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Income business cycles

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Abstract

Using a wide variety of business cycle dating and filtering techniques, this paper documents the cyclical behavior of the post-tax income distribution in the US. First, all incomes are cyclical and co-move with the business cycle. Second, lower and higher income individuals experience significantly larger fluctuations across the business cycle than middle-income individuals. Third, these fluctuations have become smaller over the course of the Great Moderation for the bottom and the very top income individuals. With the financial crisis starting in 2007 and its repercussions, the volatilities are again increasing; however, not significantly. These findings are independent from the method to extract the business cycle component.

JEL-Classification: E01, E32, D31

Keywords: cyclicity of the income distribution, business cycle

1 Introduction

Is there a business cycle for different income percentiles and, if so, does it differ across percentiles? In this paper, we use a recently assembled dataset on cross-sectional post-tax income in the U.S. developed by Piketty et al. (2018) to shed light on these questions. Knowledge about the cyclicity of income percentiles is not only essential for the design and evaluation of stabilization policies, but also informative for theoretical models that are concerned with income heterogeneity. In order to extract the cyclical behavior of the income percentiles, we employ standard business cycle detection methods: turning point dating and filtering techniques.

We start by applying a measure that formed the basis of NBER business cycle dating. This measure detects turning points of the business cycle variable based on standardizing assumptions regarding the phases and duration of a typical cycle (Burns & Mitchell, 1946; Bry & Boschan, 1971; Harding & Pagan, 2002; Engel et al., 2005). Afterwards, we employ several commonly used filtering techniques, i.e. the Hodrick-Prescott filter, the Christiano-Fitzgerald filter, the Baxter-King filter, and the Hamilton-filter, to the dataset. In contrast to the business cycle dating methods, these filters do not rely on *a priori* specifications of phases and sequence of a standard cycle. Instead they involve rather general assumptions on higher moments of the permanent and transitory components, possible frequencies bands or a forecast structure of cycles. Interestingly, both methods yield similar results.

We present three facts on the cyclicity of U.S. income percentiles. First, all income percentiles are cyclical and co-move with the business cycle. In particular, income percentiles depict turning points in line with NBER business cycle dates. Second, individuals with very low income and individuals with very high income experience the largest income swings. In comparison, middle-incomes fluctuate less. The cycles of the top and bottom 10%tile groups reveal a significantly larger variance than the cycles of the middle 50%tile group. Third, volatilities of all income percentiles declined during the Great Moderation. The decline of

cycles' variances in the eighties is statistically significant for the bottom to middle and the top income percentile groups for cycles based on three different filters. Across all filters, volatility of the bottom and top percentile groups declined significantly. After the financial crisis of 2007/08 and its repercussions, volatilities increased again, albeit not significantly. Our paper contributes to the literature studying the interdependence of income and business cycles. On the one hand, Heathcote et al. (2010) and Bitler & Hoynes (2015) focus mainly on earnings and pre tax income of the middle to lower individuals. Parker & Vissing-Jorgensen (2009, 2010) on the other hand analyzes high-income individuals. The dataset by Piketty et al. (2018) allows us to study the cyclicity of income percentiles in an encompassing way. It is especially well suited to analyze different incomes over the business cycle, as it is informative about both the lower and upper tails of the income distribution but also matches aggregate macroeconomic data. It does so because the dataset combines survey data, tax records, and national accounts. Applying the general methods has the advantage that we do not have to take a stand on the specific sources of the business cycle fluctuations. Therefore, we are silent about the structural sources of the business cycle fluctuations and leave the thorough investigation for further research.

The remaining paper is organized in the following way. Section 2 introduces the dataset. The following section employs the turning point analyses to the time series of household percentiles. Section 4 briefly describes the different filtering techniques and provides the income business cycles. The final section concludes.

2 Data

Our analysis builds on the US household income data of Piketty et al. (2018). This data set is informative for both the lower and upper tails of the income distribution and it matches national income. In particular, Piketty et al. (2018) completes the income distribution obtained from tax records not only with survey data from the Current Population Survey and

Survey of Consumer Finances but also with aggregate macroeconomic accounting. Therefore, household incomes include the income of non-filers, tax-exempt labor, capital income, along with redistributive measures such as the incidence of taxes and the beneficiaries of non-individualized government transfers, including health expenditures and education. This ensures that the income data of Piketty et al. (2018) is not only a representative sample of the income distribution in the United States, but also consistent with macro-aggregates. We refer the reader to Piketty et al. (2018) for detailed information on the construction of the microdataset. For our analysis, we focus on yearly post tax national income, equally split among spouses from 1967 to 2019.¹ We obtain real incomes, expressed in constant 2012 US dollars, using the net national income deflator provided by the Bureau of Economic Analysis. To investigate the cyclical component of the income distribution, we calculate the income percentiles for each year in the sample: We sort the observed incomes $x_n \in X$, $n = 1, \dots, N$ in ascending order with N being the total number of observed persons each year. We approximate the cumulative distribution function by $F_X(x_n) = \sum_{i=1}^n w_i / \sum_{i=1}^N w_i$, where w_n is the frequency weight associated to income x_n . We calculate the percentiles as the x_n for which the cumulative distribution function equals or just exceeds p , for $0 < p < 1$: $PCTL_p = \inf \{x \in X : p \leq F_X(x)\}$, where p depicts the $(p * 100)$ th percentile. We calculate income deciles correspondingly.

3 NBER business cycle dating of the income distribution

To get a first impression on the transitory component of the income distribution, we employ a turning point analysis, as suggested by Engel et al. (2005), to the time series of household income deciles. Turning points are usually selected by a simple rule of the following form

¹Like Piketty et al. (2018), we opt for the equal-split adults income measure in order to neutralize demographic trends.

$$\begin{aligned}
\text{peak at } t &= \{(y_{t-n}, \dots, y_{t-1}) < y_t > (y_{t+1}, \dots, y_{t+n})\} \\
\text{trough at } t &= \{(y_{t-n}, \dots, y_{t-1}) > y_t < (y_{t+1}, \dots, y_{t+n})\} \\
&\text{with } n = 1, \dots, N,
\end{aligned} \tag{1}$$

where a peak (trough) is detected if the level of the macroeconomic series (y_t) is larger (smaller) compared to the former N periods and is smaller (larger) N periods ahead. Usually some additional censoring procedures are applied in combination to these rules. Following Harding & Pagan (2002) and Engel et al. (2005), these include a minimum duration of expansions and contractions, complete cycles, as well as the alternation of peaks and troughs. Studies using the turning point approach focus on monthly or quarterly data (Bry & Boschan, 1971; Harding & Pagan, 2002; Engel et al., 2005). Bry & Boschan (1971) and Harding & Pagan (2002) assume that N equals six months (two quarters), minimum length of a peak (trough) is six months (two quarters) and a minimum duration of complete cycles of 15 months (two to three quarters). We convert these assumptions on quarterly frequencies to annual data by setting N (turning phase) to one year, expansion and contraction phases to last two years. We set the minimum length of a peak (trough) to two years in order to exclude the possibility that white noise, in this case yearly spikes, is picked up as turning points. This implies that a complete cycle lasts at least four years.

Table 1 compares the results of the turning point detection across the distinct income deciles and the official NBER business cycle dates. The detected turning points indicate that fluctuations of income deciles are closely linked to the business cycle. Turning points of income deciles show peaks and troughs that are remarkably close to the NBER business cycle dates. Most differences are systematic and attributable to the annual frequency of the income data, particularly when the contraction phase is short-lived. For example, turning points of the income deciles systematically summarize the two recessions in the early eighties by assumption (minimum length of trough is two years) into one. Although technically a two quarter expansion followed the contractionary phase in 1980, both recessions, in 1980

and 1981 to 1982, are often associated with the Volcker Disinflation as a common cause. Similarly, the mild recession in 2001 triggered by the dot-com bubble and the 9/11 attacks is not detected for most deciles. It is likely that turning point outcomes are driven by the within year timing. When peaks or troughs are NBER-dated at the beginning or the end of the year, the turning points of percentiles are leading or lagging by a year.

4 Filtering the income distribution

To quantify the cyclicity of the income distribution, we decompose household income percentiles into a transitory and a permanent component by filtering the time series. In order to be independent of the strengths and weaknesses of different filters, we apply the four most commonly used business cycle filters. These include the filter suggested by Hodrick & Prescott (1997) (HP filter), two band-pass filters introduced by Baxter & King (1999) (BK filter) and Christiano & Fitzgerald (2003) (CF filter), as well as the regression filter based on Hamilton (2018) (H filter).

While the HP filter is the most commonly applied filter, the band-pass filters outperform the HP filter for higher frequency components and in real time applications (Christiano & Fitzgerald, 2003). However, for certain data generating processes band-pass filters, induce spurious cycles (Murray, 2003; Hodrick, 2020). The Hamilton filter performs very well at the end of the sample and avoids the mechanical creation of spurious cycles. However, the filter amplifies cycles of durations between three to five years and the filtered trend can show implausibly large volatility (Quast & Wolters, 2020; Hodrick, 2020).

Table 1: Turning points across income deciles

NBER		1. decile		2. decile		3. decile		4. decile		5. decile	
peak	trough	peak	trough	peak	trough	peak	trough	peak	trough	peak	trough
1969 (IV)	1970 (IV)	1970	1971			1969	1971	1969	1971	1969	1971
1973 (IV)	1975 (I)	1974	1975	1974	1975	1973	1975	1973	1975	1973	1975
1980 (I)	1980 (III)	1979		1979		1979		1979		1979	
1981 (III)	1982 (IV)		1983		1982		1982		1982		1982
1990 (III)	1991 (I)	1989	1992	1990	1991						
2001 (I)	2001 (IV)	2001	2003	2001	2003	2001	2003				
2007 (IV)	2009 (II)	2007	2009	2006	2009	2006	2009	2006	2009	2007	2009
Additional turning points		1985	1986	2015	2016						
		2015	2016								
NBER		6. decile		7. decile		8. decile		9. decile		10. decile	
peak	trough	peak	trough	peak	trough	peak	trough	peak	trough	peak	trough
1969 (IV)	1970 (IV)	1970	1971	1970	1970	1969	1970	1969	1970		1970
1973 (IV)	1975 (I)	1973	1975	1973	1975	1973	1975	1973	1975	1973	1974
1980 (I)	1980 (III)	1978		1978		1978		1978		1979	1980
1981 (III)	1982 (IV)		1982		1982		1982		1982		
1990 (III)	1991 (I)	1989	1990	1989	1990	1989	1990			1988	1990
2001 (I)	2001 (IV)									2000	2002
2007 (IV)	2009 (II)	2007	2009	2006	2009	2006	2009	2006	2009		
Additional turning points										2012	2013
										2017	

Notes: The table depicts yearly turning points across income deciles and official NBER business cycle dates (quarters in brackets). Green shadings indicate that the turning points are in line with NBER business cycle dates but take into account that quarterly NBER turning points dated at the beginning or ending of the year might be deferred or anticipated in the yearly turning point detection of income deciles. Yellow shadings indicate a deviation of NBER dates of one year and red shades deviation of more than one year.

To thoroughly assess the cycles of the income distribution, we part the distribution into a fine grid: For each year of the sample, we compute percentiles from the fifth to hundredth percentile in one percentage point steps.² Then we decompose each of the logged percentile series with the four filters mentioned before, which we briefly describe hereafter.

4.1 Four business cycle filter

Hodrick-Prescott filter

Denote the logged percentile series as y_t , the permanent component τ_t , the transitory component c_t , such that $y_t = \tau_t + c_t$. In the application of the HP filter, we solve for the trend component for a given smoothing parameter, λ :

$$\min_{\{\tau\}_{t=-1}^T} \left\{ \sum_{t=1}^T (y_t - \tau_t)^2 + \lambda \sum_{t=1}^T [(\tau_t - \tau_{t-1}) - (\tau_{t-1} - \tau_{t-2})]^2 \right\} \quad (2)$$

We follow Ravn & Uhlig (2002) and set λ to 100, the fourth power of the frequency observation ratio.

Baxter-King filter

Band-pass filters isolate the cyclical component of a time series assuming a specific range of cycle durations. Basically, the band-pass filter computes a two-sided weighted moving average of the time series that retains the cyclical data components within a specified frequency band. The band-pass filter is specified as

$$y_t = \sum_{j=-\infty}^{\infty} B_j x_{t-j} \quad (3)$$

that isolates oscillations y_t within a specific periodic band, p_l and p_u , where $2 \leq p_l < p_u < \infty$ from a stochastic process x_t . p_l and p_u are related to a frequency band $\{(a, b) \cup (-a, -b)\} \in$

²We exclude the bottom four percentiles as these households reveal highly volatile incomes that might be driven by the imputation of non-filers and the allocation of redistributinal measures to these individuals.

$(-\pi, \pi)$ with $a = \frac{2\pi}{p_u}$ and $b = \frac{2\pi}{p_l}$. Then the ideal weights are $B_j = \frac{\sin(jb) - \sin(ja)}{\pi j}$, $B_0 = \frac{b-a}{\pi}$. The Baxter-King filter is defined as a finite approximation of the ideal band-pass filter for the observed finite sample x_t with $t = 1, \dots, T$. The BK filter is of fixed length with a predetermined number of lead and lag terms for computing the weighted moving average and takes the form

$$\hat{y}_t = \sum_{j=-n}^n \hat{B}_j x_{t-j} \quad (4)$$

with n being the length of lags. The weights of the BK filter, \hat{B}_j , are time-invariant as they depend only on the specified frequency band. They are found by the inverse Fourier transform of the frequency response function $\hat{B}_j = \frac{1}{2\pi} \int_{-\pi}^{\pi} \beta(\omega) \exp(i\omega j)$ with i being the imaginary number $\sqrt{-1}$ and ω the frequency measured in radians ($\pi \leq \omega \leq -\pi$). We set p_l to two years, p_u to eight years, and n to three years.

Christiano-Fitzgerald filter

In contrast to the BK filter, band-pass filter variant by Christiano & Fitzgerald (2003) is a full asymmetric filter with time-varying data-dependent weights and takes the form

$$\begin{aligned} \hat{y}_t &= \sum_{j=-f}^p \hat{B}_{t,j} x_{t+j} \text{ with } p = t - 1 \text{ and } f = T - t \\ \hat{B}_{t,j} &= \min_{\hat{B}_{t,j}, j=-f, \dots, p} E\{(y_t - \hat{y}_t)^2 | x\} \end{aligned} \quad (5)$$

Like the filter by Baxter & King (1999), the CF filter requires a minimum and maximum cycle length that we set to a frequency band of two to eight years following Christiano & Fitzgerald (2003). We do not assume that the underlying data has a drift.

Hamilton filter

The filter proposed by Hamilton (2018), extracts the cyclical component of time series using forecast errors of a projection based on a univariate autoregression model and takes the

following form

$$y_{t+h} = \beta_0 + \sum_{j=1}^p \beta_j y_{t-j+1} + v_{t+h} \quad (6)$$

where the cyclical component of the time series is then given by the residuals v_{t+h} . We follow Hamilton (2018), who proposes to use a two year horizon for business cycle analysis based on annual data and estimate the Hamilton filter with $h = 2$ and $p = 1$.

4.2 Income business cycles

Figures 1a to d show deviations of income percentiles from their respective trend³ extracted with the aforementioned filters. In general and in line with our findings in Section 3, we observe that all income percentiles fluctuate strongly and co-move with the business cycle across all filters. That is, incomes build up during expansions and bottom during recessions. For instance, the most dramatic drop across income percentiles occurred during the 1980 to 1982 recession and the financial crisis. Furthermore, incomes of the upper percentiles (red) seem to lead the business cycle during most upswings.

While it is remarkable that the co-movement of income percentiles with the business cycle holds independent of the specific filter, differences emerge in the size of the cycles amplitude. In particular, the cycles from the band-pass filters feature smaller amplitudes for the bottom ten percentile cycles than the HP filter. This particularly holds for the CF filter. Therefore, the cycles of the band-pass filters, in particular the CF filter, depict more turning points outside the NBER recessions than the HP and H filter. In contrast, the percentile cycles from the Hamilton filter reveal larger amplitudes than the HP filter cycles and also depict a slightly altered duration of cycles that are possibly related to the autoregressive structure of the Hamilton filter.

Despite the differences in amplitudes, one feature of the income cycles stands out for all filters: lower- (blue) and higher-income (red) percentiles experience higher fluctuations than

³The filtered trends follow dynamics commonly documented in the literature and decile trends are displayed in the appendix A.1a to d.

middle-income individuals (green and yellow). This is also quantified in Table 2, which reports the variances of pooled groups of percentile cycles from the distinct filters and over the full as well as subsamples.⁴ Across samples and filters, the variances of the first and last percentile cycle groups are larger than those of the median income group by at least one third. Our results combine those of previous studies. Examining survey-based data⁵, Heathcote et al. (2010) finds that lower earnings incomes fluctuate substantially more along the business cycles than higher earnings incomes. Using tax return data for high-income households assembled by Piketty & Saez (2003), Parker & Vissing-Jorgensen (2009, 2010) show that high-income households are much more volatile around recessions and booms compared to aggregate national income data. The different data sources of these studies, surveys and administrative data, vary with respect to the information content at the tails of the income distribution⁶ and the types of income covered. Since we use the dataset of Piketty et al. (2018) that combines these two data sources and matches it with aggregate data, we view our results as combination of the outcomes of Heathcote et al. (2010) and Parker & Vissing-Jorgensen (2009, 2010).

Another striking feature is shown by figure 1a to d, together with Table 2: the volatilities of all income deciles declined as the Great Moderation progressed from 1985 to 2006. This is shown in columns two and three of Table 2, which contrast the time periods 1967-1989 and 1990-2006 for each filter. Since the start of the global financial crisis, variances again increased.

To test whether differences across variances of subsamples and pooled percentile groups are statistically significant, we apply the Brown-Forsythe test (Brown & Forsythe, 1974).

To be able to perform the BF test, we have to pool over percentile groups as to ensure

⁴Since we need to pool the percentile cycles to perform the Brown-Forsythe test for differences across populations variances, we opt to show the test-related pooled group variances right away. In accordance with the test, the variances displayed in Table 2 are average sums of squared deviations from the populations' median rather than mean.

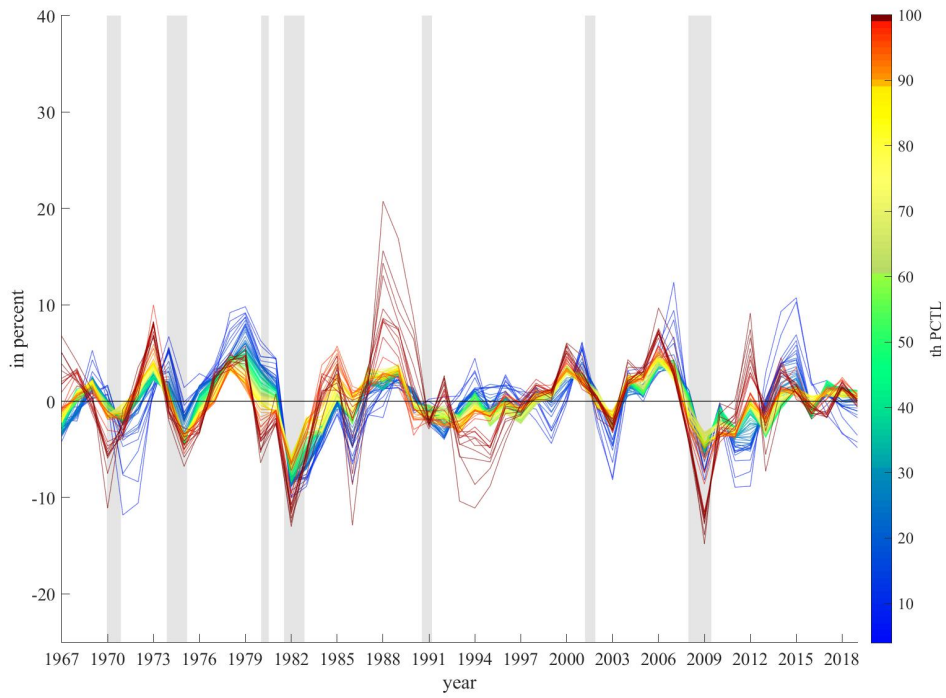
⁵In particular, the authors use and compare data from Current Population Survey (CPS), Panel Study of Income Dynamics (PSID) and the Consumer Expenditure Survey (CEX).

⁶High-income individuals are less well covered in surveys and tax data tend to be less informative about very low income individuals that do not file tax reports.

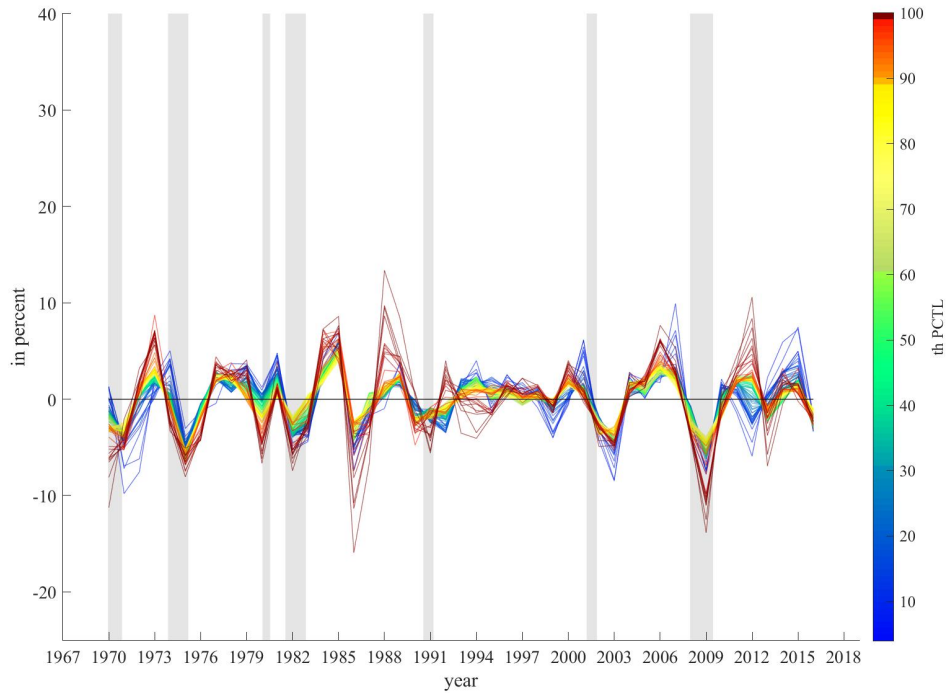
an acceptable number of observations for each population. Under the null hypothesis that variances of populations compared are equal, the Brown-Forsythe test is the F statistic from a one-way analysis of variance (ANOVA) on the absolute deviations of the pooled observations from the percentile cycles groups over the specified (sub)samples from their respective medians. Since the test is based on the deviations of the median, it is quite robust and retains statistical power even when the data is not normally distributed (Derrick et al., 2018). This, in turn, is particularly relevant for the pooled groups of percentile cycles at the lower and upper ends of the income distribution for specific subsamples. Table 3 displays the p-values of the BF test of equal variance across percentile groups and subsamples. With the test results, we can document that, within a 90% confidence interval, variances up the seventh group of percentile cycles (up to 70th percentile) and the top 10th percentile cycles are statistically different, in this case smaller, during the Great Moderation compared to the previous 17 years. Although Table 2 indicates that variances across most percentile groups increased again since 2006, the rise in variances is statistically significant only for the two lowest percentile cycles group. These results hold across all filters except for the Christiano-Fitzgerald filter for which null hypothesis of equal variance can only be rejected for the lowest and highest group of percentile cycles comparing the Great Moderation and two decades before. In line with the visual inspection of cycles, across all filters, variances of the lower percentile cycles (5th – 10th) and the upper percentile cycles (91st – 99.99th) are statistically different from the middle percentile cycle group (51st – 60th) at a 5% significant level.

Figure 1: Cycles of income percentiles

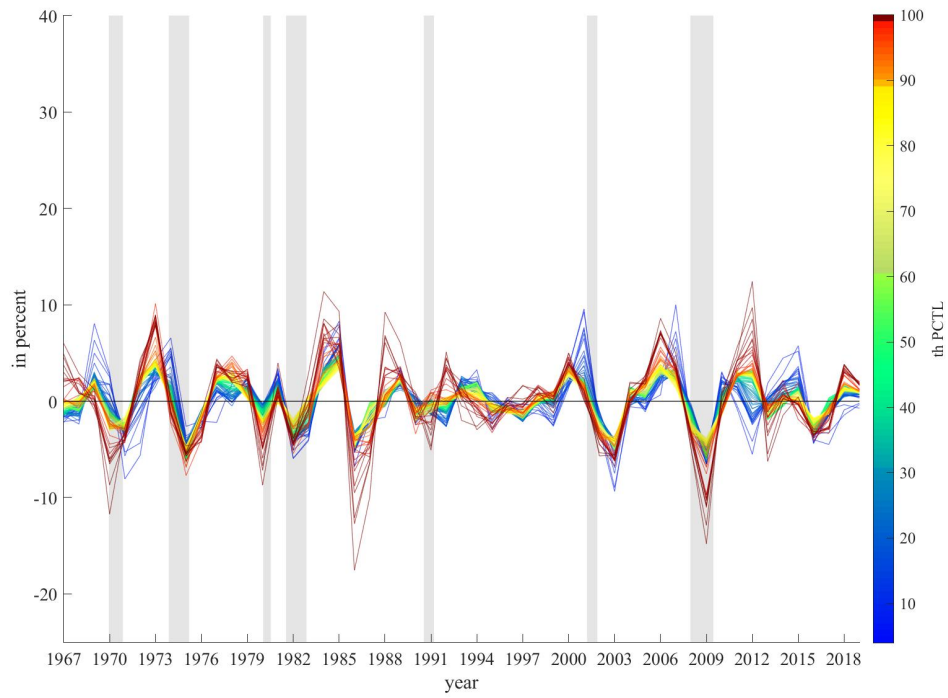
(a) Hodrick-Prescott filter



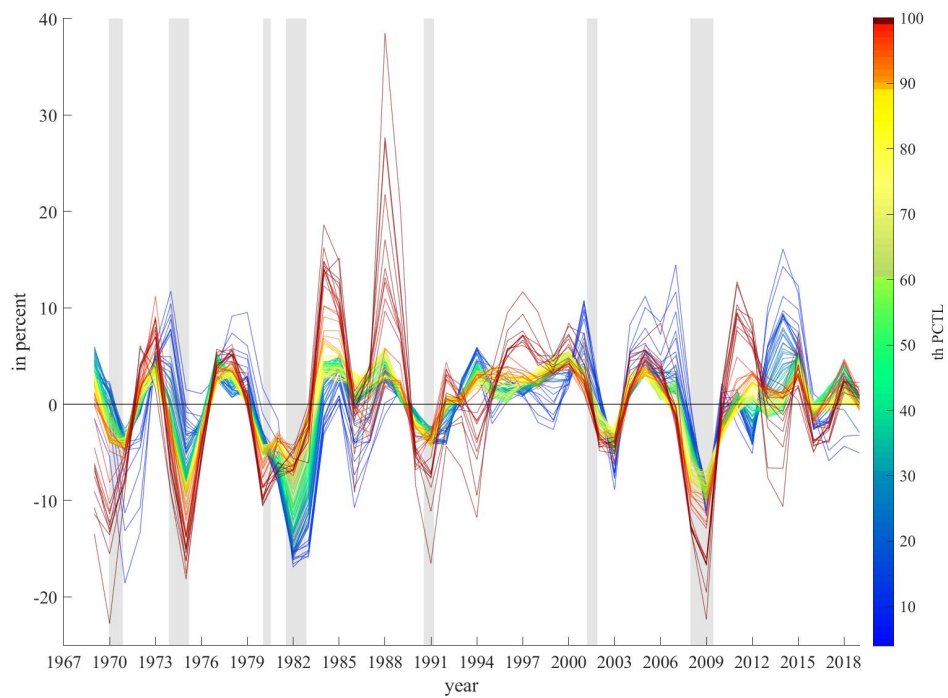
(b) Baxter-King filter



(c) Christiano-Fitzgerald filter



(d) Hamilton filter



Notes: Cycles from filtered income percentiles. Shaded area indicate NBER-dated recessions.

Table 2: Variances of the income distribution cycles across deciles

percentile groups	HP Filter				Baxter-King Filter			
	1967-2019	1967-1984	1985-2006	2007-2019	1967-2019	1967-1984	1985-2006	2007-2019
5 th – 10 th	19,13	28,70	8,41	24,88	12,86	13,83	10,32	17,47
11 th – 20 th	9,31	16,05	4,11	8,81	6,86	7,17	6,17	7,98
21 st – 30 th	7,46	13,50	3,12	6,70	5,53	7,11	4,13	5,95
31 st – 40 th	6,80	11,99	3,22	5,72	5,75	7,09	4,29	6,84
41 st – 50 th	6,17	10,24	3,52	4,91	5,56	6,65	4,36	6,30
51 st – 60 th	5,77	8,16	4,17	4,72	5,43	6,02	4,59	5,75
61 st – 70 th	5,09	7,08	4,19	3,66	4,78	5,46	4,01	4,62
71 st – 80 th	4,66	5,87	3,92	3,89	4,60	5,42	3,88	4,08
81 st – 90 th	5,09	5,96	4,12	5,19	5,08	5,85	4,33	4,95
91 st – 99.99 th	15,92	16,80	14,87	13,85	14,29	17,00	11,06	16,15

percentile groups	Christiano-Fitzgerald Filter				Hamilton Filter			
	1967-2019	1967-1984	1985-2006	2007-2019	1967-2019	1967-1984	1985-2006	2007-2019
5 th – 10 th	11,47	11,47	11,36	11,75	34,26	53,43	17,80	36,62
11 th – 20 th	5,72	5,53	5,96	5,77	20,74	35,53	8,24	20,29
21 st – 30 th	4,94	5,90	4,38	5,24	17,02	31,55	5,81	14,45
31 st – 40 th	5,39	6,54	4,73	6,02	15,97	28,14	5,70	14,01
41 st – 50 th	5,35	6,23	4,69	5,69	14,45	23,41	6,35	12,44
51 st – 60 th	5,26	5,44	5,18	5,23	13,91	19,85	6,71	12,78
61 st – 70 th	4,60	4,94	4,54	4,24	12,20	16,77	6,17	9,94
71 st – 80 th	4,41	4,72	4,45	3,99	11,28	14,81	5,51	9,79
81 st – 90 th	5,01	5,41	4,83	4,74	12,94	16,45	6,57	12,94
91 st – 99.99 th	14,33	15,69	12,67	15,13	40,79	57,33	20,12	46,56

Notes: The table shows the variance of the income distribution cycles across pooled groups of percentiles for different subsamples. The variances are computed using deviations of group medians rather than means.

Table 3: P-values of Brown-Forsythe test for the equality of group variances

percentile groups	1967-1984 vs. 1985-2006				1985-2006 vs. 2007-2019				5. decile vs. other deciles			
	HP	BK	CF	H	HP	BK	CF	H	HP	BK	CF	H
5 th – 10 th	0,00	0,04	0,07	0,00	0,00	0,01	0,37	0,00	0,00	0,00	0,00	0,00
11 th – 20 th	0,00	0,03	0,31	0,00	0,00	0,04	0,78	0,00	0,00	0,08	0,53	0,00
21 st – 30 th	0,00	0,00	0,00	0,00	0,00	0,06	0,49	0,00	0,18	0,53	0,47	0,81
31 st – 40 th	0,00	0,00	0,01	0,00	0,00	0,08	0,96	0,00	0,71	0,73	0,85	0,81
41 st – 50 th	0,00	0,00	0,02	0,00	0,14	0,01	0,52	0,04	1,00	1,00	1,00	1,00
51 st – 60 th	0,00	0,00	0,27	0,00	0,68	0,01	0,60	0,47	0,72	0,94	0,90	0,73
61 st – 70 th	0,01	0,00	0,25	0,00	0,11	0,01	0,49	0,44	0,22	0,26	0,19	0,34
71 st – 80 th	0,07	0,00	0,43	0,00	0,23	0,04	0,70	0,18	0,03	0,07	0,04	0,23
81 st – 90 th	0,32	0,00	0,23	0,00	0,84	0,02	0,47	0,04	0,28	0,63	0,48	0,98
91 st – 99.99 th	0,03	0,00	0,00	0,00	0,55	0,00	0,08	0,12	0,00	0,00	0,00	0,00

Notes: The first two blocks of the table show the p-values of the Brown-Forsythe test for the equality of percentile group variances of distinct subsamples. The last block of the table depicts the p-values of the Brown-Forsythe test for the equality of percentile group variances and the middle percentile group from the 41st to the 50th percentile. The null hypothesis is that the population variances are equal. The table displays the test results for the HP filter (HP), the Baxter-King filter (BK), the Christiano-Fitzgerald filter (CF), and the Hamilton filter (H).

5 Conclusion

In this paper, we document the cyclical behavior of post-tax income percentiles for the U.S. from 1967 to 2019. First, all income percentiles co-move with the business cycle. Second, lower and higher income individuals experience significantly larger fluctuations across the business cycle than middle-income individuals. Third, these fluctuations have become smaller over the course of the Great Moderation for individuals at the bottom and the very top of the income distribution. With the financial crisis of 2007/08 and its repercussions, the volatilities once again increased, albeit not significantly. These findings are independent from the method to extract the business cycle component. The turning point analyses as well as the most commonly employed filtering techniques confirm the findings.

These findings help to further deepen our understanding of business cycles. Changes in the income distribution are an important driver of business cycles fluctuations itself. Therefore, the results are informative for business cycle models that deal with the implications of income heterogeneity. While the application of the different methods has the advantage that we do not need to take a stand on the specific sources of the business cycle fluctuations, our analysis cannot explain the reasons for the stronger fluctuations of the lower- and higher-income percentile households. Furthermore, the analysis is silent about the nature of the rise and fall of the volatilities. For these questions, a thorough structural investigation is needed, which we leave for further research.

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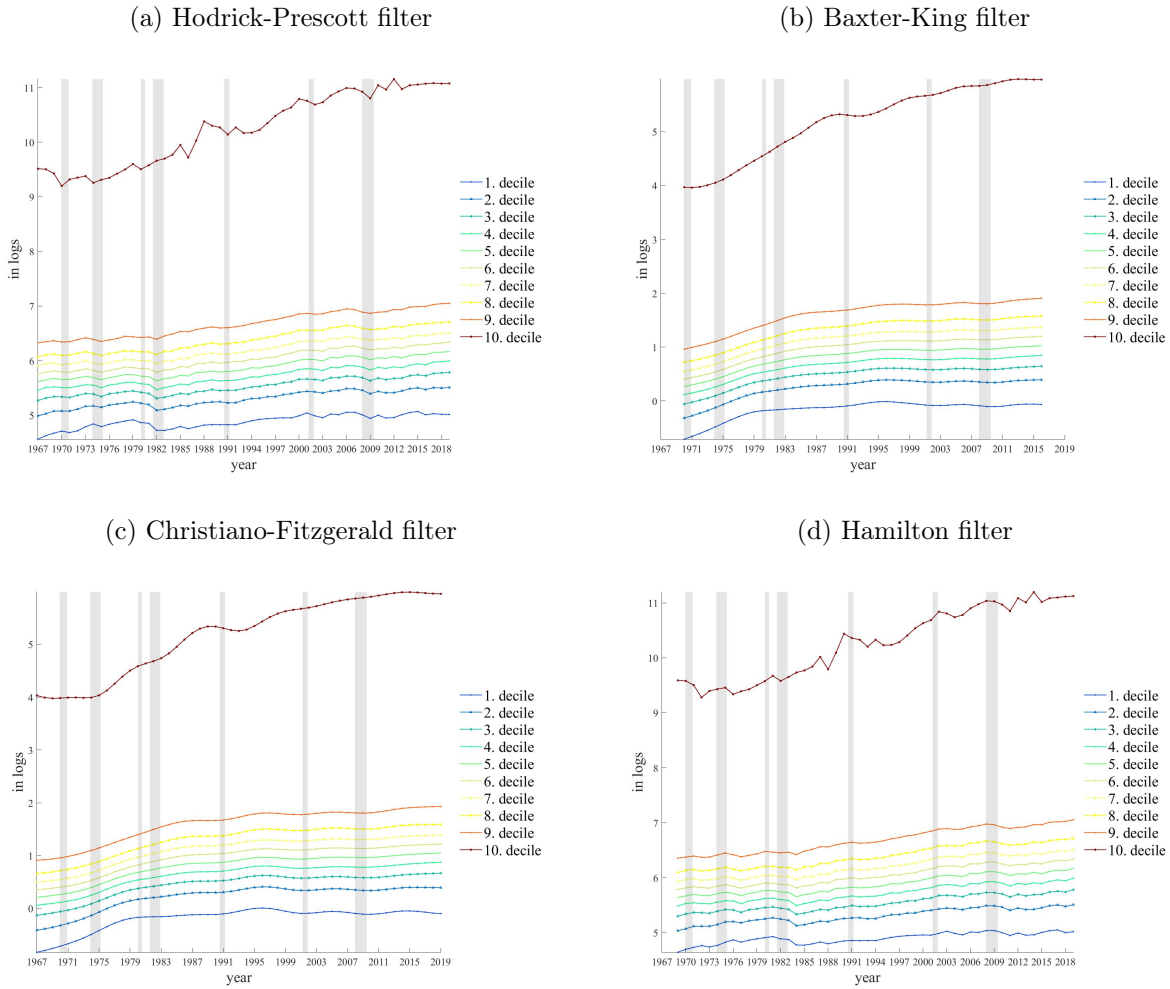
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A Appendix

Figure A.1: Trends of income percentiles



Notes: Trends from filtered income percentiles. Shaded area indicate NBER-dated recessions.