The Increase in Income Cyclicality of High-Income Households and its Relation to the Rise in Top Income Shares*

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Abstract: We document that there has been a large increase in the cyclicality of the incomes of high-income households that coincides with the rise in their share of total income. In the U.S., since the early 1980s, the incomes of those in the top 1% of the income distribution, which are on average 11 times the average income, have been 2.4 times as cyclical as average income resulting in the top 1% bearing 28% of aggregate income fluctuations. Prior to the early 1980s, the income of the top 1% was slightly less cyclical than that of the average household. The change in top 1% income cyclicality is to a large extent due to an increase in the share and cyclicality of wages and salaries. This high cyclicality among top incomes is also found i) for households without stock options, ii) for changes in income for the same set of households over time, iii) for post-tax, post-transfer income, and iv) for consumption in the available data. We contrast the cyclicality of the top 1% with the cyclicalities of groups further down the income distribution, and reconcile our findings with the earlier literature. We document a link between the increased income share and increased income cyclicality of the top 1%, finding that the cyclicality of the top 1% increases decade by decade as the top 1% income share increases, and across countries increases in income cyclicality of the top 1% are highly correlated with increases in top 1% income shares. This close relationship suggests a common cause, which we conjecture is technological change that increase the optimal production scale of the most talented.

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Since the early 1970's, economic inequality in the United States – as measured by the distribution of wages and salaries, of income more broadly, or of consumption expenditures – has been steadily increasing.[1] The consensus explanation for the general increase in inequality is that recent changes in technology have complemented skills, specifically that the spread of information and communication technologies has benefitted the productivity of the educated and skilled more than the unskilled. However, accompanying this steady rise in inequality, has been a much larger and more rapid increase in the income share of those at the very top of the income distribution. The share of (non-capital gains) income accruing to those in the top 1% income distribution has been increasing since the early 1980s, from around 8% to around 18% in 2008 (Piketty and Saez (2003), updated to 2008 by Piketty and Saez). The income share for those in the top 0.01% of the distribution has increased from around 0.7% in the early 1980s to 3.3% in 2008. Both the suddenness and the magnitude of this increase have shifted the perceptions about the importance of technological change as the cause of increased income inequality and raised the possibility of an important role for factors such as ". . . changes in labor market institutions, fiscal policy, or more generally social norms regarding pay inequality . . .".[2]

In this paper, we bring together a variety of data sets to show that, as first argued in Parker and Vissing-Jorgensen (2009), another fundamental shift has occurred for the income distribution in the US economy. During the past quarter century the incomes of high-income households have become much more sensitive to aggregate income fluctuations than they were previously. Prior to the early 1980s, the incomes of high-income households were more often than not less cyclical than the incomes of average households. But since around 1982, the incomes of high-income households— the top 1% of the income distribution and higher – have become highly exposed to the fluctuations in aggregate income, with the incomes of the top 1% being more than twice as sensitive to aggregate income fluctuations as the income of the average household.

The fact that the increase in the cyclicality of the top 1% coincides with the increase in the top 1% income share -- both starting in the early 1980s -- suggests that a common cause underlies both

[1] For wages and salaries, this change was first documented by Bound and Johnson (1992) and Katz and Murphy (1992). The increase that began in the 1970's and 1980's continued through the 1990's and into the 2000's, mostly in the top half of the wage distribution (Autor, Katz and Kearney (2008)). For consumption, see Cutler and Katz (1991), Attanasio and Davis (1996), and Heathcote, Perri and Violante (2010). While the survey information on households suggests that the increase in the overall distribution of inequality in expenditures has been significantly less than that observed for income, this may partially be an issue of measurement of expenditures. See, Parker, Vissing Jorgensen and Ziebarth (2010), and Aguiar and Bils (2010).

[2] Piketty and Saez (2003) p.3.

phenomena. We provide further evidence for a link between increased income inequality and increased income cyclicality at the top by documenting that i) across *groups* within the top 1%, higher average income is associated with higher income cyclicality in the 1982-2008 period, ii) across *decades*, the cyclicality of the top 1% increases decade by decade as the top 1% income share increases, and iii) across *countries*, increases in income cyclicality of the top 1% are highly correlated with increases in top 1% income shares.

We argue that a natural candidate cause of both changes is the rapid technological progress in information and communication technologies (ICT) since the early 1980s. We conjecture that ICT improvements have increased the ability of the most talented workers to handle more work or scale their ideas and argue that such a change would naturally cause both a the incomes of the highest paid to rise and an increase in the sensitivity of their earnings to economic fluctuations. The intuition is that individuals who have less decreasing returns to scale will operate at a greater scale (i.e. with more production inputs) and have lower ratios of revenues to production costs. Fluctuations in revenues over the business cycle therefore make their earnings fluctuate more in percentage terms.

Expanding on these contributions, the paper begins by focusing on the details of the change in cyclicality of the top income groups in the U.S. We use the Piketty and Saez (2003) (extended) data from tax records to show that the high level of top-income cyclicality occurred across all recent business cycles. The average income accruing to those in the very top of the income distribution has moved substantially more (in percentage terms) than the overall average in each boom and each recession since 1982, on average rising 5.0 percentage points more per year in each boom and falling 3.7 percentage points more per year more in each recession. Importantly, as noted, this increase in the cyclicality of the incomes of the rich occurs at almost exactly the same time as start of the rapid growth of the income shares of these high-income groups, suggesting a common causal factor behind both changes.

This main fact is not simply due to capital or entrepreneurial income. High-income households (those in the top 1%) have a significant share of income from wages and salaries (including bonuses) and this type of income has roughly the same exposure to fluctuations as their non-wage income. Wage and salary income is also a major source of the change in cyclicality of top incomes. Prior to 1982, the wage and salary income of high-income households was roughly acyclical while after 1982 it has been highly cyclical.

Further, while high-income households are more likely to have stock options our main finding is not driven by the endogenous timing of stock options. In the period since 1997 for which we have data, only about 20% of households in the top 1% have stock options (i.e. were given stock options during the last year and/or currently own stock options), and the income cyclicality of households in the top 1% is roughly similar if one leaves out households with stock options. To be clear, this evidence is in no way ruling out a causal explanation that involves the general rise in pay for performance. It simply ensures

that the fact is not spuriously generated by a correlation between the timing of options exercise behavior and aggregate fluctuations.

Finally, as a further piece of evidence that the high cyclicality is not simply endogenous timing of income without economic significance, we show that the cyclicality of the *consumption* of households in the top of the consumption expenditure distribution – specifically the top 5% by initial consumption-- is also greater than two. While data shortcomings are probably significant, these results provide additional evidence that our finding of large exposure of top incomes to economic fluctuations is not spuriously due to problems of accurately measuring the incomes of high-income households. Further, income data are available to 2008 and consumption expenditure data to February of 2009, and show a sharp decline in the income and consumption of the top group during the current recession, consistent with the prediction made in Parker and Vissing-Jorgensen (2009) based on cyclicality estimates that excluded the current recession.

How does this new fact relate to the prior literature that concludes that low-income households bear the brunt of recessions and benefit the most from expansions? Using the Current Population Survey (CPS), we show that many of the old facts about cyclicality are still true in recent data in that low-education households for example have more cyclical income than high education households. Nor does the greater cyclicality of the top 1% appear in the CPS prior to 1982. But even in the CPS data, when one ranks by percentiles in the income distribution, the top 1% have a higher cyclicality than the middle three quintiles of income distribution and than the rest of the top quintile in the period since 1982. The cyclicality of the top 1% is even higher measured using the CPS top 1% income series constructed by Berkhauser, Feng, Jenkins and Larrimore (2008, 2010) from underlying CPS data not subject to the top-coding applied to the public files. Furthermore, looking at the whole distribution using a data set from the Congressional Budget Office that merges the CPS with the SOI tax data on high-incomes, the same patterns are present. Consistent with the earlier literature, the sensitivity of the wage and salary income of households in the bottom two quintiles to fluctuations in aggregate (pre-tax, pre-transfer, pre-capital gains) income is higher than that of households in the third and fourth quintiles or households from the 80th to 99th percentile. But the top 1% is still highly cyclical. Thus the CPS confirms that top incomes are highly cyclical, but it is harder to observe this high cyclicality in the publicly available CPS data alone because of topcoding, and because cyclicality is high only for very high-income households. We conclude that the across the distribution of incomes, cyclicality is asymmetrically u-shaped – high for the bottom quintile of the income distribution, and the top 1% and even more cyclical for the very highest incomes.

Using the CPS also allows us to confirm that the high cyclicality of top incomes applies not just to incomes but also to households. That is, not only is the income earned at top of the income distribution

highly cyclical, households at the top of the income distribution in one year have income changes to the next year that are more cyclical than the income changes for households at other points in the income distribution.

The different cyclicalities of taxes and transfers at different points in the income distribution lead to different exposures of pre-tax, pre-transfer cash income and disposable income (income post-tax, post-transfer). We show that taxes and transfers significantly reduce the cyclicality of the bottom of the income distribution while making less difference to the cyclicality of the very top. Thus, the cyclicality of the top 1% relative to the rest of the population is even greater for disposable income than it is for pre-tax, pre-transfer income. It is important to emphasize that our results do not imply that the happiness or even utility of the top 1% is more cyclical than that of the average household or that of a poor household. We instead view our main finding primarily as providing a new fact that is informative about changes in the labor market for high earners and that is of particular relevance for theories of the recent rise in income shares of the high incomes.

Having established and explored our main finding for the U.S. we turn to evidence from Canada, which has a different tax system, slightly different culture, and better available information on top incomes from tax records. In the Canadian tax data, top income cyclicality is quite similar to that in the US during the past quarter century. The Canadian tax data is better than that available in the US in that we can track households not just income distributions, as in the CPS in the US. We show that households at the very top of the income distribution in one year have income changes to the next year that are more cyclical than the income changes for households at other points in the income distribution.[3] Finally, in Canada, the effect of government is neutral on the sensitivity of the incomes at the top of the income distribution, but there is some evidence it is more important in insuring poor households against aggregate fluctuations than is the case in the US.

Section IV of the paper presents evidence for a strong link between increased income inequality and increased income cyclicality at the top by exploiting variation across groups, decades, and countries. We split the top 1% into three groups (percentiles 99-99.9, 99.9-99.99 and 99.99-100) and document for the period since 1982 that across these groups, the higher the average income, the higher the income cyclicality. Furthermore, calculating cyclicalities by decade since 1970 we show that for a given top group, as the group's income share increases, the cyclicality of the group's income increase. Finally, across 15 countries comparing the period 1970-1985 to the period 1985-2000, countries which have

[3] In the CPS data the cyclicality is slightly less tracking changes for the same high-income households in consecutive years than when tracking the same percentiles but different households in consecutive years. In the Canadian data, the cyclicality is slightly higher when tracking the same households from one year to the next.

larger increases in the income share of the top 1% have larger increases in the income cyclicality of the top 1%.

Finally, in Section V we argue that the link between increased inequality and increased cyclicality suggests a common cause of the two phenomena and that a promising explanation for both is the rapid improvements in information and communication technologies. We present a simple production function example to show that skill-based technological progress that takes the form of lowering the degree of decreasing returns to scale for the highest skill individuals naturally leads to increases in both the incomes and cyclicality of these individuals.

I. The Changing Cyclicality of High Incomes

In this section, we lay out the changing cyclicality of the income that accrues to top percentile groups in the income distribution using the Statistics of Income (SOI) data compiled by Piketty and Saez (2003) (PS) and extended by Saez (2010). In doing so, we study the timing of the change in exposure documented by Parker and Vissing-Jorgensen (2009). We show that the dramatic increase in the cyclicality of high incomes started in the early 1980's, and that this increase is significantly due to earned income and not just due to the (potentially endogenous) timing of executive compensation. We also confirm that the prediction from Parker and Vissing-Jorgensen (2009) – that the incomes and consumption of the highest-income households would decrease the most in the current recession – turned out to be correct.

I.A The main facts

The main advantage of the PS data is that, since they are based on administrative data from the Internal Revenue Service (IRS) on individual income tax returns, the data have extensive and accurate measurement of very top of the distribution of the income in the US. However, since some low-income households do not file tax returns (even less so in earlier years) there is little detail on the low end of the income distribution and aggregate personal income data is used to fill in the incomes of the bottom 90% of the income distribution. Using this data, PS track the trend in the income share of the top percent, tenth of a percent and hundredth of a percent of the income distribution, information simply not available in survey-based datasets on wages and incomes. The detail available on tax returns allows the measurement of pre-tax (except employer payroll taxes), pre-transfer, cash income excluding realized capital gains. We are interested in excluding capital gains because our focus is on the timing of income and the data only contains measures of realized not actual capital gains.

The data has disadvantages however. Income excludes income paid as benefits (such as employer-paid health benefits and contributions to pensions) and also excludes of the employer share of

payroll taxes (Social Security, Medicare and unemployment taxes). Further, income data from tax records may be a biased measure of true income due to a variety of tax avoidance activity. Such a bias would create a problem for our analysis only if this bias varied with the business cycle, so that issues that matter to some extent for the measurement of longer-term trends – unreported income, income sheltered in 401(k)s and so excluded, and the distinction between business and personal income -- are not as significant concerns for our inferences.[4] However, since changes in avoidance behavior may follow from changes in tax rates, in much of our later analysis, we exclude years with large tax changes (such as 1986 and 1993) from our later analysis of this data, although significant changes in tax law do not have much correlation with booms and recessions.

The unit of observation in this data is a tax unit not an individual or household. There is a steady downward trend in the number of individuals per tax unit over time. This is a concern for measurement of trends if this ratio changes unevenly across income groups, but poses less of a concern for our measurement of business cycle exposure. Finally, the data are repeated cross-sections with little information on demographics or other information that could allow one to track income changes for a constant population of households. Thus, the changes in income we report are based on income and income rank for groups of households that overlap but are not completely identical across years.[5]

We begin our analysis of this data by presenting the percent growth in income across each "boom" and "recession" since 1917, where boom and recession are defined as periods during which NIPA, real, pre-tax, pre-transfer, personal income per tax unit was increasing and periods during which it was decreasing.[6] Generally, these periods line up with conventional recessions and expansions.

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[4] See Reynolds (2007) and Piketty and Saez (2007).

[5] We address each of these issues subsequently in CPS data and Canadian data, arguing that focusing on a constant set of households does not lead to materially different results for the cyclicality of the income of the top 1%.

[6] In terms of data, we use a NIPA income measure for total income instead of total taxable income from PS because tax reforms that lead to significant high-frequency changes in taxable income for top groups that could cause changes in average tax-based income, changes that might exaggerate our measures of exposure of high-income groups and changes that the BEA can account for in NIPA measures of pre-tax, pre-transfer income (prior to the availability of NIPA data from 1929 on we use the total income series from Piketty and Saez which for this early period is also based on National Accounts). In our analysis, this seems to be an important issue only for the 1986 tax reform (top group cyclicalities are higher in the 1980s if a tax based measure of aggregate income is used). As for the 1993 tax reform, Goolsbee (2000) provides evidence that executives timed the exercise of their options to take advantage of lower tax rates in 1992, thus seemingly raising aggregate income in 1992 at the expense of income in 1993. In NIPA data aggregate income growth was marginally negative from 1992-1993. In order to avoid artificially overstating our claim about extreme growth rates for top groups, we therefore include 1993 as a boom year in Table 1 even though NIPA aggregate growth was marginally negative. Note however that Liebman and Hall (2000) argue that the high incomes in 1992 may not have been tax motivated, and show that income-shifting is not evident in response the two tax reforms of the 1980's.

The dramatic increase in the exposure of high incomes to economic fluctuations began in the early 1980s. Table 1 shows the annualized percent change in average income per tax unit received by all tax units (column 1), the top 1 percent of the distribution (column 2), and a breakdown of the top percent by percentiles (columns 3 - 5). The final column reports the annualized percent change in the income per tax unit in the top 1% in excess of that of the all tax units. While the incomes of all income groups (by definition) rise in expansions and fall in recessions, since 1982, the incomes of high-income households have risen more in booms and fallen less in recessions than the incomes of the average household. According to the final column, since the end of the 1982 recession, the average income accruing to the very top of the income distribution has moved substantially more (in percent terms) than the overall average in every boom and every recession: on average rising 5.0 percentage points more per year in each boom and falling 3.7 percentage points more per year more in each recession.

Further, while one might think that it is natural for high incomes to be more cyclical, this was not so in the past. In the post-War period prior to 1982, the income of high-income households did not just move similarly to that of the average household, but more often than not it moved less with the business cycle than the income of the average household. In the post-War period (1947 on) prior to 1982, the income accruing to the top 1% co-moved less with the business cycle than the income of the average households in 9 of the 12 booms and recessions. Relative to total income per tax unit, the income accruing to the top 1% of tax units on average rose by 1.2 percentage points per year *less* in each boom and fell by 1.1 percentages points per year *less* in each recession. The difference between this period and the post-1982 period is economically huge (compared for example to fluctuations in aggregate income growth). Finally, in the period prior to 1947, when the data are of poorer quality and influenced by wartime policies, the income accruing to the top 1% does not appear systematically more or less cyclical than that of the average household.

A striking feature of this change, to which we later return, is that it coincides almost exactly with the acceleration in the share of income accruing to the highest earners, documented by PS. In PS, the income share of the top 1% reached its minimum at 7.74 percent in 1973, stayed roughly flat up to the early 1980s, and then rose by 0.36 percentage points per year thereafter to equal 17.67% in 2008. The coincident timing of the increase in top income shares and their increased exposure to fluctuations suggests a common cause for the increase in income share of very high-income households and the increase in the cyclicality of their incomes which in turn has implications for the underlying drivers of both facts, as we discuss in section IV and V.[7]

[7] It is important to note that the top income shares were large in the pre-War period, a period in which since we do not find evidence for higher cyclicality of the incomes of the top 1%. Piketty and Saez (2003)

Notice from Table 1 that as predicted by Parker and Vissing-Jorgensen (2009) incomes of the top 1% fell substantially more in the current recession -- at least based on 2007-2008 growth rates -- with an 8.4 percent fall for the top 1% of tax unit compared to a 2.6 percent fall for the average tax unit. The fall for the top 0.01% is even larger, at 12.7%. We emphasize that these numbers exclude capital gains and thus to a large extent are driven by wage and salary income which fell 3.3% from 2007 to 2008 for the average household, 6.0% for the top 1% and 17.5% for the top 0.01% (we elaborate on the role of earned income for the top groups below).

From here on, we characterize the cyclical exposure of any income group *i* by its ***beta*** or ***cyclicality*** which is the regression coefficient on the log-change in income per member in the population (Y) in a regression where the dependent variable is the log-change in income per member of income group (Y_i):

$$\Delta lnY_{i,t+1} = \alpha_i + \beta_i \, \Delta lnY_{t+1} + \epsilon_{i,t+1}$$

The beta or cyclicality is thus the elasticity of the income of group *i* with respect to average income so that if average income growth is 1%, we expect the income of group *i* to grow by β_i %.

Panel A of Table 2 presents our main finding on the change in cyclicality in terms of beta's for the top 1% of the distribution and sub-groups of the top 1% across periods. The cyclicality of the top 1% and top 0.01% of tax units are 2.39 and 3.96 times that of the average tax unit respectively post-1982. [8] These levels of cyclicality are very large increases relative to prior periods: in the periods before 1983, the cyclicality of all top groups are less than 1, except the top 0.01% for the period from 1917 to 1947.

These different betas and the larger share of income earned by top groups together translate into a disproportionate fraction of aggregate income changes falling on high-income households. Panel B of Table 2 shows how much higher average income in the top groups are relative to aggregate income per tax unit. The income per tax unit in the top groups was relatively high in 1917-1947 (137 times the average for the top 0.01%), relatively lower from 1948-82 (54 times the average for the top 0.01%) and relatively high again since 1982 (169 times the average for the top 0.01%). To estimate the average fraction of aggregate income changes borne by a group, we regress (Dollar change in real group income per tax unit) × (Group share of population)/(Lagged aggregate real income per tax unit) on the growth rate of aggregate income per tax unit. Across all groups, the numerators sum to the total real dollar change in

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argue that different factors drove the income shares of the top 1% during the period of declining inequality and during the period of increasing inequality, see our discussion in Section IV.

[8] It is also worth clarifying that there is no mechanical tendency for a group to become more exposed to the cycle as it becomes a larger share, in fact the opposite. In the limit, as a group's income becomes a larger and larger share of all income, their exposure to the aggregate tends to one.

income per tax unit, so the regression coefficients across a complete set of non-intersecting groups would sum to one.

Because of both their larger income share and larger income cyclicality, the top income groups are more cyclically exposed since 1982 than in any of the previous periods. Since 1982, the fraction of income changes borne by the top 1 percent and 0.01 percent are 28 percent and 6.3 percent -- or 28 times and 630 times their share in the population -- respectively.

I.B Wages and Salaries

To re-iterate, in all of these results, the incomes of high-income groups are measured as cash income before government transfers and taxes and the income changes are not contaminated by any endogenous timing of realizations of income reported as capital gains. That said, our results so far include income from all other taxable sources – such as entrepreneurial income, dividend, interest, and rental incomes, as well as most executive compensation. Thus, we now show that these facts are not driven by capital income or endogenous timing of executive compensation - the top of the income distribution is not more cyclical because of high capital income or more exercising of stock options in booms.

Table 3 shows, for the post-War period up to 1982 and the period since, the average share of each group's income that is of each (IRS-defined) type (Panel A) and the cyclicality of each type of income (Panel B).[9] This table shows three main points.

First, high-income tax units have only slightly less wage and salary income than average. In the period since 1982, wage and salary income comprises about two-thirds of income for the average tax unit, as much as 60 percent for the top 1%, while it constitutes 40 percent of income even for the top 0.01%.

Second, and more important, since 1982 the wage and salary income of high-income groups is much more cyclical than for all tax units. To maintain comparability across sources of income and t in the definition of an economic fluctuation, across the various sources of income, cyclicality is always defined with respect to fluctuations in aggregate pre-tax, pre-transfer income excluding capital gains. Since 1982, the wage and salary income of the top 1% (top 0.01%) has a cyclicality of 2.4 (6.2), while the cyclicality is less than one for all tax units. The cyclicality of the wage and salary income of the top 1% is about the same as the cyclicality of their overall income (and thus as the average cyclicality of their other types of income), while the cyclicality of the wage and salary income of the top 0.01% is higher than the cyclicality of all their other types of income.

[9] Following PS, wages include pensions and bonuses and "[e]ntrepreneurial income is profits from S-Corporations (entities not subject to corporate taxes and taxed only at the individual level) plus profits from Partnerships plus profits from sole proprietorship businesses (Schedule C income) plus farm income."

Third, the change in cyclicality of the top 1% is to a large extent driven by the rise in the share of wage and salary income and the change in its cyclicality, with a smaller role of increased cyclicality of dividend and interest income. Panel A of Table 3 shows that the share of wage and salary income rose by 15 percentage points for the top 1% across periods. Panel B of Table 3 shows a dramatic increase in the cyclicality of the wages and salaries of the top 1% from 0.36 in the 1947-1982 period to 2.4 in the 1982-2008 period. Across periods there is also a substantial increase in the cyclicality of dividend and interest income for the top 1%, but these two sources of income are smaller shares of income. The cyclicality of the top 1%'s entrepreneurial income is stable around two for both 1947-1982 and 1982-2008. For the top 0.01%, the change in cyclicality is more widespread across categories, but again the largest role is played by a dramatic increase in the cyclicality of the group's wage and salary income.

In sum, the top of the income distribution has a significant share of wage and salary income, and this share has risen over time and become more exposed to fluctuations in aggregate income. But earned income for high-income households is different from the earned income of the average households (besides just being larger). In particular, the timing of income earned through the granting of stock options for example is under the control of some high-income households. This raises the possibility that there has been a change in the extent to which high-income households can or do alter the timing of their compensation so that it is now more cyclical. By focusing first on income excluding capital gains and then more narrowly on wage and salary income, we have shown that the change in income cyclicality for the top groups is not driven by capital income. But the rise of stock options coincides with the rise of income inequality, and the vast majority of stock options are non-qualified options which are treated for tax purposes as wage and salary income when exercised.[10, 11] To be clear, the rise in performance-based compensation is surely part of the explanation for the main findings of this paper, not a bias. But we are concerned about the possibility that the endogenous timing of the exercise of stock options might make our measure of realized income excessively pro-cyclical even if actual economic earnings were not.

To address this issue, we show that the cyclicality of the incomes of high-income households without stock options appears to be similar to that of all households. We use the Survey of Consumer Finances (SCF) for years 1998, 2001, 2004, and 2007, which contains information on wealth and income for a stratified random sample of households and oversample rich households. These years of the SCF

[10] Qualified stock options that are taxed as capital gains when exercised and when sold provided they are held for a year and the stocks purchased with them are held for another year. The difference between the strike price and the market price however can count towards the AMT.

[11] We do not deal with the accounting treatment of stock options for financial reporting, which differs from the tax treatment for the individual; for example it allows corporations to deduct more on their tax returns than they expense on their financial statements.

also include the responses to two questions about stock options. The first question asks whether the household received stock options during the past year, the second asks whether the household has a valuable asset not otherwise recorded in the interview and then asks the household to state what it is, with one of the possible responses being that it is stock options. SCF data are not top coded with the exception that a household is dropped if it has a net worth greater than the least wealthy person in the Forbes list of the wealthiest 400 people in the US.[12]

Panel A of Table 4 shows that on average about 20% of households in the top 1% of the income distribution have stock options. The final column of Panel B shows the cyclicality of the income growth (of non-capital gains income, based on aggregate income calculated from SCF data, and using 3-year real log growth rates) of different income groups of households and with smaller magnitude. The high cyclicality of the top 1% confirms our main findings of higher cyclicality for higher incomes, although now for households. Importantly, the higher measured cyclicality is as large for high-income households without stock options (Panel C) as for all high-income households. When total average income falls by one percent, the average income of households in the top 1% fall by 1.85 percent on average and by 1.78 percent for those in the top 1% who do not have stock options. Thus, we conclude that the timing of executive stock options does not appear to be the cause of the high cyclicality of incomes of high earners.

I.C Consumption

We next turn to the question of whether the high cyclicality of income for high-income households leads to a high cyclicality of consumption spending. This evidence constitutes a further test of our main finding as well as evidence on welfare implications and the extent to which these fluctuations are due to endogenous timing of income. Unfortunately, the available survey data on expenditures do not contain many high-income and high-consumption households and also has issues of reporting and top-coding.[13] Nonetheless, our analysis shows higher cyclicality for high consumption households.

We use the Consumer Expenditure Survey (CEX) to construct measures of household-level spending from January 1982 to February 2009 for different groups ranked by their interview expenditure level in the previous quarter. Our consumption measure is non-durables plus some services, with the main categories of excluded services being health care, education and housing (except the nondurable and service components of household operations). For each household we construct log-consumption growth

[12] This should not affect our results substantially since the top 400 families only correspond to a tiny fraction of even the top 0.01%.

[13] The way the Consumer Expenditure Survey is structured, the respondent burden rises with expenditure level. More interviewee time is required to report more expenditure. Further, there is evidence that under-reporting rises with expenditure level. See Parker, Vissing-Jorgensen, and Ziebarth (2010) and Aguiar and Bils (2010).

rates from one quarter to the next and average these across households in a given group (using survey weights). We then construct annual log-growth rates by summing four quarterly log-growth rates. We regress the four-quarter log-growth rates in consumption per household for each group on the log-growth of NIPA Personal Income (i.e. pre-tax pre-transfer income), NIPA Disposable Income (i.e. post-tax post-transfer), and NIPA Personal Consumption Expenditures on nondurables and services, as well as CEX average consumption for all households (using our consumption definition). Table 5 shows that the sensitivity of the consumption of households in the top 5% (ranked by initial consumption) to aggregate income fluctuations is between 2.0 and 2.7, depending on the income measure used, while the sensitivity to aggregate consumption fluctuations is above 4. [14] This compares to a sensitivity of the consumption of the full set of CEX households substantially less than one with respect to NIPA incomes.[15]

The implications of this higher cyclicality are born out in the expenditure response of high-consumption households to the current deep recession. Figure 1 shows that the CEX consumption in the recent recession has fallen substantially more for high-expenditure households, about 10% from 2007 to 2008 consistent with the prediction made in Parker and Vissing-Jorgensen (2009) that the consumption of the top groups would decline more than that of the average household in the current recession.[16]

These results provide additional evidence that the high cyclicality of top incomes is not due to the endogenous timing of compensation but instead impacts standard of living for top households. It is important to emphasize, however, that presumably a given percentage decline in expenditure has greater welfare implications for a low-expenditure household than a high-expenditure household. This point, along with the lack of foundation for interpersonal welfare comparisons, suggests that one not conclude that high-income households suffer more from recessions than low-income households. That said the magnitude of the changes that we document provide potentially important information about the evolution of the labor market for highly compensated individuals.

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[14] The sensitivities of top household consumption to NIPA consumption are a bit lower than similar statistics for a shorter sample reported in Parker and Vissing-Jorgensen (2009). Rather than being due to sample, the difference is due to the revisions to NIPA data, especially in the NIPA price indexes.

[15] We note that data shortcomings in the CEX are far more severe than the SOI data, with high income groups generally thought to be underrepresented in the CEX and some CEX consumption categories top-coded.

[16] For readability the figure focuses on annual data, calculated as within-year averages (using survey weights) of quarterly consumption values across households in a given group (times 4). Furthermore, because we are interested in showing the level of growth rates, not only their beta with respect to aggregates, we sort households based on current consumption rather than consumption in the previous quarter. The latter is theoretically meaningful but with measurement error in consumption leads to a mechanical negative bias in growth rates for top groups. As discussed in Parker and Vissing-Jorgensen (2009) this does not impact beta estimation when using log-growth rates but would bias this figure.

To conclude, we find a dramatic increase in the cyclicality of top incomes. This increase occurs for both total (non-capital gains) income as well as for wage and salary income alone, and top groups' expenditures are also highly cyclical during the post-1982 period.

II. Cyclicalities Across the Full Income Distribution and The Impact of Transfers and Taxes

In this section, we use data on the full income distribution of households to reconcile our findings with the conventional wisdom that low-income households are the most affected by the booms and recession. Further, in studying the entire distribution, we also characterize how the tax and transfer system changes the cyclicality of take-home income. Finally, we track individual households rather than the top incomes for partially different households across years and show that, in recent years, the incomes of the group of households in the top 1% in one year is highly cyclical from this year to the next.

II.A Relation to the Stylized Facts

Previous studies have shown that the incomes of low-income households are more cyclical because unemployment falls primarily on the poor (Clark and Summers (1981)) while the wages of low-wage households have approximately the same exposure to the business cycle as that of high-wage households (Solon, Barsky and Parker (1994)). The flip side of this, that economic booms raise the standards of living of low-income households by more than high-income households, is often cited as a reason to pursue policies to spur an aggregate recovery over policies to insure low-income households (Card and Blank (1993), Hines, Hoynes, and Krueger (2001)). Blank (1989) for example concludes that ". . .the income distribution narrows in times of economic expansion."

There are three reasons why the conventional wisdom might have under-estimated the cyclicality of top incomes: the time period -- high-income cyclicality only rose in the 1980's; the focus was not on the very top of the distribution; and top-coding of incomes masks changes in income at the top end of the income distribution in the main data sets used in this literature (such as the Panel Study of Income Dynamics and the Current Population Survey (CPS)). In this section, we first show that income cyclicality by race or education group in the CPS supports the conventional view even in the more recent period. The cyclicality of the top 1% also appears low in the CPS pre-1982. However, after 1982, even in this conventional survey dataset which has topcoded high incomes, high-income cyclicality is observable for the top 1% and even higher cyclicality can be measured from versions of the data not subject to the top-coding imposed on the public-release files. Finally, to further overcome the issue of topcoding, we study a data set from the Congressional Budget Office (CBO) that merges the CPS and SOI data and show that the tails of the income distribution are more exposed than the middle since 1980.

To begin, we follow some of the earlier literature and track income groups using March Current Population Surveys (CPS) for years 1982 to 2008. The unit of observation is a census-defined family and the definition of income is the standard Census definition which is pre-tax, post-transfer income. We drop changes across years with major topcode changes, and note that after 1996, the data provides the mean income for families above the topcoded amount, while before they simply report the income topcode amount in place of the unknown actual income when topcoded. Following some of the earlier literature, panels A and B of Table 6 study the exposure of incomes of minorities and low-education households as lower-income households and white and high-education households as higher-income households. Even during the recent period from 1982 on, the conventional facts about cyclicality hold in this analysis in that low-education households for example are more exposed to economic fluctuations than high-education households. Black and whites have a similar exposure of family income. But not that even in the CPS data, the highest education group has a larger exposure than the middle two groups.

Turning to the top 1%, the first column of Panel C shows that up to 1982, the top 1% of income in the CPS was less cyclical than the average, with a beta of 0.67. Thus the previous literature is entirely correct about the period is studies. A somewhat different picture emerges when one ranks by percentiles in the income distribution and focuses on the top 1% in the period since 1982. Using the publicly available CPS files, the top 1% of the income distribution has an income cyclicality greater than two which is higher cyclicality than any education group. And using internal data from the CPS as compiled by Burkhauser, Feng, Jenkins, and Larrimore (2008, 2009), which is only subject to high-end censoring due to internal record-length, the CPS survey data shows an even higher cyclicality of the top 1% and one that is very similar to that of the PS data from Table 3 when measures in terms of tax units.[17] We conclude that conventional survey data shows that top income groups (by family income) have high cyclicality of income in recent years.

II.B. Cyclicalities Across the Full Income Distribution

We next turn to data that integrates the data used so far. We use data from the Congressional Budget Office (2008) that merges the IRS SOI data and data from the Current Population Survey (CPS) to construct income per effective householder for each individual in the US.[18] Consistent with our analysis of the CPS and with the earlier literature, we document that the cyclicality of the wage and salary income

[17] To use this data which report shares, we replace the share in the public data with the share in the Burkhauser et al. data and recalculate total income and use this total to measure fluctuations and changes in average income of the top 1%. This implies greater error when using a top 1% based on tax units instead of families.

[18] The effective number of households is simply the square root of the household size.

of households in the bottom two quintiles to fluctuations in aggregate income is higher than that of households in the third and fourth quintiles or households from the 80th to 99th percentile, but still lower than that of the top 1%.

The two most important differences between the SOI-CPS data and the SOI data used in Tables 1, 2 and 3 are the unit of analysis and the definition of income used to sort households. In the SOI-CPS data the unit of analysis is the individual not the tax unit and the income measure used to construct percentile groups is pre-tax, *post-transfer* income *including* capital gains (per effective householder), with imputed taxes added to household income (employer contributions to Social Security in proportion to wages and corporate taxes in proportion to capital income).

In terms of advantages, as noted, the SOI-CPS data measure income per effective householder and rank individuals rather than tax units. Second, the data provide information on incomes throughout the income distribution, not just information on households that file incomes taxes. Third, the data contain information on taxes and transfers, information we use subsequently to better understand the role of government in the cyclicality of disposable income across groups.[19] The main disadvantage relative to the SOI data alone is that the income definition used to sort households into quintiles etc. includes capital gains, so households are sorted on a different measure of income than households were sorted on in the SOI data we used (pre-tax, pre-transfer income excluding capital gains). The second significant disadvantage is that the time-period covered by the data is short. The data are only available from 1979.[20]

Table 7 shows statistics about the income distribution and cyclicality across quintiles, in detail for the top quintile, and then in further detail for the top 1%.

First, Table 7 confirms our earlier findings for top income groups for this different set of choices about income measurement and unit of analysis. Similarly to Panel B of Table 2, the top 1% in the SOI-CPS data (sorted as explained above) earn about ten times the average pre-tax, pre-transfer income excluding capital gains, and the top 0.01% earn about 140 times the average income (Panel A). Panel B shows that all household groupings besides the top 1% get 60-70 percent of their income from wages and salaries. This number drops to 44% for the top 1% and 25% for the top 0.01%.[21] The first two rows of Table 7 Panel C confirm our main findings on post-1982 cyclicality of top income groups (compare to

[19] The tax information comes primarily from the SOI data that cover all but the lowest income groups, and taxes are inferred for the lowest income groups. The information on benefits comes from the CPS which covers well households that receive benefits.

[20] Since this data has different advantages and disadvantages relative to the IRS SOI data alone, the analysis of this section also provides some evidence on the robustness of our main findings.

[21] The somewhat smaller role of wages for the top groups compared to Panel A of Table 3 is likely due to the SOI-CPS groups being defined using incomes that include capital gains.

Panel B of Table 3). For the top 1%, both wages and salaries and overall pre-tax, pre-transfer income per householder excluding capital gains are more than twice as cyclical as the average income of all households, and for households in the top 0.01%, both wages and salaries and overall income are around five times as cyclical as average.

Second, the bottom end of the income distribution is also more cyclically exposed than the average, although not as much as the very top. The bottom two quintiles of households earn 18 and 47 percent as much as the average respectively.[22] And across the income distribution apart from the top 1%, 60-70% of income comes from wages and salaries. The bottom two quintiles have significantly higher exposure to the cycle than all groups below the 95th percentile of the income distribution. This is true for wage and salary income alone (first row of Panel C), and all income (pre-tax, pre-transfer, pre-capital gains) (second row of Panel C). Thus, even in this period of high exposure of very high-income groups, it is still the case that households in the lowest quintile income group has a higher exposure to aggregate fluctuations than households in the middle part and upper-middle part of the income distribution.

The cyclicality of income is asymmetrically u-shaped, higher than average for the bottom two quintiles, lower in the middle and upper-middle part of the income distribution, and dramatically higher for the top 1% and 0.01%.

II.C The Cyclicality of Post-Tax, Post-Transfer Incomes

The different cyclicality of the incomes of different groups in the income distribution leads to different cyclicality of taxes and transfers, and therefore different cyclicality of disposable income and ultimately different cyclicality of consumption. We document next that taxes and transfers reduce the cyclicality of income for almost all groups, but do not noticeably change the income cyclicality of the very top income groups. The main impact of taxes and transfers on cyclicality is that transfers substantially lower the cyclicality of incomes of the bottom two quintiles. We also investigate the role of capital gains.

First, Panel A of Table 7 shows that adding transfers to our definition of income raises the incomes of the lowest two quintiles, but makes a small difference to the incomes at the top (the ratio of top to average incomes falls slightly since aggregate income is higher including transfers). Next, adding capital gains to income works similarly but at the other end of the distribution – adding capital gains mainly increases the incomes of the top groups such that the ratio of group income to average income

[22] Note that the differences in these percentiles are reduced because the income reported is different from that used for sorting into percentiles.

increases for the top groups and falls for the bottom groups. Finally, subtracting taxes lowers the incomes of top groups the most and so raises the relative incomes of the bottom quintiles.

Second, Panel C of Table 7 shows that the cyclicality of the bottom income groups is significantly reduced by transfers, not altered by including capital gains, and further reduced by taxes. In terms of cyclicality of disposable income (income post-tax post-transfer including capital gains) at the bottom of the distribution, the cyclicality of income for the bottom quintile changes from 0.94 for pre-tax, pre-transfer, pre-capital gains income to 0.56 for post-tax, post-transfer income including capital gains, with the difference driven by primarily transfer income, which is large in magnitude for the bottom quintile (about 42% of the pre-tax, pre-transfer, pre-capital gains income) and countercyclical. Focusing just on the role of transfers, the baseline cyclicality of pre-tax, pre-transfers income excluding capital gains is around 1 for the bottom two quintiles and is 2.6 for the top 1%. Adding transfers to income reduces the cyclicality of the bottom two quintiles to 0.59 and 0.71 respectively, and makes little difference elsewhere in the distribution. Transfers also reduce the cyclicality of middle income groups, although less than low-income groups, while transfers does not affect the cyclicality of incomes above the 90th percentile.

Third, the cyclicality of the upper-middle and top-income groups is significantly raised by capital gains while other factors matter little. Capital gains increases the cyclicality for all groups, and its importance rises steadily with income, corresponding to the larger fraction of incomes coming from capital gains for higher-income groups. Including capital gains raises the cyclicality of the top 1% from 2.58 to 3.45. Notice that the betas reported in Panel C are all with respect to aggregate pre-tax, pre-transfer income excluding capital gains. The post-tax, post-transfer income including capital gains of the top 1% has an even higher cyclicality of 4.15 with respect to aggregate post-tax, post-transfer income including capital gains.

Fourth, taxes lower the cyclicality of income for almost all groups modestly, by about 0.1.

Overall, the cyclicality of the middle income groups is the most stable across different income measures relative to that of the top and bottom of the income distribution. The cyclicality of the lowest income groups is significantly reduced by transfers, and the cyclicality of the top income groups is significantly raised by including realized capital gains.

II.D The Cyclicality of Same-Family Income

So far, because we use the US data sets that have good coverage of the top end of the income distribution, our analysis measures the cyclicality of the top 1% in the income distribution, a group which presumably contains somewhat different tax units or households from year to year. That is, these datasets sort households or tax units into groups based on percentiles of current income and tracks the income

distribution. This approach raises the possibility that our main result could be different than the cyclicality of the incomes of the group that are in the top 1% in the first year. Such a difference could arise from a correlation between individual income risks and aggregate fluctuations. In this subsection we show that the large expose of the top 1% in the income distribution is robust to focusing on a constant set of families from one year to the next.[23]

We link families across our March Current Population Survey extracts for years 1982 to 2009 (which we also use in Section II.A). In each year, we categorize families into percentiles, and then take the subsample of those that can be tracked to the following survey year and calculate the change in average income for each income group the entire population from this set of families. Thus, we construct annual log-change in average income for groups of families that, in the first year of the change, are all within a certain part of the income distribution.

Table 8 is constructed based on the public CPS data. Panel A shows the distribution of income cyclicality across the income distribution based on groups that contains partially different sets of families from year to year. Panel B tracks the income changes across each pair of years for families at a given point in the distribution in the first year (in other words, we follow families that are in a given group in year t-1 to year t). The panel data confirms that families in the top 1% of the income distribution have a much higher cyclicality than the average family, and a similar cyclicality to that estimated without using panel data. We also see the same u-shape in the panel data, so that families at the bottom of the income distribution also have more cyclical income than the average family. In fact, when excluding years with major tax changes, the true panel data suggests that the cyclical exposure of the incomes of families at the bottom of the distribution is even higher than at the very top, although the statistical uncertainty is so large that this difference is not significant. (And we note again that the CPS, especially the publicly available data, does not measure the incomes of the top 1% very well.)

To summarize the main results of Sections II.A to II.D, first, it is harder to observe the high cyclicality of the top 1% in conventional datasets, notably in the CPS alone, because of topcoding and the fact that cyclicality is high only for very high-income families. Second, in looking at the entire distribution of incomes, cyclicality of incomes pre-tax, pre-transfer, excluding capital gains is asymmetrically u-shaped – high for the bottom two quintiles of the income distribution, then low up to around the 95th percentile (even up to the 99th percentile when focusing on wages and salaries), and very high for the top 1% and especially the top 0.1% and top 0.01% of families. Third, transfers significantly reduce the cyclicality of the bottom of the income distribution, equating cyclicality across the distribution

[23] We also note that our consumption analysis focused on a constant set of households from one year to the next, though the CEX data does not contain sufficient coverage of the very top to decompose the top 5% of households.

except for the very top. The realization of capital gains increases the measured cyclicality of incomes of the very top, while taxes and transfers make little difference at the very top. Finally, the high cyclicality of the top 1% is robust to focusing on families that are in the top 1% in year t-1 and following the same families to year t.

III. Canada

Saez and Veal (2005) show that Canada has also had a large increase in income inequality at the high end of the income distribution that roughly coincides temporally with the U.S. increase but that is slightly less extreme than the US increase. Canada has a slightly different tax system and culture but presumably is impacted by the same changes economics factors such as technology, trade etc. as the U.S. Thus, to provide both another observation on the cyclicality of top incomes and to provide information about possible causes, we analyze the cyclicality of Canadian top incomes. There are also a number of ways in which the Canadian data is better than the US data.

Our data come from the Longitudinal Administrative Databank, which contains records for all tax returns filed in Canada from 1982 to 2007. Working with Statistics Canada, we extracted information on the average incomes of tax units in different groups in the income distribution, both as repeated cross-sections and tracking the households in different groups in the income distribution in a given year into the following year, as we were able to do in the CPS. Further, we obtained income by type of income, as in the SOI data from Piketty and Saez, and also tax and transfer information, as in the SOI-CPS data from the CBO. We asked Statistics Canada to rank households and construct groups based on income calculated from pre-tax pre-transfer income excluding capital gains.

Table 9 contains our analysis of the exposure of pre-tax, pre-transfer income excluding capital gains for different income groups to aggregate income fluctuations for both sampling procedures (same households from year to year, or not).

First, Panel A of Table 9 shows that income inequality in Canada is similar for the top 1% relative to the US, but slightly less for the top 0.1% and 0.01%, although this point should be qualified by possible differences in tax laws and tax-avoidance by high-income households between countries.[24] Second, compared to Table 2, Panel B shows that the top 1% in Canada and the US get similar shares of their income from wages and salaries, about 60%. However, in Canada, the top 0.01% get 70% of their income from wages and salaries while this number is only 40% in the US. In Canada, while the share of earned income peaks for the upper-middle class, it is higher for the top quintile than the bottom two. At

[24] Compared to Table 2, the top 1% At the low end, the difference between Table 7 and 9 are likely significantly due to the fact that in Table 7 the income distribution and household rankings are based on an income measure that includes capital gains.

the ends of the income distribution, the wage and salary share is 66% for the bottom quintile, 58% for the top 1% and 70% for the top 0.01%.

Turning to our main point of interest, Panel C shows that the exposure pattern found in the U.S. data is also present in the Canadian data. While the top 1% and 0.01% have cyclicalities of 2.4 and 4.0 in the recent period in the U.S. (Table 2 Panel A), in Canada these cyclicalities are 1.6 and 3.3 respectively.

Canada has also seen in increase in inequality at the top end of the income distribution, and it also has high cyclicality of top incomes in the recent period.

Fourth, and what we could not observe in the US tax data, Panel D of Table 9 shows that in Canada the income changes that occur for the households in the top 1% in one year from that year to the subsequent year are highly exposed to the fluctuations in aggregate Canadian income. Unlike our analysis of the CPS, the exposure for the same households over time is actually greater than the income exposure for the income received by the top 1% in each year, although again not statistically significantly so (and within the top 1% the impact of focusing on a constant set of households differs across the three sub-groups).

Finally, Table 9 shows the effect of capital gains, taxes and transfers in Canada, as Table 7 studied for the US. In Canada, the government has little effect on the sensitivity of the incomes at the top of the income distribution, both when measured in terms of the average income in the top of the distribution and the change in average income for households starting at the top of the distribution. At the bottom end of the distribution the effect of taxes and transfers is far larger in Canada than in the U.S. In the cross-sectional data in Canada, the exposure of the lowest income quintile pre-tax pre-transfer is over 6 -- much larger than the U.S. -- while the exposure after transfers is 0.19 – 0.23 – similar to the U.S.[25] While one might be tempted to credit the Canadian welfare state, it seems unlikely that the US and Canada are truly so different in the exposure of pre- versus post-transfer incomes. Instead, the large impact of transfers on the cyclicality of the bottom group in Canada is likely due to a larger fraction of bottom Canadian households filing taxes compared to the US. This results in a lot of filers with essentially zero pre-tax, pre-transfer incomes in the bottom group in Canada. With very low average incomes, even moderate transfers can change the cyclicality substantially.

IV. The Link Between Income Cyclicality and Income Shares of High-Income Households

Having explored in detail the rise in the cyclicality of high incomes in the last three decades, we now show that the increase in the cyclicality of high-incomes is closely related to the rise in the share of

[25] In the U.S., the corresponding numbers are 0.94 and 0.19 – 0.56.

income accruing to the top of the income distribution. Specifically, we present four pieces of evidence that *the higher the level of income inequality, the higher the income cyclicality of the rich*. We exploit variation across groups, time and countries. First (as already discussed), the increase in the income share of the top 1% starts at almost exactly the same time as the increase in the income cyclicality of the top 1%. Second, in the post-1982 period, the higher a group is in the income distribution (within the top 1%), the higher is the group's income cyclicality. Third, across decades, as the income share of a given top group increases, the cyclicality of its income increases. Fourth, across countries, countries with larger increases in the income share of the top 1% have larger increases in the income cyclicality of the top 1%. The tight link between inequality and cyclicality at the top end of the income distribution in the past quarter century strongly suggests that these two phenomena share a common cause.

First, as already alluded to, the top 1% income share starts rising precisely when income cyclicality for the top 1% rises above one. Table 1 documents that the increase in the cyclicality of the income of the top 1% started in the recovery following the 1982 recession. Figure 2 complements this by plotting the income shares from PS data which show that the dramatic rise in top income shares also started in the early 1980s.[26]

Figure 2 also shows that cyclicality and share of top incomes are not linked in the first half of the twentieth century: the top income shares were large in the pre-War period, a period in which since we do not find evidence for higher cyclicality of the incomes of the top 1%. Piketty and Saez (2003) argue that different factors drove the income shares of the top 1% during the period of declining inequality and during the period of increasing inequality. PS argue that the decline in the income share of the top 1% and higher from around 1928 to 1960 was driven in large part by declines in capital income (income from dividends and interest) due to a combination of the Great Depression and large tax increases enacted to finance the wars, including large increases in corporate income taxes that mechanically reduced distributions to stockholders. In contrast, an increase in wage and salary income is the key driver of the more recent increase in the income share of the top 1%. Both the lack of correspondence between top 1% income share and cyclicality and different income composition in the earlier period suggests that the change in top income shares from 1928 to 1960 was not driven by the same factors as the more recent changes. This is consistent with our explanation for the recent changes. The ICT revolution did not happen in reverse in the early to mid part of the twentieth century.

Turning to our second piece of evidence of a link between the cyclicality and the income shares of the top 1%, for groups further up the income distribution within the top 1%, there is both a larger

[26] As for Table 1, 2 and 3, these shares are for income excluding capital gains and the data come from Piketty and Saez (2003) as updated in Saez (2010).

income share (relative to the size of the group) and a larger income cyclicality during the period since 1982. Figure 3 graphs the cyclicality of income for each income group on the left axis, and the ratio of that group's average income to the average income of all tax units on the right axis.[27] Panel A focuses on incomes pre-tax, pre-transfers and excluding capital gains, and, since we argue that the high cyclicality of wage and salary income is a key driver of the high overall cyclicality of the incomes of the top 1%, Panel B focuses on wage and salary income. It is apparent from both graphs that groups that are higher up in the income distribution within the top 1%, have both higher income shares and higher income cyclicality. Inequality at the top is extreme, with the incomes of the top 0.01% being more than 100 times the average income. Similarly, cyclicality at the top is extreme, with the income cyclicality of the top 0.01% being about 4 times the cyclicality of the average (6 times when focusing on wages and salaries). This again suggests a link between the level of income inequality and income cyclicality.

Third, over time since the start of increasing top-shares, as a group's income share has increased, so has its cyclicality. To show this, we estimate betas for each high-income group and decade, and the ratio of each group's average income to the average income of all tax units for each group and decade. Figure 4 plots decadal betas against decadal income shares in separate graphs for each income group. Panel A focuses on pre-tax, pre-transfer income excluding capital gains while Panel B focuses on wage and salary income. For each group, both cyclicalities and average income ratios increase over time, leading to a positive association between a group's cyclicality and its average income ratio. This pattern is present both in overall income (pre-tax, pre-transfer, excluding capital gains) and in wage and salary income. In Panels A and B the bottom right graph plots the four decades for each of the three groups (99-99.9, 99.9-99.99, and 99.99-100) in one picture. It is clear that the relation between average incomes and cyclicalities is strengthening over time, with no apparent relation in the 1970s and a strong relation in the 2000s.

Finally, we show that countries with the largest increases in the income shares of the top 1% also experience the largest increases in the cyclicality of the incomes of the top 1%. We use the dataset constructed from tax records from Atkinson, Piketty and Saez (2010) which contains annual time-series for the incomes of the top 1% for 22 countries. We focus on relating changes in top-income shares to changes in top-income cyclicality rather than on post-1982 levels of each variable because of the differences across countries in tax systems and the consequent differences in measurement of top income shares, as well as the host of other differences that exist across counties.[28] We compare the last fifteen

[27] From Tables 2 and 3 and the same calculations for other income groups.

[28] For example whether the unit of analysis is the family or the individual. See Atkinson, Piketty and Saez (2010) Table 3 and related text.

years of the dataset 1985-2000, with the previous 15 years, 1970-1985. Of the 22 countries, 14 have at data for at least 5 years in each of these periods (of these 14 countries all but two have data for 12 or more years in each of these periods, with Spain and Portugal having fewer years of data in the 1970-1985 period).[29] As shown in Figure 5 Panel A there is a positive relation between the increase in top 1% betas and the increase in top 1% income shares. The relation is statistically significant and has an R^2 of 0.26. A data issue of particular concern is that for 4 of the 15 countries income includes capital gains. For robustness we drop these four countries (the UK, Australia, New Zealand and Norway) in Panel B, and again find that countries in which the income shares of the top 1% have increased the most also have seen the largest increases in the cyclicality of the incomes of the top 1%.

Overall, four different approaches all suggest that during the post-1982 period *the higher the level of income inequality, the higher the income cyclicality of the rich*: the timing of the start in the increase in the top 1% incomes share coincides with the increase in the top 1% cyclicality; higher average income is associated with higher income cyclicality across top income groups; increases in average income for any given top income group are associated with increases in income cyclicality across decades; and across countries, the larger the increases in the income share of the top 1% over time, the larger increase in the cyclicality of the income of the top 1%.

V. The Labor Market, Technical change, Changes in High-income Shares and Cyclicality

In the first two sections of the paper, we document a large increase in cyclicality at the top end of the income distribution. The previous section shows that this increase empirically is closely tied to recent increases in income shares at the top end of the income distribution, across time, across high-income groups, and across countries. This section argues using a simple example that increases in the scale at which top earners operate naturally leads to both phenomena.

V.1 Existing Theories for Increasing Top 1% Income Shares

The leading explanation for the broad increase in wage and income inequality that started in the 1970's is that technical change over this period has complemented the skills of high-skill workers(Autor, Katz and Kearney (2009), Acemoglu and Autor (2010)). There is also evidence that changing economic institutions or regulation (such as minimum wages and unionization) have increased income inequality at the low end of the distribution. At the very top of the income distribution, PS argue that the speed and

[29] In this data set US aggregate income is based on tax records. This biases upward the beta of the top 1% in the period which includes the 1986 tax reform (if incomes are distorted by tax reform effects more so for the top 1%). We therefore drop the growth rates for 1987 and 1988 for the US but could alternatively use NIPA aggregate income for the US as in our prior analysis.

size of the increases in relative earnings are inconsistent with the main existing theories of skill-biased technological change and that the evidence from top income shares instead suggests an important role for changing fiscal policy or social norms about high earnings. Finally, there is a well-developed literature on the rise in relative compensation for a subset of top earners, CEOs. Among the proposed explanations for the rise in relative CEO pay are: (a) an increase managerial power (rent extraction, captured boards); (b) a shift in social norms regarding compensation; and intensified competition for managerial talent due to (c) a demand shift from specific to general skills, (d) an increase in the size of firms, and (e) skill-based technological change (Kaplan and Rauh (2010) and Bertrand (2009)).

Top executives are a minority of highly-compensated individuals.[30] Kaplan and Rauh (2010) documents that only about 5% of the earners in the top 0.01% consists of executives of nonfinancial firms and shows that investment bankers, managers at hedge, VC, and private equity funds, mutual fund managers, lawyers, and to a smaller extent athletes and celebrities all comprise significant fractions of the top-income groups. Kaplan and Rauh (2010) argue that the fact that pay has increased dramatically at the top end in each of these various sectors is evidence against theories (a), (b) and (c). Specific skill rather than general skill seems more important for lawyers, hedge fund managers, investment bankers and professional athletes. Also, increased managerial power does not seem relevant for the pay of many occupations among top earners. Expanding on the argument of Gabaix and Landier (2008) that increased CEO pay can be explained by increased firm size, Kaplan and Rauh (2010) further show that the leading financial services firms, law firms, and hedge, VC, and PE funds have grown larger over time (measured by capital or output). But, as Bertrand (2009) and others have argued, this does not fully explain the increase in CEO pay (and the top 1% income share), however, since firm size was increasing prior to 1980 too. What is needed is that post-1982, the impact of firm size increases on top 1% pay is higher than it was before, i.e. some type of skill-baised technological change favoring those at the top. This would amount to a mix of theories (d) and (e).

Of these existing theories, which also predict an increase in the cyclicality of top earners? The canonical theories of skill-biased technical change require a separate assumption that the technology that complements skill is more cyclical.[31] Other theories of rising CEO pay similarly require additional

[30] Kaplan and Rauh (2010) show the importance of investment bankers and hedge fund, VC and private equity fund managers, mutual fund managers, lawyers, and to a smaller extent athletes and celebrities. Looking at the Decennial Census files, we find that doctors also constitute a significant fraction of the top 1%.

[31] One argument for this would be to assume that the latest technologies that complement the skills of the most highly paid are tied to new investment (in physical capital of higher quality, in equipment and software, or in organizational capital). Then since investment is highly pro-cyclical, skill-biased technical change could lead to both higher incomes and higher cyclicality of the incomes for those with the highest skills.

assumptions – that the ability of CEO's to 'steal' is cyclical or that norms about pay are highly cyclical (as for example if high pay or conspicuous consumption were more stigmatized in recession).

We propose an explanation related to change in information and communication technologies and scale, of either output or inputs. We argue that information and communication technologies have increased the ability to scale high-skills and that this naturally implies both that top incomes rise and that fluctuations in demand over the business cycle fall disproportionately on the incomes of the highest skill individuals. The next subsection describes and illustrates this mechanism.

V.2 Why Very High Incomes are Relatively Larger and More Cyclical

The rise of information and communication technologies (ICT) has allowed the most skilled in any given area to apply their talents to more – to manage more workers and capital, entertain more people, and write more papers. Thus ICT has lowered the extent to which quality declines when producing more output, i.e. made marginal revenue curves decline more slowly with output. This change has raised the size and profits of the best. We argue that the flatter marginal revenue curves for the highest earners have lead to larger fluctuations in their income relative to the rest of the population for any given change in demand, because individuals who operate at a large scale naturally will have very cyclical earnings.

The following simple formal argument illustrates how those with higher incomes also have more cyclical incomes.[32]

First, let each worker produce earnings according to

$$py - ci = Ai^{\alpha} - ci \tag{1}$$

where $0 < \alpha < 1$ and $\alpha A > c$ (or $\alpha p > c$). Second, we assume that workers earn the full net revenues they contribute to the firm, so that earnings are $\pi = Ai^{\alpha} - ci$. Very high-skill workers have higher α – they have lower diminishing marginal products when using the input. The assumption $\alpha A > c$ ensures that high-skill (high-α) workers earn more. The key change in our earnings function that generates both increased cyclicality and earnings shares for high-skill workers is that growth in ICT has shifted the distribution of α out during the period since 1982. In the extreme, pre-1980 all workers had identical α, whereas post-1982 improvements in information technology increased the α of very high-skill workers.

Three different interpretations of our revenue or earnings function are useful. First, the most obvious interpretation is that all workers produce output of identical quality, but the best produce more for given inputs and have lower diminishing returns to scale. In our equations, this corresponds to i being inputs, $y = i^{\alpha}$, $p = A$, and c being the price of the inputs. In this interpretation, the ICT revolution reduces

[32] Our earnings function is in the spirit of the equilibrium model of Lucas (1978).

returns to scale of the best workers and allows them to work with more inputs, such as a CEO managing a larger company.

A second interpretation of equation (1), is that ICT has changed markets so that high skill workers are more like superstars in the sense of Rosen (1981). That is, high-skill workers produce the same number of units of output for given inputs as other workers, but as they produce more output, the quality declines more slowly than other workers. As in Rosen (1981): "superior talent stands out and does not deteriorate so rapidly with market size as inferior talent does." In this interpretation, the ICT revolution has lowered how quickly quality declines with output for the best workers. In our equations, this corresponds to i being output ($y=i$), the price p being a function of quality that decreases with output as $p(y)= Ay^{\alpha-1}$ (so $py= Ai^{\alpha}$), and c being the marginal cost of producing another unit of output. For example, the top lawyers (in the post-1982 world) may be able to write more briefs without the quality of their legal advice suffering as much as would be the case for less-skilled lawyers (due to e.g. the impact of ICT on the ease with which past case history can be researched).

A final, and closely-related interpretation is that of an asset manager paid based on performance. In this interpretation, let i be assets under management, c be the expected return investors can earn elsewhere, and Ai^{α} be the (risk-adjusted) trading profits of the fund. [33] The earnings equation then captures the idea that the best fund managers are increasingly able to invest more money without the returns on their investments deteriorating as much as for other fund managers.

Given our assumptions, the optimal level of i is:

$$i^*=(A\alpha/c)^{1/(1-\alpha)} \tag{2}$$

with associated earnings for the worker of

$$\pi=(A\alpha/c)^{1/(1-\alpha)}c(1-\alpha)/\alpha. \tag{3}$$

Equation 3 delivers our two main results.

First, because workers with higher α earn higher incomes (by assumption), income inequality increases when the α of top earners increase. In equation (3), $d\pi/d\alpha >0$. This occurs because (i) high-skill workers generate more revenues for equal inputs, and (ii) high-skill workers are optimally matched with more inputs because they have lower decreasing returns to scale.[34]

[33] This structure corresponds to a setting with no management fees and a 100% carry, but the results should carry over to a more standard 2% fee, 20% carry compensation contract.

[34] And in a market equilibrium, endogenous adjustment of p would also re-allocate away from low α workers.

Second, an increase in the α of high-α workers increases the cyclicality of their earnings. Assume that business cycle fluctuations are driven by fluctuation in A, representing either market demand shocks or technology/cost shocks.[35] The percentage change in profits depends on α as

$$dln\pi/dlnA=1/(1-\alpha) \tag{4}$$

which is positive and increasing in α. Thus the cyclicality of the earnings of a worker is increasing in skill and increases if the worker's α rises. Note that $dln\pi/dlnA$ does not depend on whether i is adjusted optimally in response to the change in A, since by the envelope theorem $d\pi/di=0$ at the initial value of A. Thus, the high cyclicality of earnings is not driven by a higher cyclicality of inputs, but by the increased sensitivity of earnings to demand that comes from working with a higher level of inputs. That said, the size and revenues of higher-skill workers is more cyclical (just not the cause of greater income cyclicality).

To get a sense of what changes in returns to scale can lead to differences in income shares and cyclicality across workers on the scale we observe, we set $A=1$ (prior to any fluctuations), $c=0.1$, and consider four groups of households, representing group 0-99, 99-99.9, 99.9-99.99, and 99.99-100. We choose four values of α such that for each group, the average ratio of its earnings to total earnings matches that in the post-1982 US data. The values of α which approximately match these ratios and the implied cyclicality of earnings are[36]

Group	α	dlnπ/dlnA=1/(1-α)
0-99	0.05	1.05
99-99.9	0.62	2.63
99.9-99.99	0.70	3.33
99.99-100	0.76	4.17.

The intuition for the very different cyclicalities is that higher skill workers optimally are working with more inputs i, even prior to any shocks hitting. Their gross revenues are similarly sensitive to fluctuations as those of lower skill individuals, since fluctuations in A affect the gross revenues of each worker proportionately. However, for high skill workers, inputs are larger relative to output, so ci is more substantial relative to Ai^{α} for high-skill workers. This makes their earnings $\pi=Ai^{\alpha}-ci$ more cyclical. For

[35] That is, one can equivalently introduce an additional technology parameter B so $y=Bi^{\alpha}$ in the interpretation where $p=A$, $y=i^{\alpha}$ and $y=Bi$ in the interpretation where $p= Ay^{\alpha-1}$ and $y=i$, and represent the business cycle by technology shocks via a fluctuating value of B.

[36] The cyclicalities $dln\pi/dlnA$ do not correspond to our estimated betas since we lack a market equilibrium and a measure of aggregate income and here only measure sensitivities to the shock A. However, because fluctuations in total income are driven by the shock A, the ratios of the groups' values of dlnπ/dlnA will be the same as the ratios of the groups' values of dlnπ/dln(Total income).

low skill workers, inputs are small relative to revenues, so earnings $\pi = Ai^{\alpha} - ci$ fluctuates about the same in percentage terms as revenues.

VI. Conclusion

Coinciding with the increase in the income share of top earners has been an increase in the cyclicality of the incomes of top earners, over time, across groups of top earners, and across countries. We have detailed many features of this shift. The increased cyclicality and its link to increased income shares should help understand the reasons behind the increase in top income shares and changes in the labor market.

We propose that the information and communications revolution provides a natural way to think about how technological change may have raised both top-income shares and top-income cyclicality. Our brief analysis of our posited mechanism leaves open many questions, of how well these changes would match other documented regularities about pay at the top of the income distribution, such as the detailed shape of the distribution for example. That said, the high cyclicality that we document for top incomes since the early 1980s, including wages and salaries, appears linked to increases in top-earning shares empirically. And the change in earnings relation that we suggest -- increased scale or increased "superstar"-type production by top earners – generates a simple connection between shares and cyclicality as the earnings of those operating at a larger scale naturally become more sensitive to the business cycle.

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Table 1. Percent Change in Real Income Per Tax Unit at Annual Rates, 1917-2008

Period	(1) All tax units	(2) Top 1%	(3) p99-p99.9	(4) p99.9-p99.99	(5) Top 0.01%	(6) Top 1% less All tax units (2) - (1)
Panel A: Periods with increases in aggregate personal income per tax unit						
2003-2007	1.8	7.8	5.6	8.7	13.9	6.0
1991-2000	2.6	5.8	4.4	7.5	9.0	3.2
1982-1989	2.2	7.9	6.0	10.7	14.3	5.7
1980-1981	0.8	-2.7	-3.3	-1.3	-0.7	-3.5
1975-1979	1.6	1.4	0.9	2.4	3.7	-0.2
1958-1973	2.6	1.9	2.0	1.6	1.0	-0.8
1954-1957	3.7	2.6	3.1	1.0	2.0	-1.1
1949-1953	5.0	-0.1	0.9	-2.0	-4.1	-5.1
1947-1948	1.4	4.7	3.3	8.4	7.5	3.3
1938-1944	11.0	3.6	4.5	3.0	-0.7	-7.4
1933-1937	8.3	9.3	9.7	9.1	7.8	1.0
1924-1929	1.8	4.3	3.0	4.1	10.4	2.5
1921-1923	12.1	10.3	9.9	9.7	14.1	-1.8
Panel B: Periods with decreases in aggregate personal income per tax unit						
2007-2008	-2.6	-8.4	-6.7	-8.9	-12.7	-5.8
2000-2003	-2.3	-5.8	-4.3	-7.7	-8.3	-3.5
1989-1991	-1.7	-3.5	-2.2	-6.0	-5.6	-1.8
1981-1982	-1.4	2.4	0.3	4.6	15.7	3.9
1979-1980	-2.7	-0.9	-1.5	-0.5	3.6	1.8
1973-1975	-4.5	-2.5	-3.2	-1.2	1.9	2.0
1957-1958	-1.9	-4.7	-4.3	-5.7	-6.1	-2.8
1953-1954	-1.1	2.2	2.5	0.2	3.7	3.2
1948-1949	-2.3	-4.1	-4.1	-5.3	-1.2	-1.8
1944-1947	-5.5	-0.4	0.6	-2.6	-2.4	5.1
1937-1938	-8.0	-17.7	-14.4	-22.6	-24.0	-9.7
1929-1933	-9.5	-12.8	-11.8	-12.5	-17.7	-3.4
1923-1924	-1.2	7.5	6.0	8.8	13.3	8.7
1917-1921	-7.6	-10.5	-6.1	-13.2	-22.0	-2.9

Note: Income is pre-tax, pre-transfer income excluding capital gains. Top incomes are based on authors' calculations using IRS SOI income as compiled by Saez (2010) (http://elsa.berkeley.edu/~saez/TabFig2008.xls) extending Piketty and Saez (2003). Income per tax unit for all tax units is calculated using NIPA table as (Compensation of employees+proprietors' income+rental income+interest income+dividend income, all from NIPA)/(Number of tax units, from Saez (2008)). Beta is the coefficient in a regression of income per tax unit of all households onto income per tax unit of the group in the column.

Table 2. Cyclicality of Real Income Per Tax Unit, 1917-2008

	All tax units	Top 1%	p99-p99.9	p99.9-p99.99	Top 0.01%
Panel A. Cyclicality of income group					
1982-2008	1.00	2.39	1.75	3.08	3.96
		(0.57)	(0.38)	(0.80)	(1.11)
1947-1982	1.00	0.72	0.81	0.63	0.02
		(0.20)	(0.16)	(0.36)	(0.36)
1917-1947	1.00	0.90	0.82	0.94	1.12
		(0.17)	(0.14)	(0.20)	(0.31)
Panel B. Average income in group to average for all tax units					
1983-2008	1.0	11.0	7.4	29.5	168.9
1948-1982	1.0	7.4	6.0	15.7	54.3
1917-1947	1.0	11.7	8.3	31.5	136.8
Panel C. Fraction of aggregate income change borne by income group					
1982-2008	1.00	0.278	0.052	0.088	0.063
		(0.047)	(0.024)	(0.016)	(0.014)
1947-1982	1.00	0.056	0.046	0.010	-0.000
		(0.016)	(0.010)	(0.007)	(0.002)
1917-1947	1.00	0.107	0.065	0.027	0.015
		(0.027)	(0.015)	(0.008)	(0.005)

Note: See notes for Table 1. Cyclicality (or beta) is the coefficient in a regression of log income change per tax unit for the group in a given column on log income change per tax unit for all tax units. The fraction of aggregate income change borne by group is the coefficient in a regression of (Change in group income per tax unit) × (Group share of population)/ (Lagged aggregate income per tax unit) on the growth rate of aggregate income per tax unit.

Table 3. Income Composition and Cyclicality of Top Income Growth by Type of Income, 1947-2008

Type of income	All tax units	Top 1%	p99-p99.9	p99.9-p99.99	Top 0.01%	All tax units	Top 1%	p99-p99.9	p99.9-p99.99	Top 0.01%
Period:	1947-1982					1982-2008				
Panel A. Average percent of income from source										
Total pre-tax, pre-transfer income excluding capital gains	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Wages and salaries	71.9	45.2	49.4	38.8	20.3	67.3	60.3	67.4	53.5	40.0
Entrepreneurial income	13.1	28.3	31.2	23.7	11.1	10.2	22.8	19.5	25.8	32.0
Dividends	3.5	17.5	11.1	27.1	56.2	5.0	6.8	5.1	8.4	12.3
Interest	8.2	5.3	5.0	5.8	6.9	15.3	7.7	6.2	8.9	12.2
Rent	3.4	3.8	3.4	4.6	5.4	2.1	2.4	1.9	3.5	3.5
Panel B. Beta of group category income growth										
Total	1.00	0.72	0.81	0.63	0.02	1.00	2.39	1.75	3.08	3.96
		(0.20)	(0.16)	(0.36)	(0.36)		(0.57)	(0.38)	(0.80)	(1.11)
Wages and salaries	1.12	0.36	0.44	0.20	-0.54	0.87	2.38	1.32	3.61	6.20
	(0.05)	(0.14)	(0.13)	(0.27)	(0.85)	(0.06)	(0.58)	(0.31)	(1.08)	(1.93)
Entrepreneurial income	1.39	1.87	2.08	1.82	-1.54	1.33	2.07	2.29	0.76	1.53
	(0.25)	(0.68)	(0.59)	(0.99)	(2.52)	(0.33)	(1.31)	(1.13)	(2.91)	(1.78)
Dividends	1.16	0.85	0.96	0.83	0.62	1.24	2.65	3.37	2.33	1.64
	(0.29)	(0.38)	(0.39)	(0.68)	(0.34)	(0.57)	(1.26)	(0.97)	(1.62)	(1.93)
Interest	0.00	-0.10	-0.14	-0.04	0.06	1.54	4.52	4.41	5.24	3.84
	(0.19)	(0.48)	(0.44)	(0.66)	(0.80)	(0.39)	(1.28)	(1.18)	(1.22)	(1.71)
Rent	0.62	-0.44	-0.17	-0.73	-1.14	-1.36	-0.26	-0.49	-0.37	-0.54
	(0.41)	(0.87)	(0.98)	(0.93)	(1.53)	(1.29)	(1.61)	(3.61)	(2.07)	(1.54)
Panel C. Unemployment rate beta of group total income growth										
Beta	-0.021	-0.015	-0.017	-0.013	-0.006	-0.023	-0.058	-0.043	-0.076	-0.091
	(0.002)	(0.005)	(0.004)	(0.009)	(0.009)	(0.004)	(0.018)	(0.012)	(0.025)	(0.035)

Notes: See notes for Tables 1 and 2. Unemployment rate beta is the coefficient in a regression of change in the prime-age male unemployment rate on log change in income per tax unit for the group in a given column.

Table 4. Income cyclicality of households with executive stock options, 1997-2006

	1997	2000	2003	2006	Growth rates 1997-2000	2000-2003	2003-2006	Cyclicality
Panel A: Fraction of households with executive stock options								
All	12%	12%	10%	9%				
Top 10 pct	23%	21%	19%	24%				
Top 1 pct	21%	14%	24%	27%				
Panel B: Average income of all households in group (with/without c								
All	62,587	73,311	72,217	75,425	16%	-2%	4%	1.00
Top 10 pct	246,897	308,582	295,868	329,878	22%	-4%	11%	1.46
Top 1 pct	930,834	1,222,238	1,127,105	1,372,170	27%	-8%	20%	1.85
Panel C: Average income for households without options								
All	58,077	69,773	67,878	68,807	18%	-3%	1%	1.25
Top 10 pct	244,897	316,078	294,361	326,041	26%	-7%	10%	1.81
Top 1 pct	889,520	1,213,199	1,205,944	1,385,690	31%	-1%	14%	1.78

Note: Groups are defined based on income excluding capital gains and incomes tabulated also exclude capital gains. The data are from the 1998, 2001, 2004, and 2007 Survey of Consumer Finances which report incomes in the prior calendar years. Income is measured in 2006 dollars.

Table 5. Cyclicality of Consumption in CEX, January 1982 to February 2009

Groups defined based on last period's consumption

	All CEX households	Highest quintile	Top 10%	Top 5%
Panel A: Average group consumption to average consumption of all households				
Ratio's of expenditures	1	1.83	2.16	2.52
Panel B: Beta of group's consumption with NIPA pre-tax pre-transfer personal income				
Cyclicality	0.63	1.10	1.75	2.04
	(0.14)	(0.25)	(0.54)	(0.49)
Panel C: Beta of group's consumption with NIPA post-tax post-transfer personal income				
Cyclicality	0.65	1.34	2.27	2.70
	(0.22)	(0.30)	(0.70)	(0.55)
Panel D: Beta of group's consumption with NIPA non-durables and services				
Cyclicality	1.12	2.49	3.47	4.35
	(0.26)	(0.49)	(0.93)	(0.96)
Panel E: Beta of group's consumption with CEX consumption for all households				
Cyclicality	1	1.60	1.91	2.44
		(0.08)	(0.18)	(0.29)
Panel F. Fraction of CEX consumption fluctuations borne by group				
Cyclicality	1	0.57	0.42	0.33
		(0.04)	(0.04)	(0.04)

Notes: Author's calculations based on Consumer Expenditure Survey data on spending in January 1982 to February 2009. All regressions use four-quarter growth rates. Consumption includes nondurable goods and some services. Betas are coefficients in regressions of log changes in consumption per household for the group in a given column on log-change in aggregate variable. The fraction of aggregate consumption fluctuations borne by group is the coefficient in a regression of (Change in group consumption per household) × (Group share of population)/ (Lagged aggregate consumption per household) on the growth rate of aggregate consumption per household.

Table 6. Cyclicality of Income in Current Population Survey by Group

	1982 - 2008 unless noted otherwise										
	Panel A: Cyclicality by race			*Panel B: Cyclicality by education*				*Panel C: Top 1% cyclicality*			
	White	Black	Other	Less than high school	Some high school	Some College	College graduate	Families public use CPS 1968-82	Families public use CPS	Households Census Bureau CPS	Tax Units Census Bureau Census
All years	1.00	1.12	-0.02	1.59	0.85	0.92	1.16	0.67	2.26	3.09	2.54
	(0.03)	(0.30)	(1.27)	(0.21)	(0.13)	(0.15)	(0.13)	(0.31)	(0.80)	(0.75)	(0.41)
Ecluding years with major tax changes	1.00	1.09	-0.37	1.60	0.85	0.86	1.20	0.67	2.33	2.65	2.50
	(0.03)	(0.33)	(1.41)	(0.24)	(0.15)	(0.15)	(0.14)	(0.31)	(0.90)	(0.50)	(0.43)

Notes: Standard errors in parentheses. Public use data uses data the March CPS files from 1968 to 2009. The unit of observation is the family, and income is measured as pre-tax post-transfer income excluding capital gains. Major topcode change years are dropped in the public data, which are 1980-81, 1983-84, 1994-95, and 2001-02. We do not use income data 1973 to 1975 due to the fact that 1975 data is missing weights and 1973 and 1974 have more than 1% of the income data topcoded. In Panel C, the CEnsus Bureau CPS top 1% data are based on data from Burkhauser et al. (2010), as provided by the authors updated through the 2007 CPS. The series on tax units uses an income definition that excludes benefits income and the tax units data is adjusted for jumps in the series due to changes in internal topcoding. Major tax change years are 1985-86, 1991-92, and 1992-93.

Table 7. Cyclicality of Disposable Income by Type of Income and Income Group, Merged IRS-SOI and CPS data, 1979-2005

Type of income	Lowest quintile	Second quintile	Middle quintile	Fourth quintile	p80-p90	p90-p95	p95-p99	Top 1%	p99-p99.9	p99.9-p99.99	Top 0.01%
Panel A. Average income in group to average for all households for different definitions of income											
Pre-tax, pre-transfer excl. cap. gains	0.18	0.47	0.78	1.15	1.58	2.04	3.02	10.55	5.66	27.92	140.54
Pre-tax, post-transfer excl. cap. gains	0.23	0.52	0.80	1.13	1.53	1.95	2.88	9.92	5.36	26.13	131.26
Pre-tax, post-transfer incl. cap. gains	0.22	0.50	0.76	1.09	1.48	1.91	2.91	12.32	6.24	34.64	228.16
Post-tax, post-transfer incl. cap. gains	0.26	0.55	0.81	1.11	1.46	1.85	2.75	10.72	6.93	29.52	193.20
Panel B. Average percent of pre-tax , pre-transfer income excl. capital gains from different sources of income											
1. Wages and salaries	61.95	68.03	70.22	72.76	73.24	70.59	62.33	43.89	64.77	37.59	25.35
3. Proprietors' & other business	5.03	4.04	3.21	3.10	3.83	5.57	11.39	20.63	25.74	22.61	22.62
4. Interest and dividends	3.16	3.18	4.20	4.54	5.03	6.68	10.48	19.40	22.07	22.76	26.33
5. In-kind income	20.87	12.87	8.87	6.52	5.08	4.24	3.11	1.02	1.87	0.42	0.06
6. Imputed taxes	5.60	5.89	6.15	6.31	6.35	6.46	6.76	11.46	11.34	13.45	23.42
8. Total pre-tax income	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
9. Cash transfers	41.86	18.28	10.09	5.76	3.66	2.98	2.36	0.89	1.58	0.38	0.10
10. Capital gains	0.38	0.37	0.50	0.77	1.32	2.32	5.89	31.18	22.94	41.66	94.52
11. Taxes	-10.42	-15.74	-18.90	-21.40	-23.66	-25.40	-28.29	-41.63	-47.26	-46.66	-64.82
12. Post-tax, post-transfer income incl. cap. gains	131.82	102.91	91.69	85.12	81.32	79.90	79.97	90.44	77.27	95.38	129.81
Panel C. Beta of group category of different incomes to aggregate pre-tax, pre-transfer income, excl. capital gains											
Wages and salaries	0.88	1.08	0.76	0.72	0.74	0.32	0.56	2.22	1.31	3.65	5.72
	(0.30)	(0.27)	(0.14)	(0.11)	(0.13)	(0.14)	(0.15)	(0.69)	(0.49)	(1.11)	(2.12)
Pre-tax, pre-transfer excl. cap. gains	0.94	1.03	0.77	0.71	0.72	0.63	1.05	2.59	1.06	3.36	4.59
(8)	(0.24)	(0.20)	(0.10)	(0.06)	(0.08)	(0.09)	(0.10)	(0.47)	(0.59)	(0.68)	(1.19)
Pre-tax, post-transfer excl. cap. gains	0.59	0.71	0.59	0.59	0.66	0.63	1.04	2.58	1.05	3.35	4.59
(8+9)	(0.19)	(0.16)	(0.09)	(0.06)	(0.07)	(0.08)	(0.10)	(0.46)	(0.56)	(0.68)	(1.18)
Pre-tax, post-transfer incl. cap. gains	0.62	0.73	0.62	0.64	0.72	0.75	1.30	3.45	1.94	4.07	5.66
(8+9+10)	(0.18)	(0.15)	(0.08)	(0.07)	(0.08)	(0.10)	(0.18)	(0.72)	(0.32)	(1.21)	(1.57)
Post-tax, post-transfer incl. cap. gains	0.56	0.61	0.51	0.52	0.59	0.65	1.13	3.36	2.30	4.07	5.76
(8+9+10+11)	(0.19)	(0.15)	(0.10)	(0.08)	(0.10)	(0.12)	(0.22)	(0.86)	(0.56)	(1.41)	(1.80)
Panel D. Fraction of aggregate income change borne by group for different definitions of income											
Pre-tax, pre-transfer excl. cap. gains	0.034	0.100	0.123	0.163	0.114	0.064	0.127	0.278	0.052	0.088	0.063
	(0.008)	(0.020)	(0.016)	(0.015)	(0.013)	(0.009)	(0.012)	(0.047)	(0.024)	(0.016)	(0.014)
Post-tax, post-transfer incl. cap. gains	0.018	0.054	0.064	0.096	0.079	0.058	0.137	0.471	0.178	0.167	0.158
	(0.009)	(0.015)	(0.015)	(0.016)	(0.010)	(0.007)	(0.009)	(0.044)	(0.016)	(0.018)	(0.018)

Notes: Standard errors in parentheses. Groups are defined by ranking all people by household-level pre-tax post transfer income including capital gains with income adjusted for household size by dividing by the square root of the number of people in the household. Source: Congressional Budget Office and author's calculations.

Table 8. The Cyclicality of Income for the Same Families Year to Year, CPS, 1982-2008

	Bottom quintile	Second quintile	Third quintile	Fourth quintile	P80-90	P90-95	P95-99	Top 1%
Panel A. Cyclicality estimates using repeated cross-sections (not panel data)								
All years	1.56	0.95	0.74	0.71	0.70	0.74	1.70	2.26
	(0.20)	(0.14)	(0.13)	(0.11)	(0.10)	(0.13)	(0.30)	(0.80)
Excluding years with major tax changes	1.54	0.91	0.71	0.71	0.71	0.72	1.78	2.33
	(0.20)	(0.14)	(0.14)	(0.12)	(0.11)	(0.14)	(0.33)	(0.90)
Panel B. Cyclicality estimates using income changes for the same families (panel data)								
All years	0.61	0.72	0.67	0.55	1.02	1.33	1.47	3.09
	(1.06)	(0.46)	(0.44)	(0.30)	(0.19)	(0.30)	(0.75)	(2.00)
Excluding years with major tax changes	0.40	0.67	0.67	0.53	0.98	1.38	1.50	3.23
	(1.10)	(0.43)	(0.44)	(0.31)	(0.21)	(0.33)	(0.76)	(1.86)

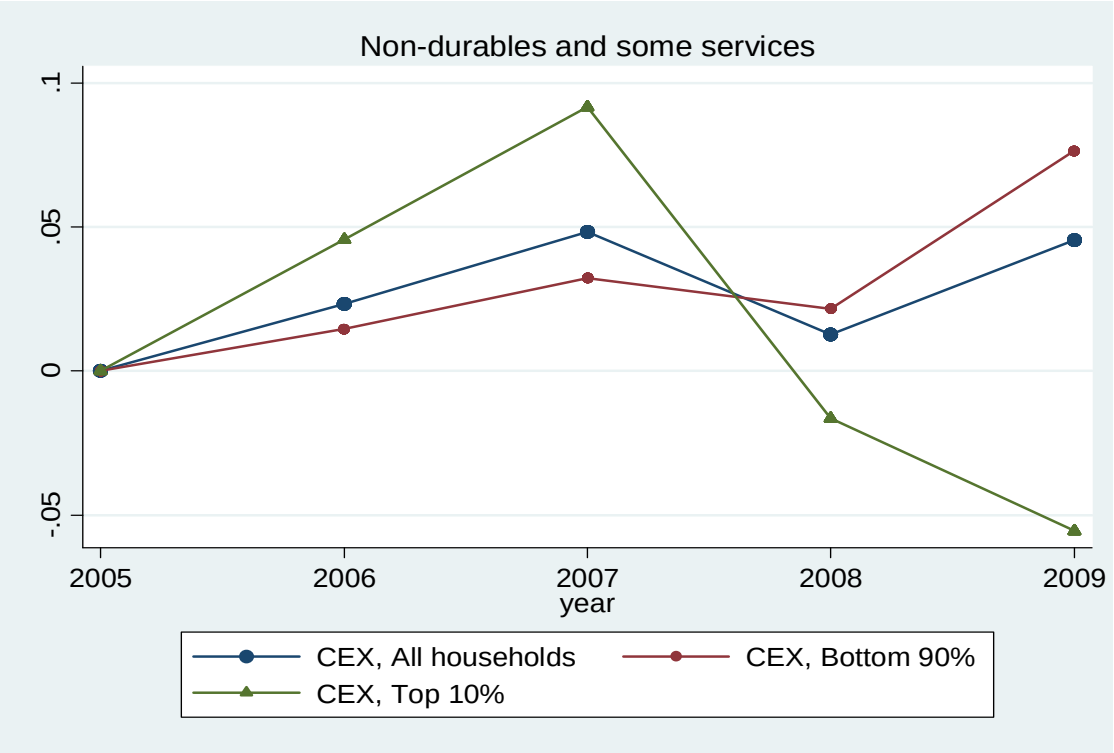
Notes: Standard errors in parentheses. Income is pre-tax post transfer income excluding capital gains, and groups are defined by ranking all families by this income measure. Panel A is based on ranking families in each year and constructing average income in that year for each group. Panel B ranks families in each year and tracks the income of families in each group to the following year. Panel B uses only the subset of families that can be tracked across years. Families and individuals cannot be matched across survey years 1985 to 1986 and 1995-96. We exclude changes across years with major changes in topcoding, which are 1983-84, 1994-95, and 2001-02. Major tax change years are 1985-86, 1991-92, and 1992-93. Source: March CPS files 1983-2009.

Table 9. Cyclicality of Income, Taxes, and Transfers by Income Group in Canada, 1982-2007

Type of income	Lowest quintile	Second quintile	Middle quintile	Fourth quintile	P80-P90	P90-P95	P95-P99	Top 1%	P99-P99.9	P99.9-P99.99	Top 0.01%
Panel A. Average income in group to average for all families for different definitions of income											
Pre-tax, pre-transfer excl. cap gains	0.04	0.32	0.73	1.26	1.85	2.43	3.41	8.81	6.99	20.12	70.59
Pre-tax, post-transfer excl. cap gains	0.21	0.43	0.76	1.19	1.70	2.20	3.07	7.86	6.25	17.90	62.66
Pre-tax, post-transfer incl. cap gains	0.22	0.43	0.75	1.18	1.68	2.19	3.10	8.34	6.59	19.38	65.82
Post-tax, post-transfer incl. cap gains	0.26	0.49	0.80	1.19	1.65	2.09	2.87	6.89	5.57	15.27	50.77
Panel B. Average percent of pre-tax, pre-transfer income excluding capital gains from different sources of income											
Wages and salaries	65.7	59.5	74.2	83.2	86.2	85.5	77.9	60.5	58.1	65.0	70.0
Pensions	18.0	14.5	9.8	5.5	3.5	2.9	2.9	2.2	2.5	1.7	0.7
Business and Professional income	-20.1	6.2	4.7	3.6	3.4	4.0	8.2	17.4	21.0	10.6	3.0
Dividends and interest	27.9	11.6	6.6	4.5	4.1	4.6	7.0	14.6	13.1	17.4	21.2
Other investment income	8.5	8.2	4.7	3.2	2.8	2.9	4.0	5.3	5.2	5.4	5.1
Panel C. Beta of group type of income to average pre-tax, pre-transfer income excluding capital gains for all families											
Pre-tax, pre-transfer excl. cap gains	6.38	2.01	1.14	0.77	0.68	0.67	0.78	1.61	1.28	2.20	3.30
	(0.91)	(0.14)	(0.05)	(0.03)	(0.03)	(0.04)	(0.04)	(0.19)	(0.13)	(0.33)	(0.63)
Pre-tax, post-transfer excl. cap gains	0.19	1.01	0.81	0.66	0.63	0.65	0.77	1.60	1.27	2.20	3.30
	(0.29)	(0.11)	(0.06)	(0.04)	(0.03)	(0.04)	(0.04)	(0.19)	(0.13)	(0.33)	(0.63)
Pre-tax, post-transfer incl. cap gains	0.18	0.89	0.69	0.55	0.53	0.53	0.63	1.53	1.16	2.28	3.17
	(0.29)	(0.23)	(0.19)	(0.18)	(0.18)	(0.19)	(0.24)	(0.39)	(0.35)	(0.54)	(0.70)
Post-tax, post-transfer incl. cap gains	0.23	1.01	0.80	0.65	0.62	0.64	0.76	1.64	1.29	2.36	3.21
	(0.29)	(0.08)	(0.05)	(0.05)	(0.05)	(0.07)	(0.10)	(0.34)	(0.27)	(0.55)	(0.71)
Panel D. Same-household beta of group type of income to average pre-tax, pre-transfer income excluding capital gains											
Pre-tax, pre-transfer excl. cap gains	7.77	1.87	1.06	0.77	0.73	0.78	1.04	1.77	1.69	2.38	2.15
	(2.78)	(0.22)	(0.07)	(0.05)	(0.08)	(0.11)	(0.16)	(0.21)	(0.21)	(0.30)	(0.75)
Pre-tax, post-transfer excl. cap gains	-0.09	1.01	0.74	0.65	0.64	0.71	0.99	1.75	1.66	2.36	2.14
	(0.64)	(0.19)	(0.08)	(0.05)	(0.08)	(0.10)	(0.15)	(0.20)	(0.21)	(0.29)	(0.75)
Pre-tax, post-transfer incl. cap gains	-0.14	0.89	0.65	0.54	0.55	0.60	0.87	1.61	1.51	2.17	2.26
	(0.63)	(0.26)	(0.21)	(0.18)	(0.20)	(0.22)	(0.29)	(0.39)	(0.38)	(0.48)	(0.85)
Post-tax, post-transfer incl. cap gains	-0.09	1.00	0.75	0.64	0.65	0.71	1.00	1.73	1.65	2.25	2.29
	(2.68)	(1.04)	(0.48)	(0.72)	(0.22)	(0.10)	(0.06)	(0.09)	(0.13)	(0.19)	(0.41)

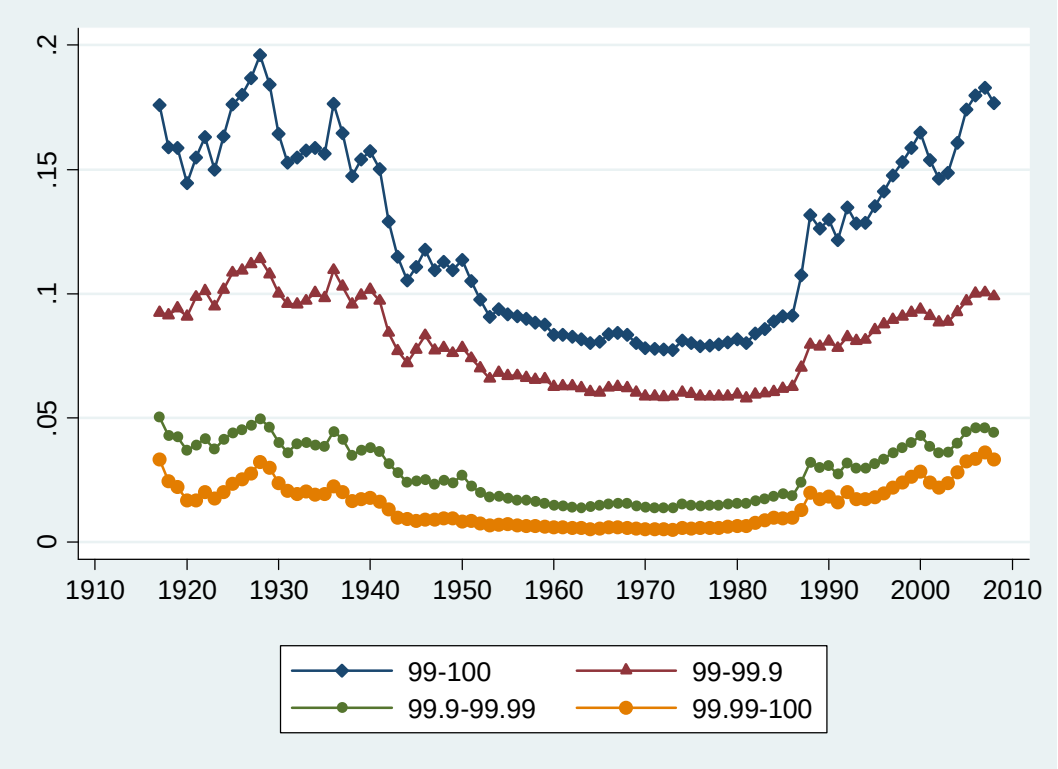
Notes: See notes for Table 2. Standard errors in parentheses. Households are ranked by pre-tax, pre-transfer income excluding capital gains in each year. All betas for income measures that inclulde capital gains exclude changes to and from 1994 as it is an outlier due to a tax change (see Saez and Veal (2005)). Authors' calculations based statistics extracted from the Longitudinal Administrative Databank at Statistics Canada.

Figure 1: Cumulative log-change in real expenditure per household, 2005 - 2009



Note: CEX data based on author's calculations. See notes to Table 5.

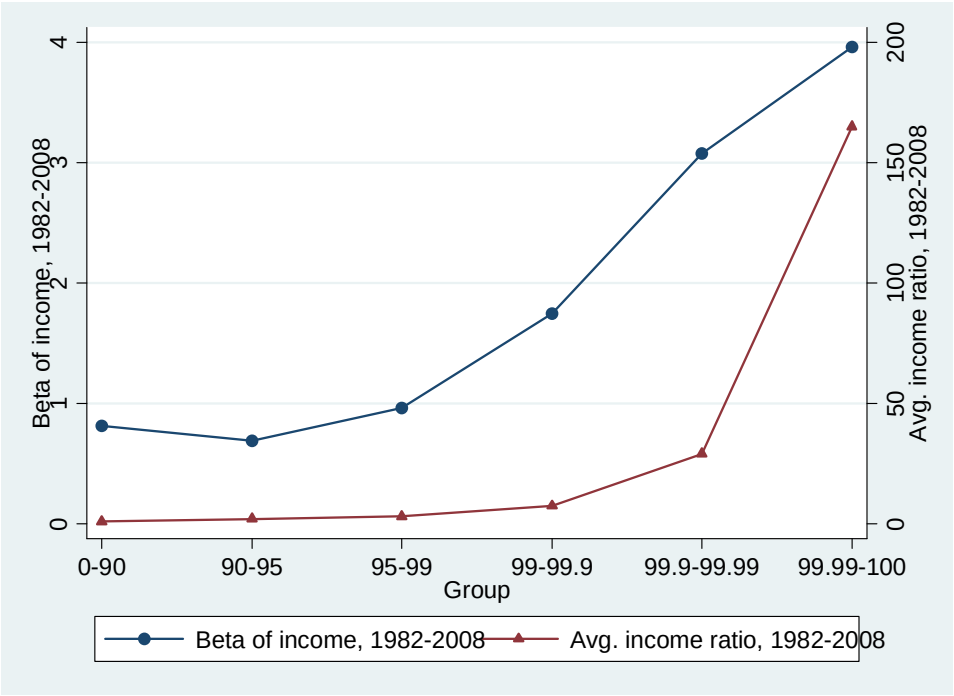
Figure 2. Income Share of the Top 1%, 1917-2008



Note: The income shares graphed are based on pre-tax, pre-transfer income, excluding capital gains

Figure 3. Group Betas and Ratios of Group Income to Average Income, 1982-2008

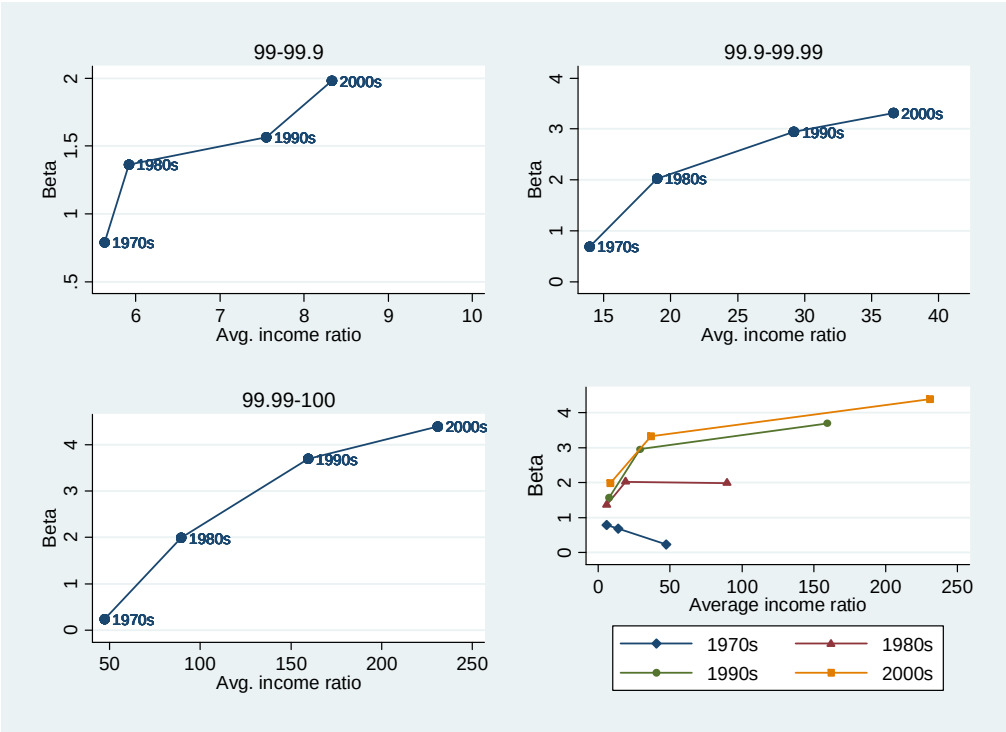
Panel A. Pre-tax, pre-transfer income excluding capital gains



Panel B. Wage and salary income

Figure 4. Changes in Betas and Ratios of Group Income to Average Income Across Decades

Panel A. Pre-tax, pre-transfer income excluding capital gains



Panel B. Wage and salary income

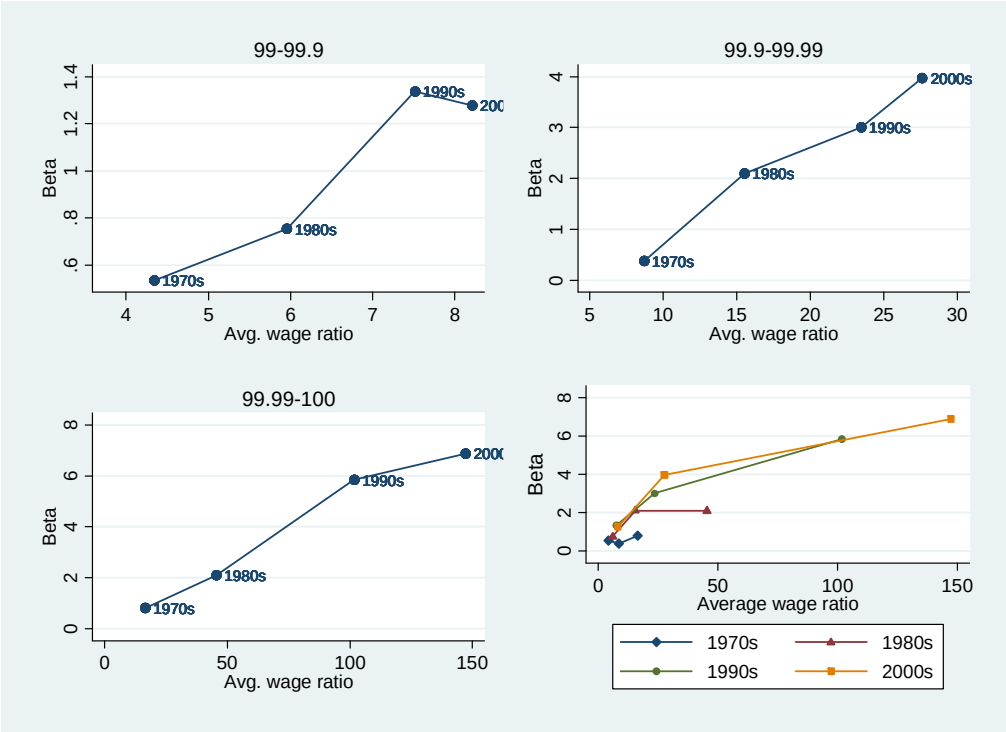
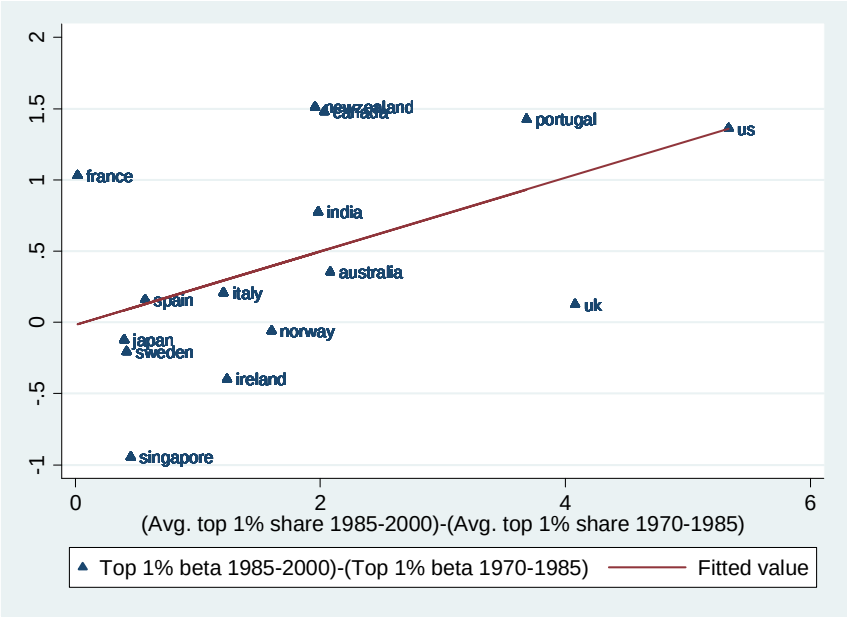


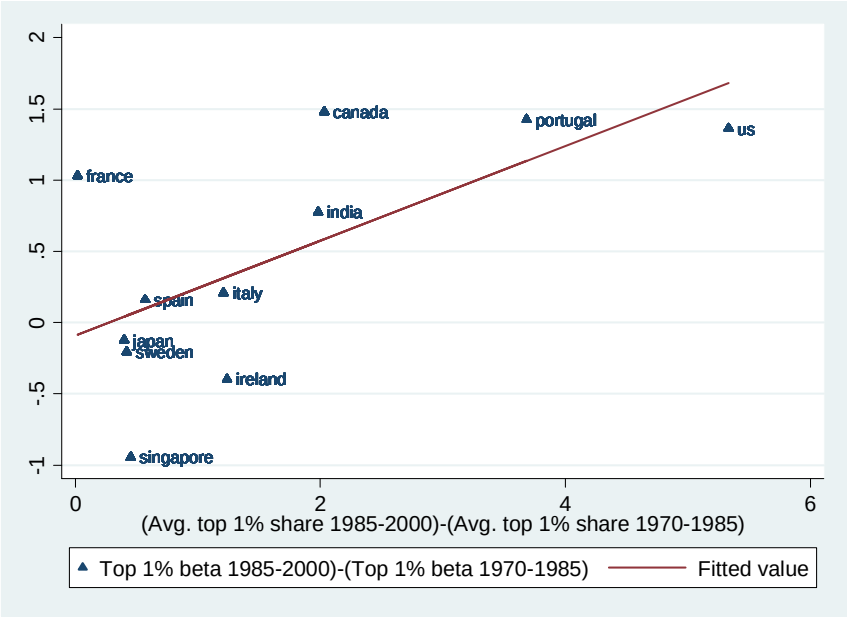
Figure 5. Changes in Beta of Top 1% and Changes in Income Share of Top 1%, 1970-2000

Panel A. All 15 countries



Note: The fitted value is from an OLS regression relating the change in top 1% beta to the change in average top 1% income shares. The slope coefficient in this regression is 0.26 (heteroscedasticity robust standard error=0.11) and the R2 is 0.26.

Panel B. Dropping 4 countries for which income includes capital gains



Note: The fitted value is from an OLS regression relating the change in top 1% beta to the change in average top 1% income shares. The slope coefficient in this regression is 0.33 (heteroscedasticity robust standard error=0.11) and the R2 is 0.43.