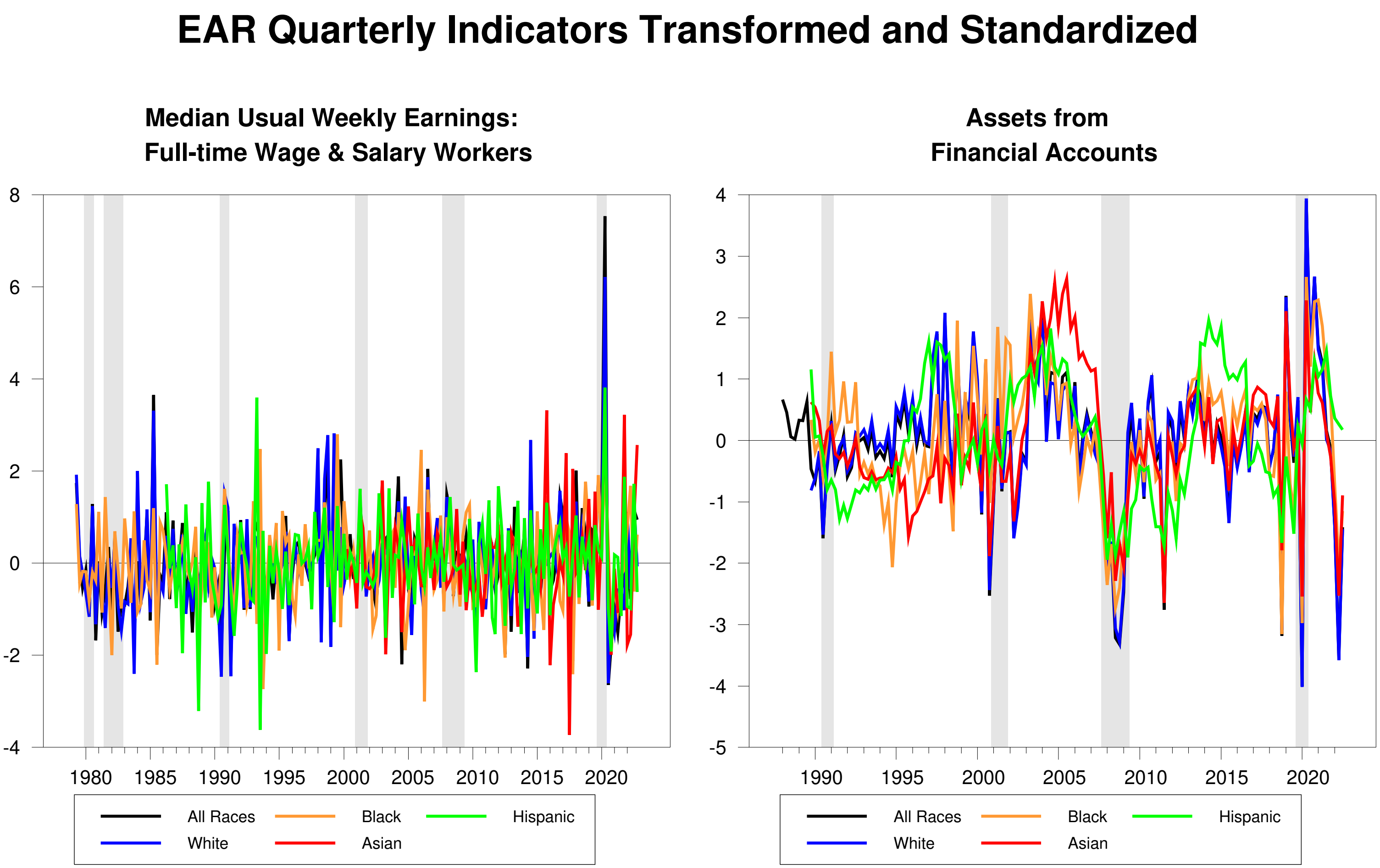

Figure 5: Quarterly Standardized Indicator Variables

EAR Annual Indicators Transformed and Standardized

Figure 6: Annual and Triennial Standardized Indicator Variables

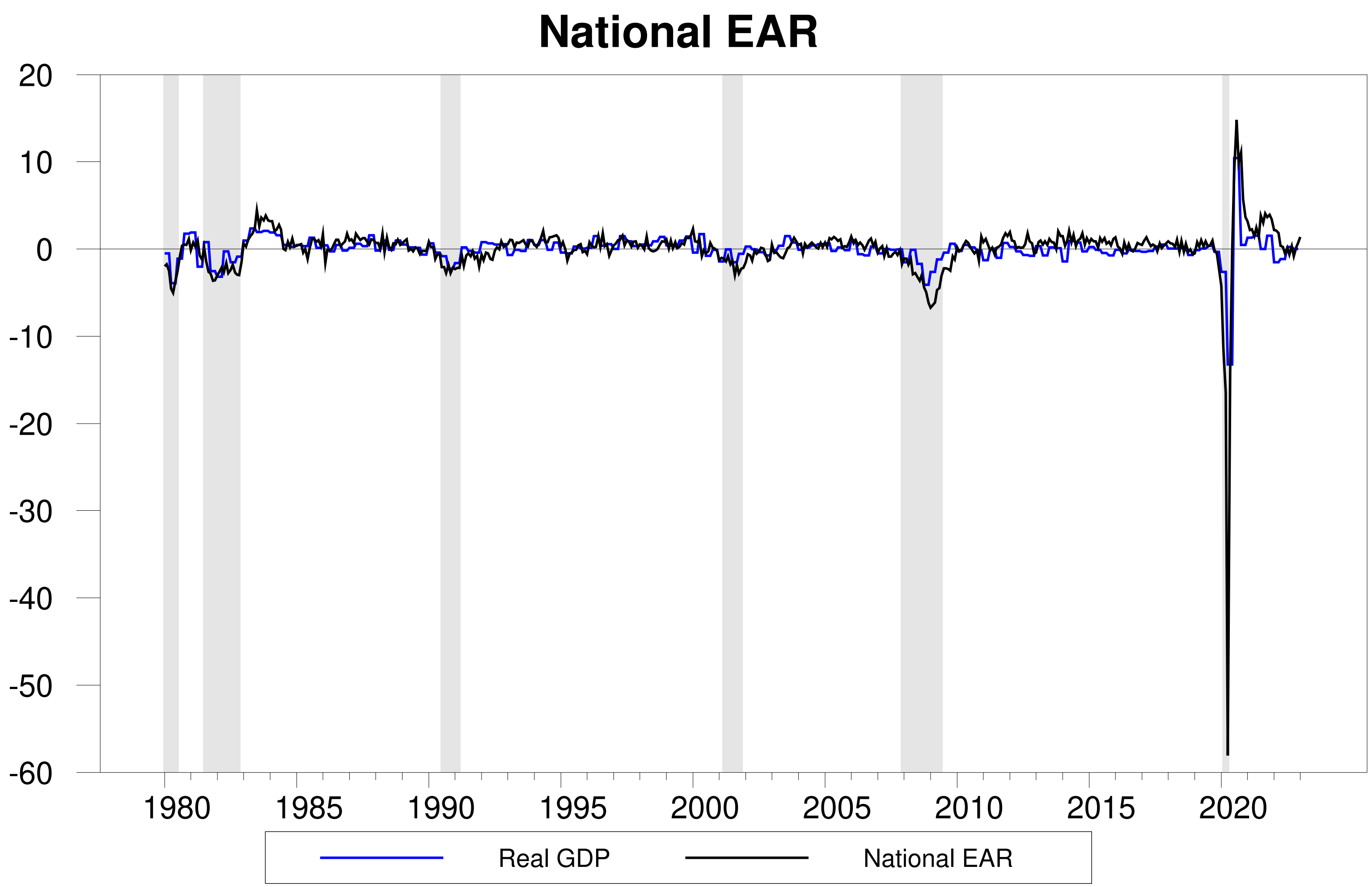

Figure 7: National EAR Full-Time Series

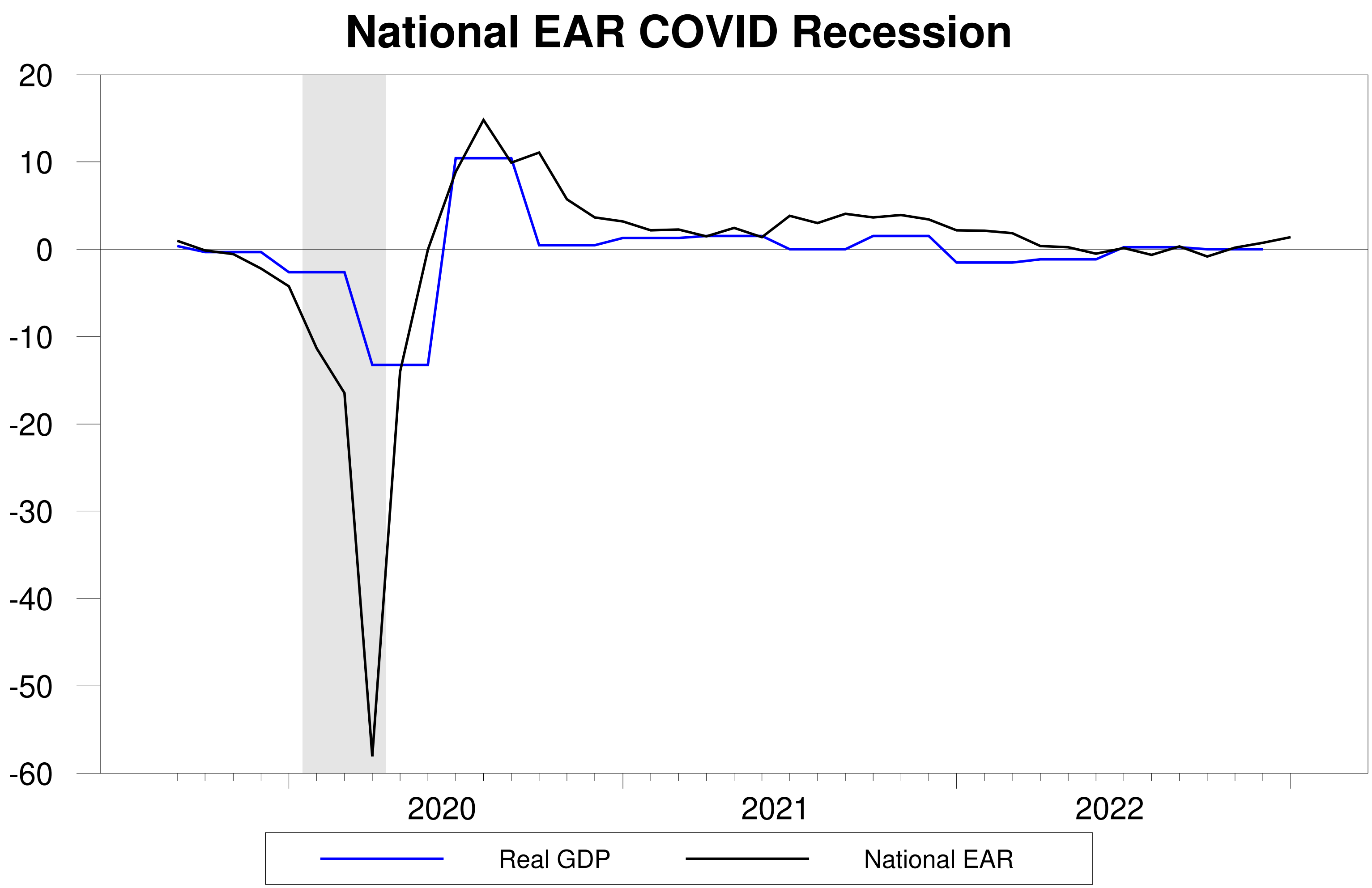

Figure 8: National EAR During COVID-19 Recession

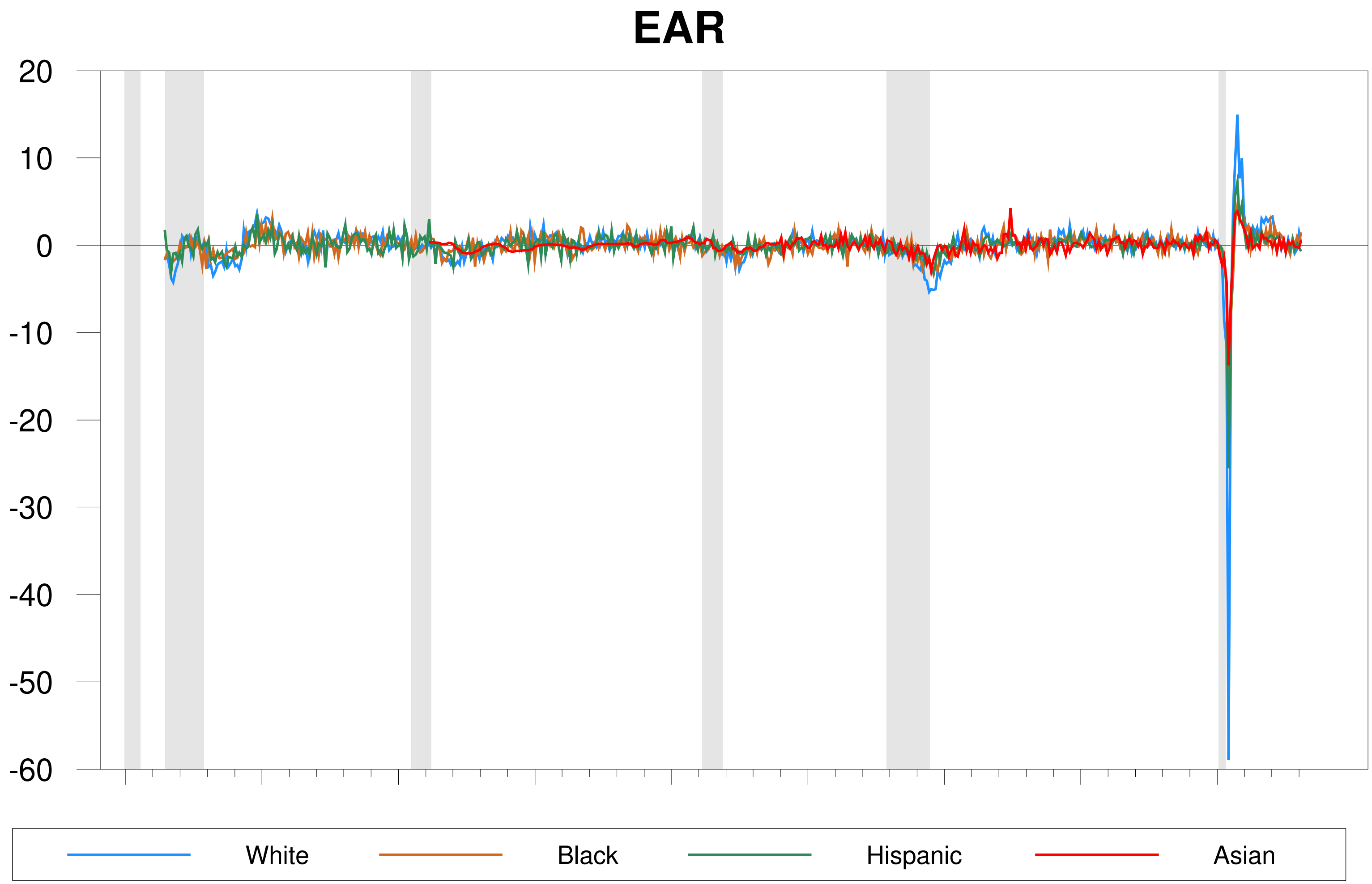

Figure 9: All Races Full-Time Series

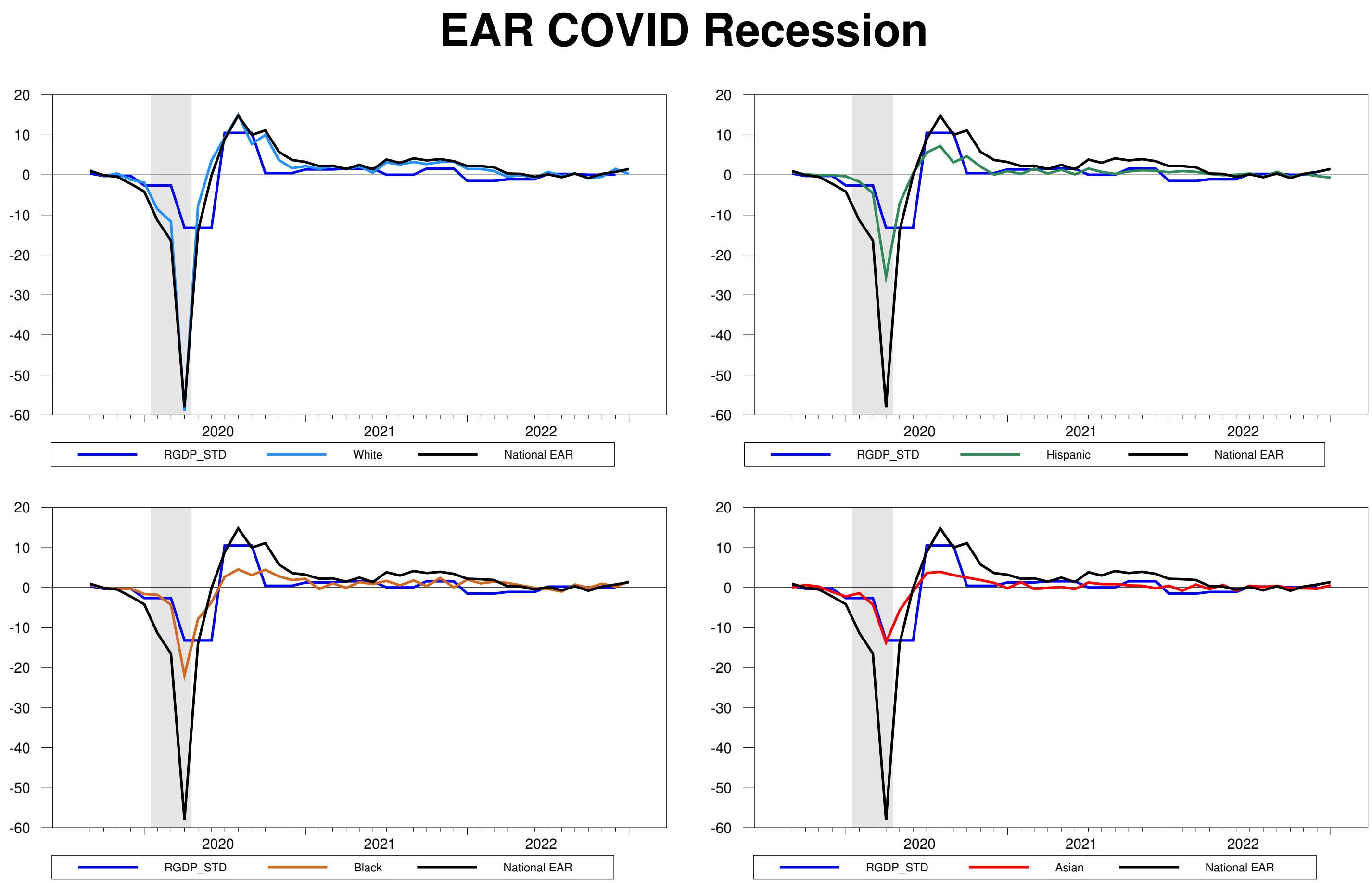

Figure 10: Races vs. GDP and National EAR COVID-19 Recession

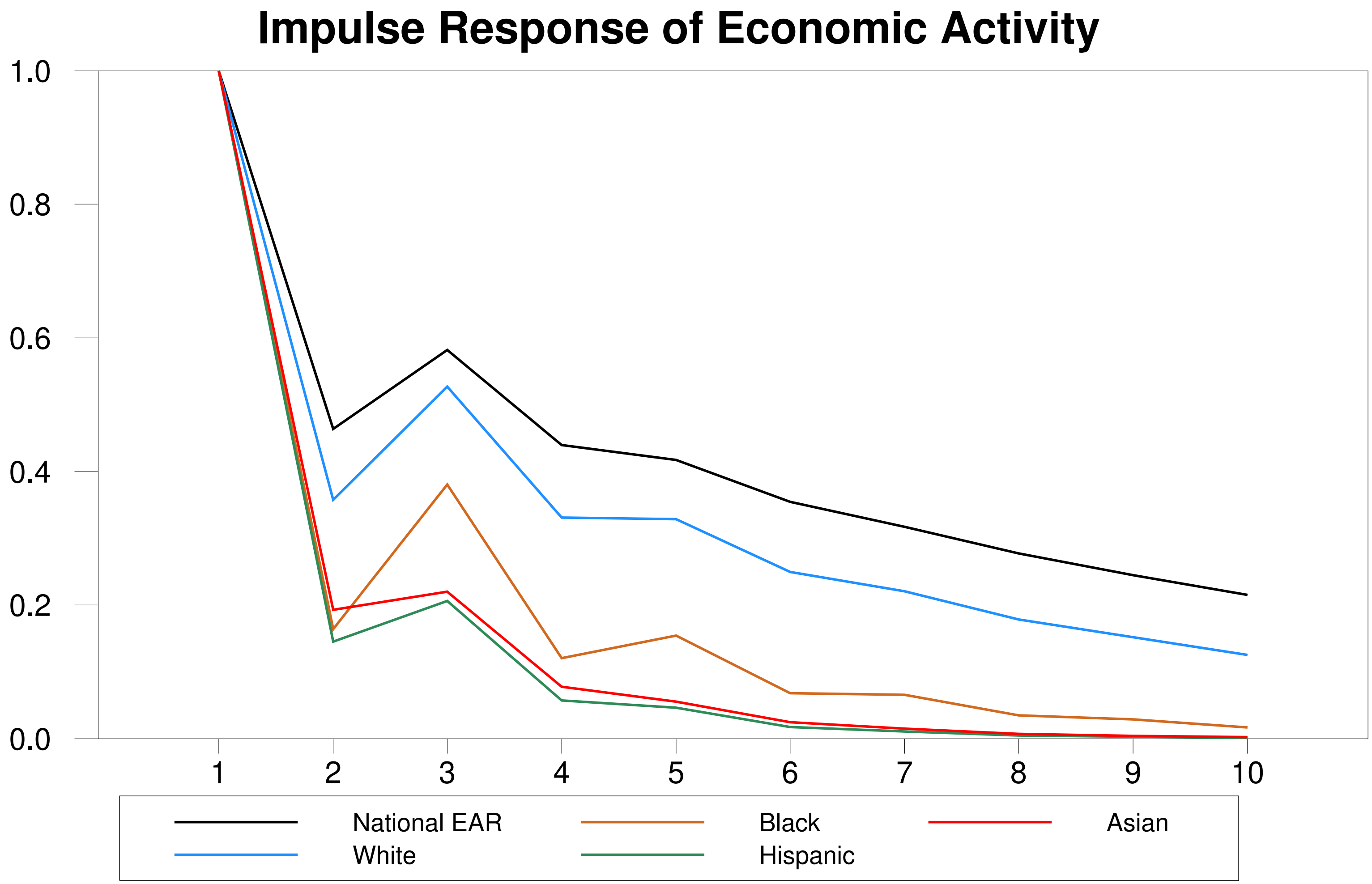

Figure 11: Impulse Response Functions

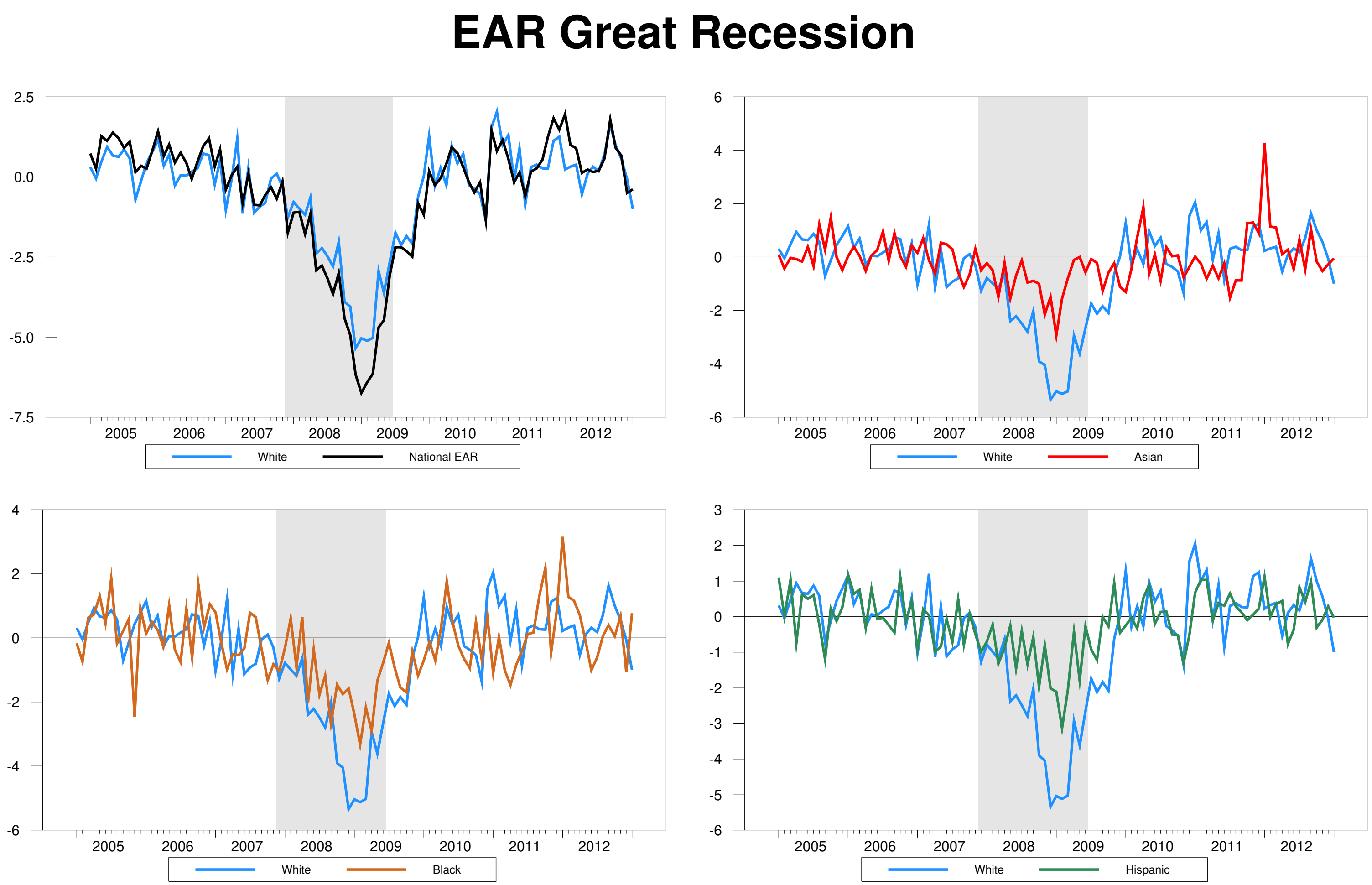

Figure 12: Great Recession: White EAR Plotted with Other Races

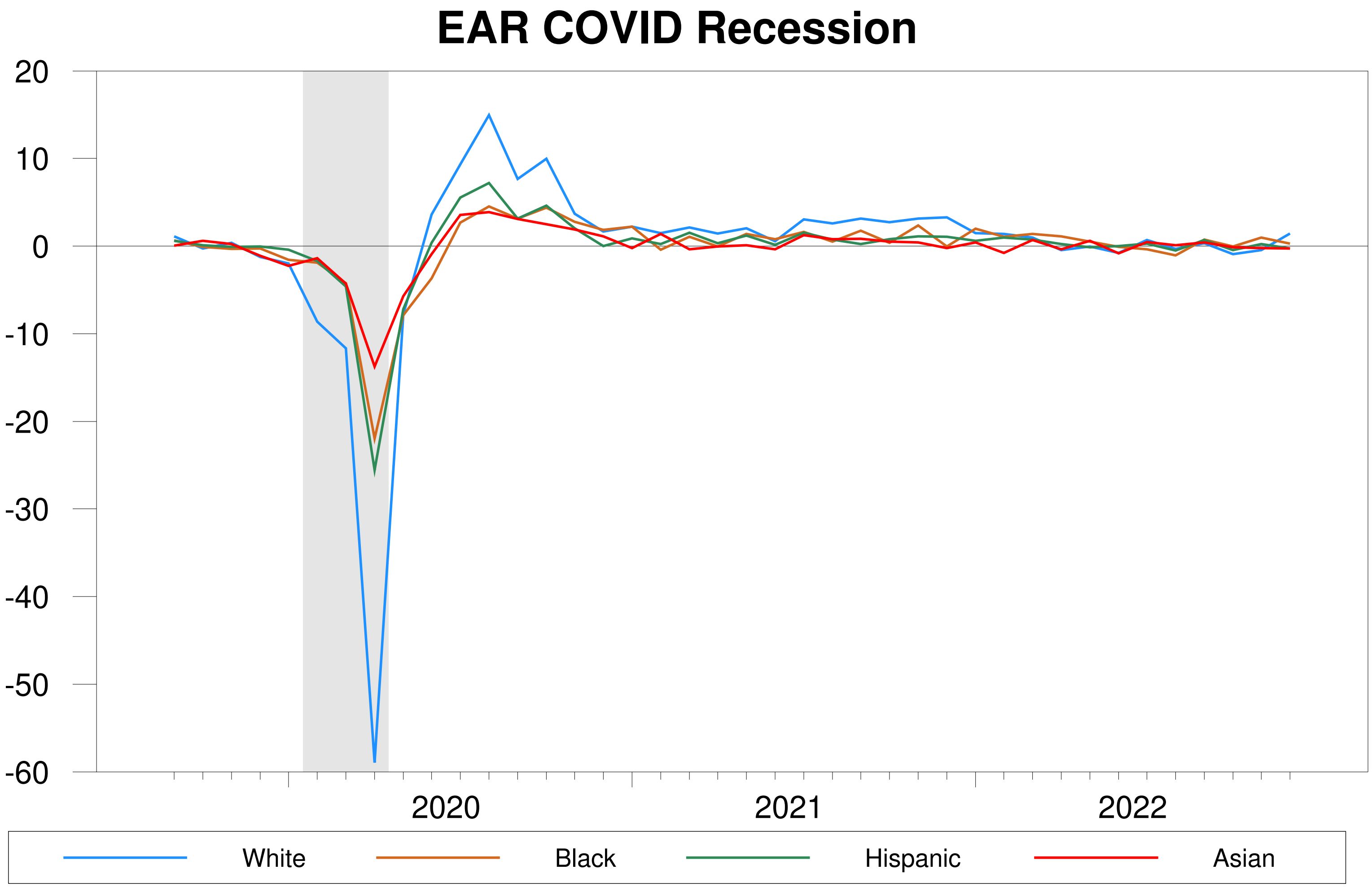

Figure 13: COVID-19 Recession: All Races Together

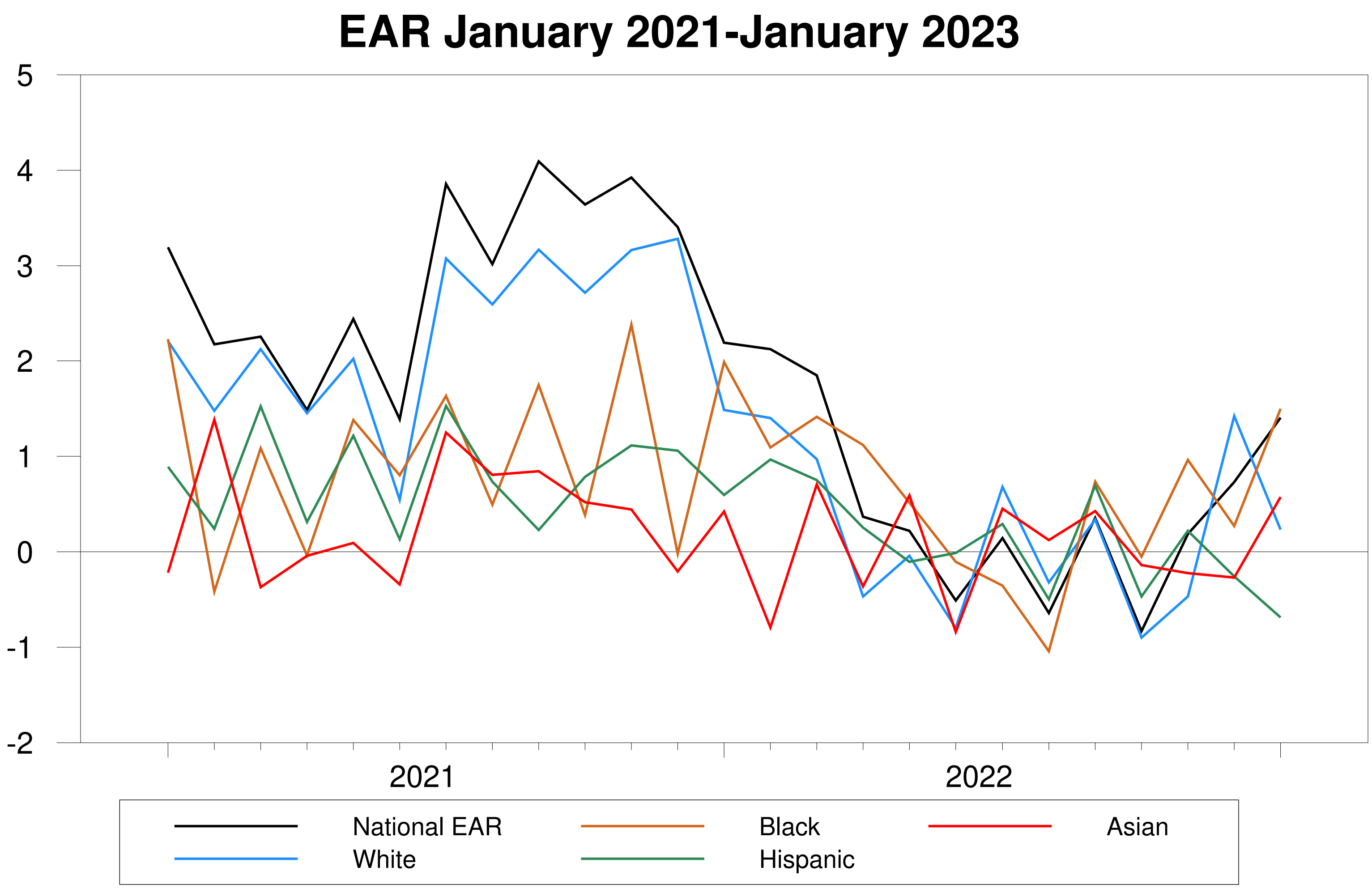

Figure 14: All Races Together Post COVID-19 Recession

Table 1: Statistical Summary of Transformed Monthly Variables

	Mean	Median	Std Dev	Min	Max	Nobs
Average Weekly Hours						
All	0.006	0.000	7.311	-48.329	51.482	492
White	-0.083	-0.063	11.030	-74.393	67.014	239
Black	-0.088	0.050	11.226	-48.379	51.519	239
Asian	-0.180	-0.189	13.645	-73.193	81.328	239
Hispanic	-0.119	-0.140	9.377	-54.461	53.192	239
Civilian Employment						
	Mean	Median	Std Dev	Min	Max	Nobs
All	1.188	1.387	3.086	-10.230	18.026	492
White	0.869	1.060	3.089	-8.990	13.008	492
Black	1.849	1.495	8.815	-23.965	32.243	492
Asian	3.415	3.253	13.892	-40.367	107.564	203
Hispanic	4.412	3.575	14.186	-35.465	145.283	492
Unemployment Rate						
	Mean	Median	Std Dev	Min	Max	Nobs
All	-0.005	0.000	0.168	-0.700	0.600	492
White	-0.004	0.000	0.163	-0.600	0.600	492
Black	-0.013	0.000	0.504	-1.800	1.500	492
Asian	-0.014	0.000	0.538	-1.500	1.900	203
Hispanic	-0.009	0.000	0.473	-1.900	1.700	492

Note: The sample periods for all data end in December 2019. See appendix 7.1 for more details about variables and sample periods.

Table 2: Statistical Summary of Transformed Quarterly Variables

Median Weekly Earnings						
	Mean	Median	Std Dev	Min	Max	Nobs
All	0.322	0.366	2.982	-6.484	11.206	163
White	0.336	0.333	3.156	-7.439	10.780	163
Black	0.300	0.507	7.811	-23.178	22.140	163
Asian	1.446	0.563	11.149	-40.091	38.437	79
Hispanic	0.540	0.775	7.988	-28.397	29.316	135
Assets						
	Mean	Median	Std Dev	Min	Max	Nobs
All	3.375	3.796	6.224	-17.314	18.031	128
White	2.977	3.474	6.572	-18.601	18.326	121
Black	3.659	3.787	5.887	-14.905	17.699	121
Other	6.337	4.519	9.399	-18.515	31.048	121
Hispanic	3.593	3.081	9.380	-14.651	21.936	121

Note: The sample periods for all data end in Q4 2019.The “Other” classification consists of respondents identifying as Asian, American Indian, Alaska Native, Native Hawaiian, Pacific Islander, other race, and all respondents reporting more than one racial identification. See appendix 7.1 for more details about variables and sample periods.

Table 3: Statistical Summary of Transformed Annual Variables

	Mean	Median	Std Dev	Min	Max	Nobs
Poverty Rate						
All	-0.022	-0.100	0.638	-1.300	1.300	41
White	0.010	-0.100	0.564	-1.100	1.200	41
Black	-0.288	-0.200	1.275	-2.500	1.700	41
Asian	-0.275	-0.350	1.350	-3.200	2.600	32
Hispanic	-0.144	-0.100	1.499	-2.900	3.900	41
Median Household Income						
All	0.573	0.778	2.269	-3.630	6.585	41
White	0.627	0.492	2.045	-2.665	5.590	39
Black	0.712	0.011	3.444	-4.573	7.604	41
Asian	1.076	1.582	4.091	-8.918	10.065	32
Hispanic	0.674	0.679	3.479	-6.663	6.880	41
Total Average Expenditures						
All	0.505	0.597	2.110	-4.550	4.594	35
White*	0.788	1.190	2.597	-4.438	4.517	16
Black	1.166	1.708	3.190	-6.060	5.897	16
Asian	1.119	1.877	4.591	-10.863	7.855	16
Hispanic	0.861	0.173	3.774	-5.978	7.638	25
Median Net Worth (data are triennial)						
All	-1.380	0.697	6.554	-18.018	3.360	10
White	-1.315	-0.122	5.118	-12.244	3.236	10
Black	1.452	0.320	10.259	-12.449	22.997	10
Other	-2.044	-2.337	8.704	-14.979	11.959	10
Hispanic	1.891	3.223	10.168	-11.921	14.725	10

* White is defined as White and All Other Races, a group that comprises such races as Native Americans, Alaskan Natives, Pacific Islanders, and those reporting more than one race.

Note: The sample periods for all data end in 2019. The "Other" classification consists of respondents identifying as Asian, American Indian, Alaska Native, Native Hawaiian, Pacific Islander, other race, and all respondents reporting more than one racial identification. See appendix 7.1 for more details about variables and sample periods.

Table 4: Kalman Filter Estimation for All Population

Variable	Coeff	Std Error	T-Stat	Signif
RHO1	0.464	0.107	4.325	0.000
RHO2	0.367	0.106	3.473	0.001
GAM_E	0.438	0.044	10.061	0.000
GAM_U	-0.587	0.061	-9.682	0.000
GAM_H	0.112	0.027	4.090	0.000
GAM_W	-0.003	0.019	-0.152	0.879
GAM_A	0.094	0.029	3.215	0.001
GAM_P	-0.036	0.008	-4.786	0.000
GAM_I	0.031	0.011	2.811	0.005
GAM_C	0.034	0.012	2.702	0.007
GAM_N	0.037	0.005	6.795	0.000

Table 5: Kalman Filter Estimation for White Population

Variable	Coeff	Std Error	T-Stat	Signif
W_RHO1	0.357	0.062	5.754	0.000
W_RHO2	0.399	0.069	5.806	0.000
W_GAM_E	0.485	0.047	10.290	0.000
W_GAM_U	-0.685	0.066	-10.382	0.000
W_GAM_H	0.110	0.046	2.373	0.018
W_GAM_W	-0.004	0.022	-0.167	0.867
W_GAM_A	0.105	0.035	2.996	0.003
W_GAM_P	-0.044	0.010	-4.326	0.000
W_GAM_I	0.045	0.014	3.182	0.001
W_GAM_C	0.040	0.018	2.211	0.027
W_GAM_N	0.035	0.010	3.520	0.000

Table 6: Kalman Filter Estimation for Black Population

Variable	Coeff	Std Error	T-Stat	Signif
B_RHO1	0.164	0.066	2.498	0.012
B_RHO2	0.353	0.069	5.131	0.000
B_GAM_E	0.685	0.064	10.663	0.000
B_GAM_U	-0.715	0.061	-11.701	0.000
B_GAM_H	0.063	0.063	0.999	0.318
B_GAM_W	0.016	0.034	0.467	0.641
B_GAM_A	0.034	0.038	0.899	0.369
B_GAM_P	-0.068	0.022	-3.072	0.002
B_GAM_I	0.069	0.023	2.949	0.003
B_GAM_C	0.073	0.031	2.305	0.021
B_GAM_N	0.037	0.011	3.464	0.001

Table 7: Kalman Filter Estimation for Hispanic Population

Variable	Coeff	Std Error	T-Stat	Signif
H_RHO1	0.146	0.100	1.456	0.145
H_RHO2	0.186	0.127	1.465	0.143
H_GAM_E	0.441	0.067	6.579	0.000
H_GAM_U	-0.773	0.113	-6.831	0.000
H_GAM_H	0.128	0.105	1.210	0.226
H_GAM_W	0.022	0.051	0.424	0.671
H_GAM_A	0.007	0.030	0.225	0.822
H_GAM_P	-0.123	0.031	-3.973	0.000
H_GAM_I	0.110	0.033	3.360	0.001
H_GAM_C	0.089	0.049	1.801	0.072
H_GAM_N	0.008	0.031	0.244	0.807

Table 8: Kalman Filter Estimation for Asian Population

Variable	Coeff	Std Error	T-Stat	Signif
A_RHO1	0.194	0.211	0.920	0.357
A_RHO2	0.177	0.193	0.918	0.359
A_GAM_E	0.568	0.119	4.767	0.000
A_GAM_U	-0.388	0.104	-3.743	0.000
A_GAM_H	0.126	0.087	1.451	0.147
A_GAM_W	0.050	0.069	0.733	0.464
A_GAM_A	0.119	0.053	2.265	0.023
A_GAM_P	-0.102	0.051	-2.000	0.045
A_GAM_I	0.114	0.051	2.249	0.024
A_GAM_C	0.065	0.058	1.130	0.259
A_GAM_N	0.018	0.044	0.419	0.675

7 Appendix

7.1 Details About the Indicators

7.1.1 Monthly Indicators

Where possible the sample period used to standardize the data and estimate the model parameters is January 1979-December 2019 for all monthly variables. For White, Black, Asian, and Hispanic average weekly hours data, the sample period does not begin until January 2003. The sample period for Asian civilian employment and unemployment rate begins in January 2003.

All monthly variables come from the monthly Current Population Survey (CPS) household survey, published by the BLS. The CPS uses the following categories to define race; White, Black or African American, Asian, American Indian or Alaska Native, Native Hawaiian or Other Pacific Islander. Hispanic or Latino ethnicity is a separate demographic concept from race, therefore people of Hispanic and Latino ethnicity may be of any race and are included in the aforementioned race groups. Since 2003 people who identify with two or more races are categorized separately as "Two or More Races." Hispanic or Latino ethnicity refers to people who identify themselves as Hispanic, Latino, or Spanish in the survey process (BLS [2023]).

7.1.2 Quarterly Indicators

Median weekly earnings are also published by the BLS and are from the CPS. Race and ethnicity are defined the same way as the monthly indicators used in EAR. Where possible the sample period used to standardize the data and estimate the model parameters for weekly earnings is Q1 1979-Q4 2019. The sample period for Asian weekly earnings is Q1 2000-Q4 2019, while for Hispanic it is Q1 1986-Q4 2019.

Assets are published by the Board of Governors but from different datasets. The "All" measure comes from the Financial Accounts of the United States dataset, while the measures for the demographic groups come from the Distributional Financial Accounts (DFAs). The DFAs "uses distributional information from the SCF to allocate the aggregate measures of assets..." Therefore the racial demographic groups are defined as they are in the SCF. The SCF "group(s) respondents into four classifications based on their responses to the racial identification question: White non-Hispanic, Black non-Hispanic, Hispanic or Latino, and other or multiple race. The "other or multiple race" classification consists of respondents identifying as Asian, American Indian, Alaska Native, Native Hawaiian, Pacific Islander, other race, and all respondents reporting more than one racial identification" (Bhutta et al. [2020]). The sample period used to standardize the data and estimate the model parameters for "All" is Q4:1987-Q4:2019, while for the racial groups, the sample period is Q3:1989-Q4:2019.

7.1.3 Annual Indicators

Where possible, my sample period used to standardize the data and estimate the model parameters is 1979-2019 for all annual variables. For Asian poverty rate and median household income the sample period is from 1987-2019. All net-worth data have a sample period of 1989-2019. White, Black and Asian expenditures has a sample period of 2003-2019, while "All" starts in 1984 and Hispanic starts in 1994.

The Census Bureau conducts the Current Population Survey Annual Social and Economic Supplement (CPS ASEC). The poverty rate and the median household income in my index are from the CPS ASEC. Race for the poverty rate and income are defined the same as they are in the CPS. "Beginning in January 2003, revisions to race categories took effect. Respondents were allowed to report more than one race, making selections from a 'flash-card.' The six race groups are: White, Black or African American, American Indian or Alaskan Native, Asian, Native Hawaiian or Other Pacific Islander, and Other. The last category includes any other race except the five mentioned"(Census [2021]).

The Board of Governors publishes the net-worth indicator every three years in the SCF.

The SCF "group(s) respondents into four classifications based on their responses to the racial identification question: White non-Hispanic, Black non-Hispanic, Hispanic or Latino, and other or multiple race. The 'other or multiple race' classification consists of respondents identifying as Asian, American Indian, Alaska Native, Native Hawaiian, Pacific Islander, other race, and all respondents reporting more than one racial identification" (Bhutta et al. [2020].

Lastly, the annual expenditures are published by the BLS from its Consumer Expenditure Survey (CE). Families are included in three racial groups: Black or African-American; Asian; and White and All Other Races. The "All Other Races" group comprises such races as Native Americans, Alaskan Natives, Pacific Islanders, and those reporting more than one race (BLS [2005]).

7.2 EAR Kalman Filter Model

I impose the following conventions for all non-monthly observation indicators:

$$
\begin{aligned}
\widetilde{Y_t^{(Q)}} &= \begin{cases} Y_t^{(Q)}, & \text{if t = last month of the quarter} \\ N/A, & \text{else} \end{cases} \\
\widetilde{Y_t^{(A)}} &= \begin{cases} Y_t^{(A)}, & \text{if t = last month of the year} \\ N/A, & \text{else} \end{cases} \\
\widetilde{Y_t^{(3A)}} &= \begin{cases} Y_t^{(3A)}, & \text{if t = last month of the year of the survey} \\ N/A, & \text{else} \end{cases}
\end{aligned}
\tag{7}
$$

Simply put, for each non-monthly observation I treat $\tilde{Y}_t = Y_t$ when it is the last month of the indicator's period, and missing for all other months.

Since the nine indicators are of mixed observation frequency, I impose aggregation equations on non-monthly indicators, a treatment proposed by Harvey [1990]. Given that we take the first difference or growth rate, all transformed variables are economic flows. As you can see in equations 3-5, all variables are dependent on the common component, C_t. The variables $C_t^{(Q)}$, $(C_t^{(A)})$, and $(C_t^{(3A)})$ are the cumulative sums, or Harvey aggregator, of the monthly C_t values over the quarter, year, and three years, respectively. Taking advantage of equation 7, the Harvey aggregator equations, (Harvey and Pierse [1984], Harvey [1990]), are given by

$$\begin{aligned} C_t^{(Q)} &= \xi_t^{(Q)} C_{t-1}^{(Q)} + C_t = \xi_t^{(Q)} C_{t-1}^{(Q)} + \rho_1 C_{t-1} + \rho_2 C_{t-2} + \eta_t \\ C_t^{(A)} &= \xi_t^{(A)} C_{t-1}^{(A)} + C_t = \xi_t^{(A)} C_{t-1}^{(A)} + \rho_1 C_{t-1} + \rho_2 C_{t-2} + \eta_t \\ C_t^{(3A)} &= \xi_t^{(3A)} C_{t-1}^{(3A)} + C_t = \xi_t^{(3A)} C_{t-1}^{(3A)} + \rho_1 C_{t-1} + \rho_2 C_{t-2} + \eta_t, \end{aligned} \tag{8}$$

where

$$\begin{aligned} \xi_t^{(Q)} &= \begin{cases} 0, & \text{if t = first month of the quarter} \\ 1, & \text{else} \end{cases} \\ \xi_t^{(A)} &= \begin{cases} 0, & \text{if t = first month of the year} \\ 1, & \text{else} \end{cases} \\ \xi_t^{(3A)} &= \begin{cases} 0, & \text{if t = first month after the year of the survey} \\ 1, & \text{else.} \end{cases} \end{aligned} \tag{9}$$

For the quarterly, annual, and triennial indicators the EAR index (C_t) is indirectly included in the models through the cumulation variables in equation 8. Equation 9 defines the zero-one dummy variables that tell the cumulation equations where to begin the cumulation of the monthly EAR index values (C_t) over the quarter, year, and three years.

The state space representation for the structural model is given by equations 10 and 11:

$$\begin{bmatrix} C_t \\ C_{t-1} \\ C_t^{(Q)} \\ C_t^{(A)} \\ C_t^{(3A)} \end{bmatrix} = \begin{bmatrix} \rho_1 & \rho_2 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ \rho_1 & \rho_2 & \xi_t^{(Q)} & 0 & 0 \\ \rho_1 & \rho_2 & 0 & \xi_t^{(A)} & 0 \\ \rho_1 & \rho_2 & 0 & 0 & \xi_t^{(3A)} \end{bmatrix} \begin{bmatrix} C_{t-1} \\ C_{t-2} \\ C_{t-1}^{(Q)} \\ C_{t-1}^{(A)} \\ C_{t-1}^{(3A)} \end{bmatrix} + \begin{bmatrix} \eta_t \\ 0 \\ \eta_t \\ \eta_t \\ \eta_t \end{bmatrix}, \tag{10}$$

$$
\begin{bmatrix} HOURS_t \\ EMPLOY_t \\ UNEMP_t \\ \widetilde{WAGES}_t \\ \widetilde{ASSETS}_t \\ \widetilde{POV}_t \\ \widetilde{INC}_t \\ \widetilde{CEX}_t \\ \widetilde{NET}_t \end{bmatrix}
=
\begin{bmatrix}
\phi_1^H & \phi_2^H & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & \phi_1^E & \phi_2^E & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & \phi_1^U & \phi_2^U & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & \phi_1^W & \phi_2^W & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \phi_1^A & \phi_2^A & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \phi_1^P & \phi_2^P & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \phi_1^I & \phi_2^I & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \phi_1^C & \phi_2^C & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \phi_1^N & \phi_2^N
\end{bmatrix}
\begin{bmatrix} HOURS_{t-1} \\ HOURS_{t-2} \\ EMPLOY_{t-1} \\ EMPLOY_{t-2} \\ UNEMP_{t-1} \\ UNEMP_{t-2} \\ \widetilde{WAGES}_{t-3} \\ \widetilde{WAGES}_{t-6} \\ \widetilde{ASSETS}_{t-3} \\ \widetilde{ASSETS}_{t-6} \\ \widetilde{POV}_{t-12} \\ \widetilde{POV}_{t-24} \\ \widetilde{INC}_{t-12} \\ \widetilde{INC}_{t-24} \\ \widetilde{CEX}_{t-12} \\ \widetilde{CEX}_{t-24} \\ \widetilde{NET}_{t-36} \\ \widetilde{NET}_{t-72} \end{bmatrix}
\tag{11}
$$

$$
+ \begin{bmatrix}
\gamma^H & 0 & 0 & 0 & 0 \\
\gamma^E & 0 & 0 & 0 & 0 \\
\gamma^U & 0 & 0 & 0 & 0 \\
0 & 0 & \gamma^W & 0 & 0 \\
0 & 0 & \gamma^A & 0 & 0 \\
0 & 0 & 0 & \gamma^P & 0 \\
0 & 0 & 0 & \gamma^I & 0 \\
0 & 0 & 0 & \gamma^C & 0 \\
0 & 0 & 0 & 0 & \gamma^N
\end{bmatrix}
\begin{bmatrix} C_t \\ C_{t-1} \\ C_t^{(Q)} \\ C_t^{(A)} \\ C_t^{(3A)} \end{bmatrix}
+ \begin{bmatrix} e_t^H \\ e_t^E \\ e_t^U \\ e_t^W \\ e_t^A \\ e_t^P \\ e_t^I \\ e_t^C \\ e_t^N \end{bmatrix},
$$

where:

$$\begin{bmatrix} \eta_t \\ e_t^H \\ e_t^E \\ e_t^U \\ e_t^W \\ e_t^A \\ e_t^P \\ e_t^I \\ e_t^C \\ e_t^N \end{bmatrix} \overset{iid}{\sim} N\left(\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \sigma_H^2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \sigma_E^2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \sigma_U^2 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \sigma_W^2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \sigma_A^2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \sigma_P^2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \sigma_I^2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \sigma_C^2 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \sigma_N^2 \end{bmatrix} \right)$$

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