Jobs and Income Growth of Top Earners and the Causes of Changing Income Inequality: Evidence from U.S. Tax Return Data

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Abstract:
This paper presents summary statistics on the occupations of taxpayers in the top percentile of the national income distribution and fractiles thereof, as well as the patterns of real income growth between 1979 and 2005 for top earners in each occupation, based on information reported on U.S. individual income tax returns. The data demonstrate that executives, managers, supervisors, and financial professionals account for about 60 percent of the top 0.1 percent of income earners in recent years, and can account for 70 percent of the increase in the share of national income going to the top 0.1 percent of the income distribution between 1979 and 2005. During 1979-2005 there was substantial heterogeneity in growth rates of income for top earners across occupations, and significant divergence in incomes within occupations among people in the top 1 percent. We consider the implications for various competing explanations for the substantial changes in income inequality that have occurred in the U.S. in recent times. We then use panel data on U.S. tax returns spanning the years 1987 through 2005, to estimate the elasticity of gross income with respect to net-of-tax share (that is, one minus the marginal tax rate). Information on occupation allows us to control for other influences on income in a flexible way using interactions among occupation, position in the income distribution, stock prices, housing prices, and the business cycle. We also allow for income shifting across years in response to anticipated tax changes, for the long-run effect of a tax reform to differ from the short-run effects, for heterogeneous mean-reversion across incomes, and for heterogeneous elasticities across income classes. In a specification that does all this, we estimate a significant elasticity of 0.7 among taxpayers in the top 0.1 percent of the income distribution. Outside of the top 0.1 percent of the income distribution, we find no conclusive evidence of a positive elasticity of income with respect to net-of-tax shares. We find that the estimate for the top 0.1 percent is not robust to controlling for a spline in lagged income that is very flexible at the upper reaches of the income distribution, suggesting that the method used to allow for income dynamics is very important. Allowing for income shifting across years in response to anticipated tax changes has important consequences for the estimates.

The views expressed are those of the authors and do not necessarily reflect those of the U.S. Department of the Treasury.

It is well known that the share of the nation's income going to the top percentiles of the income distribution in the United States has increased dramatically over the past three decades. Data from individual income tax returns tabulated by Piketty and Saez (2003, updated 2008) and shown in Figure 1 demonstrates that the percentage of all pre-tax income (excluding capital gains) in the United States that was received by the top 0.1 percent of income earners rose strikingly from 2.2 percent to 8.0 percent between 1981 and 2006. But until now, there has been little hard data available to the public on what these people typically do for a living, which is an economically important question. Kaplan and Rauh (2009) estimate what share of tax returns at the top of the income distribution can be accounted for through publicly-available information on top executives of publicly-traded firms, financial professionals, law partners, and professional athletes and celebrities. Despite making various extrapolations beyond what is directly available in publicly-available data sources, for the year 2004 they are only able to identify the occupations of 17.4 percent of the top 0.1 percent of income earners. As Kaplan and Rauh, among others (e.g., Gordon and Dew-Becker, 2008) have emphasized, the questions of what proportion of people in the top income percentiles are in different occupations, and how these proportions have been changing over time, have important implications for evaluating competing explanations for the rapid rise in incomes at the top. Yet until now we have had very incomplete information on these questions. One contribution of our paper is to present summary statistics tabulated from cross-sectional individual income tax return data at the U.S. Treasury Department on what share of top income earners work in each type of occupation, the shares of top incomes that are accounted for by the various occupations, mean incomes of top earners in each occupation, and how all of these have changed over selected years between 1979 and 2005. Through this method we are able to account for the occupations of almost all top earners – for example, for over 99 percent of primary taxpayers in the top 0.1 percent of the income distribution in 2004.

The second contribution of our paper is to use panel data on U.S. federal income tax returns spanning the years 1987 through 2005, which includes information on the occupation and industry of each taxpayer, to try to distinguish empirically the causal impact of marginal income tax rates, which affect the incentive to earn income, from other possible explanations for the rise in top incomes. We estimate the elasticity of gross income with respect to net-of-tax share (that is, one minus the marginal tax rate). Information on occupation allows us to control for other influences on income in a flexible way using interactions among occupation, position in the income distribution, stock prices, housing prices, and the business cycle. We also allow for income shifting across years in response to anticipated tax changes, for the long-run effect of a tax reform to differ from the short-run effects, and for heterogeneous elasticities across income classes.

Our panel data analysis contributes to the now voluminous literature on the "taxable income elasticity," recently and comprehensively reviewed by Saez, Slemrod, and Giertz (2009). Early and influential papers by Feldstein (1995, 1999) argued that the responsiveness of taxable income to changes in marginal tax rates provides information on nearly all of the margins along which individual taxpayers may adjust their behavior to avoid taxes – not only changes in hours worked, but also changes in work effort per hour, form of compensation, choice of tax-deductible consumption versus non-deductible consumption, risk taking and entrepreneurship, and so forth. Feldstein went on to argue that under certain assumptions, the elasticity of taxable income with respect to the net-of-tax-share can be a sufficient statistic to calculate the deadweight loss caused by income tax.[1] It turns out that seemingly small differences in this elasticity have dramatically different implications for the amount of deadweight loss caused by taxation. Giertz (2009) performs simulations using published tax return data, and his analysis suggests that given the current structure of taxation in the U.S., if the taxable income elasticity is 0.2, the marginal deadweight loss per additional dollar of revenue raised in the top tax bracket is $0.31 and the peak of the Laffer Curve occurs at a tax rate of 78 percent. If the elasticity is 0.8, the deadweight loss caused by raising one additional

[1] See, however, Chetty (2008) and Saez, Slemrod, and Giertz (2009) for discussion of why these assumptions may not hold.

dollar of revenue from a top-bracket taxpayer is $6.57, and the peak of the Laffer curve occurs at a tax rate of 41 percent, which is only slightly above the top marginal income tax rate that is scheduled to apply when the federal tax cut enacted in 2001 (EGTRRA) expires.

The behavior and incomes of very-high income people are of extreme quantitative importance for government revenue and for the economy, which is one motivation for our focus on their incomes in this paper. Mudry and Bryan (2009) report that the top one percent of taxpayers ranked by income paid 40 percent of federal personal income taxes in 2006, and the top 5 percent of taxpayers paid 60 percent of federal personal income taxes. This is explained by a combination of the effective progressivity of the personal income tax, and the large share of national income earned by people at the top of the distribution.[2]

In our cross-sectional analysis, we find that executives, managers, supervisors, and financial professionals account for about 60 percent of the top 0.1 percent of income earners in recent years, and can account for 70 percent of the increase in the share of national income going to the top 0.1 percent of the income distribution between 1979 and 2005. During 1979-2005 there was substantial heterogeneity in growth rates of income for top earners across occupations, and significant divergence in incomes within occupations among people in the top 1 percent. Using panel data, we estimate a significant elasticity of 0.7 among taxpayers in the top 0.1 percent of the income distribution. Outside of the top 0.1 percent of the income distribution, we find no conclusive evidence of a positive elasticity of income with respect to net-of-tax shares. However, we find that the estimate for the top 0.1 percent is not robust to controlling for a spline in lagged income that is very flexible at the upper reaches of the income distribution, suggesting that the method used to allow for income dynamics is very important. In addition, allowing for income shifting across years in response to anticipated tax changes has important consequences for the estimates.

[2] In fiscal year 2007 federal personal income tax revenues were $1.16 trillion, or 45 percent of federal revenues. Source: Economic Report of the President (2009).

The paper proceeds as follows. In the following section, we review the literature on the causes of changing income inequality and its implications for estimating taxable income elasticities. We then describe the two sources of tax data that we use in the empirical work. The following section outlines results tabulating occupations and incomes of high income taxpayers, and the section after that presents some resuts from preliminary estimates of the elasticity of taxable income accounting for the occupations of high income earners. The last section concludes.

Literature Review

The literature on the causes of rising income inequality over the past few decades has identified many factors that may contribute to rising top income shares. First, it is important to note that Piketty and Saez (2003, updated 2008), among others, have shown that wage and salary income, as well as self-employment income and closely-held business income that largely reflect labor compensation, now account for the vast majority of the incomes of top income earners, and have also been growing substantially as a share of that income in recent decades.[3] So theories to explain the rising top income shares shown in Figure 1 must largely be about compensation for labor.

One explanation for rising income inequality emphasizes that it coincided with advancing globalization, as indicated for example by increasing shares of imports and exports in GDP. This may increase the demand for the labor of high-skill workers in the U.S., because they can now sell their skills to a wider market, and highly-skilled workers are scarcer in the rest of the world than in the U.S. Globalization may similarly depress wages for lower-skilled workers, because they now have to compete with abundant low-skill workers from the rest of the world (Stolper and Samuelson, 1941; Krugman 2008).

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[3] For example, even among the top 0.01 percent of income recipients in 2005, salary income and business income (that is, self-employment income, partnership income, and S-corporation income) accounted for 80 percent of income excluding capital gains, and 64 percent of income including capital gains. Those figures were 61 percent and 46 percent, respectively, in 1979. (Source: authors' calculations based on data posted by Emanuel Saez at <http://elsa.berkeley.edu/~saez/TabFig2006.xls>).

A second hypothesis is skill-biased technical change (Katz and Murphy, 1992; Bound and Johnson, 2002; Card and DiNardo, 2002; Garicano and Rossi-Hansberg 2006; Garicano and Hubbard 2007). Technology has arguably changed over time in ways that complement the skills of highly-skilled workers, and substitute for the skills of low-skilled workers. A third hypothesis, closely related to the previous two, is the "superstar" theory suggested by Sherwin Rosen (1981). In this theory, compensation for the very best performers in each field rises over time relative to compensation for others, because both globalization and technology are enabling the best to sell their skills to a wider and wider market over time, which displaces demand for those who are less-than-the best. This is easiest to see for entertainers, but could easily apply to other professions as well.

A fourth hypothesis is that the increasing inequality may be explained to some extent by executive compensation practices (Bebchuk and Walker, 2002; Bebchuk and Grinstein, 2005; Eissa and Giertz, 2009; Friedman and Saks, 2008; Gabaix and Landier, 2008; Gordon and Dew-Becker, 2008; Kaplan and Rauh 2009; Murphy 2002; Piketty and Saez 2006). A large share of executive pay comes in the form of stock options, and almost all stock options are treated as wage and salary compensation on tax returns when they are exercised (Goolsbee 2000).[4] Because of this, the values of stock options exercised by employees are generally counted in the measures of income used in the income inequality literature.[5] It is clear that executive compensation has increased greatly over time, but there is a raging debate over why this has happened, and whether there are enough executives for this to explain much of the rise in top income shares.

[4] Federal income tax law classifies compensation in the form of stock options into two categories. "Non-qualified" stock options are treated as wage and salary income when exercised. "Incentive" stock options are taxed as capital gains a the personal level when exercised, but are denied a deduction for labor compensation from the corporate income tax. Under current law, the non-qualified options are generally much preferable from a tax standpoint compared to incentive stock options and Goolsbee (2000) indicates that almost all stock options used in executive compensation are of the non-qualified type. However, before 1986 incentive stock options were less tax disadvantaged.

[5] The taxable income elasticity and inequality literatures usually focus on income excluding capital gains, because we usually only have data on gains realizations (rather than accruals) reported on tax returns, because capital gains realizations fluctuate wildly over time, because capital gains receive different tax treatment than other income, and because capital gains have obvious alternative explanations (e.g., stock market booms and busts).

Bebchuk and Walker (2002) and Bebchuk and Grinstein (2005), among others, have argued that high and rising executive pay reflect the fact that the pay of executives is set by their peers on the board of directors, that free rider problems prevent shareholders from doing sufficient monitoring of executive compensation practices, and that the problems have been getting worse over time. Many others (for example, Murphy 2002) argue that executive pay reflects economically efficient compensation necessary to align executive incentives with those of shareholders. Gabaix and Landier (2008) argue that the increasing scale of firms has been critical to explaining rising executive pay; however, Friedman and Saks (2008) show that real executive pay grew very little between World War II and the mid-1970s despite large increases in firm size during that period, casting doubt on the Gabaix and Landier hypothesis.

A fifth hypothesis is that technological change and compensation practices in financial professions play a critical role. Philippon and Reshef (2009) show that the skill-intensity of financial sector jobs has grown dramatically since the early 1980s. Moreover, they estimate that since the mid-1990s, financial sector workers have been capturing rents that account for between 30 and 50 percent of the difference between financial sector wages and wages in other jobs. Of course, compensation of executives, financial professionals, and perhaps top earners in other fields (such as high technology) can be expected to be heavily influenced by financial market asset prices, particularly stock prices, which went up dramatically at the same time as the increase in inequality. So part of the rising inequality may simply reflect that people in these professions have compensation that is strongly tied to the stock market, and got lucky when the stock market went way up. This might be counted as a separate hypothesis or a subset of the previous two.

Another hypothesis related to the past few is that social norms and institutions in the United States may be changing over time in a way that reduces opposition to high pay (see, e.g., Piketty and Saez 2006). For example, perhaps the "outrage constraint" once played and important role in preventing executives and their peers on the board from colluding to grant excessively high pay, but social norms against high pay have weakened over time so this constraint no longer binds. Alternatively, perhaps the social norms of old were harming efficiency by preventing corporate boards from granting stock options that were sufficiently large to align the incentives of the executive with those of the shareholders.

Yet another hypothesis brings us back to taxes. Prior to TRA86, top personal income tax rates exceeded the top corporate income rate by a wide margin, so there was a strong incentive to organize one's business as a C-corporation, because it enabled one to defer paying high personal tax rates on one's income as long as it was retained within the corporation, at the cost of paying the lower corporate rate right away. After TRA86, the top personal rate was reduced below the top corporate rate, which created an incentive to change one's business to a pass-through-entity such as an S-corporation, the income of which is taxed only once at the personal level. This has important implications for the income inequality and taxable income elasticity literatures, because it suggests that part of the difference in top incomes before and after 1986 does not reflect the creation of new income, but rather income that was previously not reported in the data (which is derived from personal income tax returns) and now is. Slemrod (1996) and Gordon and Slemrod (2000) demonstrate that this factor must explain a substantial portion of the increase in top incomes around 1986. Yet, looking back at Figure 1, even if one restricts attention to the period from 1988 forward, the income share of the top 0.1% still increased from 5 percent of national income to 8 percent. Taxable income elasticity researchers studying periods spanning 1986 try imperfect methods for dealing with this such as omitting returns with any S-corporation income. One advantage of focusing our gross income elasticity analysis on panel data starting in 1987 is that it will be less subject to this problem.

One particularly promising development for the prospects of distinguishing which explanations for increasing income inequality are correct has been the collection of long historical time-series on top income shares in a variety of nations. Figure 1 shows the share of income going to the top 0.1 percent of the income distribution in the U.S., France, and Japan, based on data from Piketty and Saez (2006, updated in 2008), Moriguchi and Saez (2008), Piketty (2003), and Landais (2008). It shows that while the share going to top earners increased dramatically between 1981 and 2006 in the U.S., it was basically flat in these other countries until very recently. There is evidence of some increase in top income shares in Japan and France since the late 1990s, but the changes are far less pronounced than what has occurred in the U.S. Various authors (Atkinson, 2007; Atkinson and Salverda, 2005; Saez and Veall, 2005; and many other studies cited in Atkinson and Piketty, 2007, Saez 2006 and Roine, Vlachos, and Waldenstrom 2008) have constructed top income shares for other countries as well, and have shown that top income shares have grown sharply only in English speaking countries. Like France, other continental European countries have had flat top income shares in recent decades, with moderate upward trends beginning to emerge only after the late 1990s in countries such as France and Spain where very recent data is available.

The international data on top income shares seems inconsistent with some of the theories for rising income inequality cited above, and only partly consistent with others (Piketty and Saez 2006). For example, it is hard to see why globalization and skill-biased technological change would raise top income shares sharply in English speaking countries but not in Continental Europe or Japan where the degree of globalization and technological advancement is presumably similar. Regarding the tax hypotheses, Figure 2 shows that there were much larger and earlier cuts in top marginal income tax rates in the U.S. than in France, and in general English speaking countries had much larger reductions in top marginal income tax rates than did Continental European countries. So the fact that top income shares went way up in the English speaking countries but not in Continental Europe seems to support the theory that marginal income tax rates are an important part of the explanation for surging top income shares in English speaking countries. However, Figure 2 also shows that Japan had similarly large reductions in top marginal income tax rates to the U.S. since 1981, yet no increase in top income shares happened there, which is highly inconsistent with the tax-based theories.

Theories about executive compensation, financial market asset prices, social norms, and institutions seem to fit the data better, but have been hard to prove. While

Japan and the U.S. had similar changes in tax rates, an important difference between them is that it was illegal to compensate executives with stock options in Japan until 1997 (Bremner 1999). Executive stock options are legal in France, and stock prices went up in France too; but average executive compensation in France is less than half of what it is in the U.S., which might be explained by social norms (*The Economist*, 2008, and Alcouffe and Alcouffe 2000). This could explain why top income shares seem largely unaffected by stock prices in France. Kaplan and Rauh (2009), on the other hand, have argued that executives of publicly-traded firms represent too small of a share of top income earners in the U.S. to be able to explain much of the rise in top income shares. Part of the motivation of our present study, therefore, is to see whether more complete information on the occupations of high earners might corroborate what seems to be happening in the international data. The role of financial market asset prices in influencing top income shares is corroborated by Roine, Vlachos, and Waldenstrom (2008), who estimate regressions on cross-country data from a large number of years and find that top income shares are strongly positively correlated with stock market capitalization; they also find that higher marginal income tax rates are associated with smaller top income shares, although their tax measures are rough.

Clearly, a researcher wishing to distinguish the causal impact of marginal tax rates on income from all the other possible explanations listed above faces a difficult task. Contributors to the taxable income elasticity literature have tried various clever but imperfect methods to try to control for the kinds of factors discussed above.

First is the use of the standard difference-in-differences identification strategy (or more generally the use of fixed effects or differencing together with year dummies). But for reasons detailed above, this is almost certainly insufficient to address the kinds of omitted variable bias stories we have been talking about.

Feldstein analyzed the effect of the Tax Reform Act of 1986 (TRA86) on taxable income and gross pre-tax income. Feldstein applies a difference-in-differences approach, where people with high tax rates before the reform were the "treatment group" because they experienced a large cut in marginal tax rates (up to 50 percent before the reform and a maximum of 28 percent afterwards) and those with lower tax rates before the reform, who experienced only small marginal tax rate cuts, were the "control group." As is apparent from Figure 1, in the years around TRA86, pre-tax incomes of high-income people grew much faster than those of other people. As a result, Feldstein estimated a very large elasticity of income with respect to the net-of-tax share, in some cases in excess of one.

Feldstein's study also illustrates some of the challenges involved in distinguishing the causal effect of taxes from the effects of other factors that also influence income. In Feldstein's simple diff-in-diffs analysis, which did not control for other factors, the key identifying assumption was that there were no other factors besides taxes that influence income that were changing in different ways over time for people at different income levels, because whether someone experienced a change in tax rates was determined largely by the starting level of income before the reform. Therefore, the taxable income elasticity literature in public economics is inextricably intertwined with the literature on the causes of changing income inequality. As Figures 1 and 2 show, between 1981 and 2006 incomes of very high-income people rose sharply relative to the incomes of the rest of the population, while at the same time top marginal income tax rates were cut sharply, from 70 percent in 1980 to 35 percent as of 2006. Looked at over the period as a whole, the data appears consistent with the theory that high-income people respond to the improved incentives to earn income created by tax cuts, although there are some features of the data, such as the fact that the incomes at the top of the distribution continued to rise sharply after an increase in the to marginal tax rate from 31 percent to 39.6 percent starting in 1993, which do not seem particularly consistent with the theory. But of course, many other factors that might influence top incomes and income inequality were also changing over time.

Gruber and Saez (2002) supplemented the difference-in-differences approach by controlling for a ten-piece spline in log income from the first year of a three year difference. This effectively controls for unobservable influences on income that follow a different linear time trend at each point in the income distribution, allowing for the rate of change in the effect with respect to income to differ for each decile of the distribution. The use of the spline in income was also motivated by the apparently large degree of mean-reversion in income, which makes it difficult to distinguish the effect of a change in taxes from the effects of transitory fluctuations in income over time, together with the observation that the degree of mean-reversion appears to be heterogeneous across the income spectrum. Much of the subsequent literature has followed suit. However, we demonstrate below that whatever unmeasured factors are driving the rise in top income shares, they cannot possibly be well-described by a linear time trend.

Another approach, used for example in Auten and Carroll (1999) and Auten, Carroll, and Gee (2008), has been to make use of internal government panel data on tax returns that includes information on occupation in selected years. These authors controlled for occupation dummies in specifications that differenced the data over time, which effectively controls for a different linear time trend in unmeasured influences affecting income for each occupation, but did not control for a spline in lagged income. There is abundant evidence from the labor economics literature that increases in earnings inequality have been "fractal" in nature – almost regardless of how you define a group, including by occupation, earnings inequality has been increasing within that group (see, for example, the survey by Levy and Murnane, 1992). We demonstrate below that there has been substantial divergence in incomes within the same occupation even among people who are in the top one percent of the income distribution (which to our knowledge has not previously been demonstrated in the labor literature, due to top coding of publicly available earnings data). For these reasons, the approach used in prior taxable income elasticity papers that had information on occupation may have been insufficient to effectively control for unmeasured time-varying influences on income. Those papers also used short panels that each spanned only a single federal tax reform that moved tax rates in one direction (1985 and 1999 in Auten and Carroll, 1999 through 2005 in Auten, Carroll, and Gee), which makes it difficult to distinguish the effects of tax changes from mean reversion in income and from unmeasured time-varying influences. In our econometric analysis we use panel data spanning the years

1987 through 2005, which includes both major tax increases and tax cuts, and we will try various methods of controlling for time-varying non-tax influences on income, including ones that are considerably more flexible than those used in the previous literature, and we show that this has important impacts on the estimates. Moreover, prior papers using tax data matched with occupational information did not share much information about those occupations aside from sample means and regression coefficients. We show that there is much more that can be learned from a detailed analysis of that data.

As noted above, the elasticity of taxable income to the net-of-tax share can be used to estimate revenue impacts of tax changes and to calculate the deadweight loss of the income tax. Another elasticity of interest is the elasticity of gross income with respect to the net-of-tax share (also called the "gross income elasticity"); this is useful for calculating the deadweight loss of taxation in the same way as the taxable income elasticity is, except that it leaves out the behavioral margin of switching between non-deductible to deductible consumption. In this paper we focus on the gross income elasticity because that is most relevant to the question of whether the increases in gross income inequality shown in Figure 1 can be explained by behavioral responses to marginal tax rates; the debate over the causes of rising income inequality debate has mainly been about gross income, not taxable income. Moreover, calculations of deadweight loss based on the taxable income elasticity will tend to overstate deadweight loss when some items of deductible consumption (for example, charitable contributions) involve positive externalities (Saez, Slemrod, and Giertz 2009).[6]

[6] The taxable income elasticity literature often finds that the taxable income is more elastic than gross income with respect to the net-of-tax share (see, e.g., Gruber and Saez 2002). In Bakija and Heim (2008) we estimate that charitable contributions among high-income people are highly elastic with respect to marginal tax rates. This suggests that charitable contributions might be an important part of the explanation for why taxable income elasticities tend to be larger than gross income elasticities.

Data

For this paper, we utilize both repeated cross-sections of tax returns and a panel of tax returns.

The repeated cross-section dataset was created by merging files produced by the Statistics of Income (SOI) division of the Internal Revenue Service. Each year, a stratified random sample of tax returns is drawn, where the probability of being selected increases with income, and the highest income returns are selected with certainty.[7] As a result, these cross-sections contain complete tax return information from the highest income taxpayers in each year. Variables are collected from Form 1040 and many of the supporting schedules, and include wages and salaries, dividends and interest, capital gains, and income from closely held businesses.

Occupation and industry data were then merged together with these datasets.[8] Each year since 1916, taxpayers have been asked to identify their occupation on their federal tax form, with the current single line entry format beginning in 1933.[9] In 1979, SOI began a pilot project to convert the text entries from the tax forms to standard occupation codes (SOC's). Following the pilot project, they attempted to code occupations for the entire 1979 cross-sectional file (both primary and secondary filers, if applicable) according to the 1972 SOC classification system. To aid in this, information on the industry of the taxpayer's employer was merged into the dataset by matching the employer identification number (EIN) from the taxpayer's W-2 form to industry codes

[7] In 2004, for example, 100 percent of returns with incomes above $5 million are included in our cross-sectional sample. In order to avoid disclosure, the publicly-available versions of the cross-sectional tax return data sample even the highest income returns, and some variables from these returns are withheld or blurred. For example, in the 2004 public-use data, 33 percent of returns with incomes above $5 million are included (Weber 2007).

[8] The creation of the occupation datasets is described in Crabbe, Sailer, and Kilss; Sailer, Orcutt, and Clark; Clark, Riler, and Sailer; and Sailer and Nuriddin.

[9] This history is described in Sailer, Orcutt, and Clark. As noted by Sailer and Nuriddin, essentially no guidance is given to taxpayers on how to describe their occupation, and no categories are given from which taxpayers can choose.

from the Social Security Administration's Employer Information File, allowing identification of the taxpayer's industry of employment as well.

Occupations and industries were coded intermittently in the subsequent years, with an occupation file created for the 1993, 1997, and 1999 tax years, where the samples in 1993 and 1999 contained taxpayers in both the cross-section and panel datasets from those years. Starting in 2001, occupations and industries have been coded every year, with the most recent data coming from 2005. Across all years, occupations were coded for 90 percent of working primary filers and 84 percent of working secondary filers, and industries were coded for 87 percent of working primary filers and 77 percent of working secondary filers.

Because the occupation and industry classification systems changed a number of times,[10] to make the codes comparable across time we converted occupation codes in each year to the equivalent 2000 SOC code, and industry codes to the equivalent 1997 NAICS code. To make the occupation and industry data more amenable to studying occupations and industries that have been the focus of previous studies, we then aggregated these occupation codes into 22 occupation groups and industry codes into 11 industry groups. The occupation groupings are detailed in Appendix Table A.1. Aggregating the data in this manner also helps reduce noise that might come from taxpayers changing the description of their occupation from year to year. When looking at the very highest income groups we further aggregate occupations to prevent any cell from becoming too small.

We use different measures of income in the analysis. For our measure of gross income, we use reported adjusted gross income (AGI) less social security income, unemployment income, and state tax refunds, and add back total adjustments less half of self-employment taxes. To keep this measure consistent across years, in 1979 we add 60 percent of long-term capital gains and excluded dividends and interest. We also

[10] The 1980 SOC codes were used for the 1979 through 1997 files, and 2000 SOC codes were used for the 1999 through 2005 files. The 1972 SIC codes were used for the 1979 file, 1980 SIC codes were used for the 1993 and 1997 files, 1997 NAICS codes were used for the 1999 and 2001 files, and 2002 NAICS codes were used for the 2002 through 2005 files.

create a measure of gross income excluding capital gains, and following the previous literature focus mainly on that. Our measure of "labor and business income" adds together wages and salaries, income from sole proprietorships, and income from partnerships and S-corporations. Finally, wage and salary income comes from the relevant line from Form 1040.

Sample statistics from the merged cross-section file are presented in Appendix Table A.2. The mean income in the cross-section file is in excess of $1.5 million, though when capital gains are excluded, this figure drops to $834,490. About 25 percent of the sample derived a majority of their combined salary and business income from a closely held business, and 66 percent of the taxpayers in the sample were married.

Appendix Table A.3 presents the distribution of occupations among all primary and secondary filers in the pooled cross-section sample. For primary filers, the largest occupations are blue collar and miscellaneous (largely low-skill) service occupations (17.4 percent), executives (9.0 percent), and financial professions (6.6 percent). Taxpayers were either not working or deceased for 10.8 percent of the pooled cross-section sample, and occupations could not be identified for 8.6 percent of returns.

In both the cross-sectional and panel analyses, we need to assign tax returns to percentiles of the national income distribution (including non-taxpayers). For each year we sort returns in the internal Treasury cross-sectional data set in descending order by income and count down to compute the number of returns that represent a particular percentage of the total number of tax units in the United States for that year. We then determine the minimum income for that group and use it to assign people to percentiles.[11] The minimum income levels to qualify for the top quantiles of the distribution of income (excluding capital gains) in 2005 (measured in constant year 2007

[11] A "tax unit" is defined as a married couple or a single adult aged 20 or over, whether or not they file an income tax return. Data on total number of tax units is taken from Piketty and Saez (2003, updated 2008). Our thresholds for percentiles of the income distribution match up fairly closely to those reported in Piketty and Saez. Their estimates are based on public-use micro datasets of tax returns up through 2001 and interpolations from published tables thereafter. In this preliminary version of our paper we use the thresholds reported in Piketty and Saez to assign returns in the *panel* to percentiles, because we have not yet computed thresholds from cross-sectional data for all years included in the panel.

dollars and rounded to the nearest thousand) were: $94,000 for the top 10 percent; $129,000 for the top 5 percent, $295,000 for the top 1 percent, $450,000 for the top 0.5 percent, and $1,246,000 for the top 0.1 percent.

The panel of tax returns was created by merging three separate panels.[12] The first panel was collected from 1987 through 1996, and is known as the Family Panel.[13] This panel consists of two segments. The first is a cohort segment that was created by drawing a stratified random sample of taxpayers (including spouses and dependents) who filed in tax year 1987 and following them over the next nine years. This segment includes a random sample of taxpayers chosen because the primary taxpayer's SSN ended in one of two 4-digit combinations (known as the Continuous Work History Subsample), and a sample of taxpayers for whom sampling probabilities increased with income. The second segment is a refreshment segment consisting of taxpayers with one of the two CWHS SSN endings, who filed in at least one tax year between 1988 and 1996 but who were not filers in 1987. Overall, the Family Panel consists of 1.26 million returns, and spans the Ominibus Budget Reconciliation Acts of 1990 and 1993 (OBRA90 and OBRA93) as well as covering the end of the phase-in of TRA86.

The second panel was collected from 1999 through 2005, and is known as the Edited Panel.[14] This panel consists of a stratified random sample of tax returns drawn in 1999 (including a CWHS subsample comprised of taxpayers who had one of five 4-digit SSN endings, and a high income subsample), for which the primary and secondary filers were followed over the subsequent six years. This panel consists of more than 550,000 tax returns, and spans the two most recent major tax changes, the Economic Growth and Tax Relief Reconciliation Act (EGTRRA2001) and the Jobs and Growth Tax Relief Reconciliation Act of 2003 (JGTRRA2003).

To bridge the years between these two panels, a third panel was created by drawing from the 1997 and 1998 SOI cross-sectional files those taxpayers who had

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[12] Some of the following discussion of the panel data draws from our discussion of similar data in Bakija and Heim (2008).
[13] For more information on the Family Panel, see Cilke et al. (1999, 2000).
[14] For more information on the 1999-2005 Edited Panel, see Weber and Bryant (2005).

primary filers with one of the two CWHS endings in 1997 (or one of the five CWHS endings in 1998). This panel comprises over 67,000 tax returns.

Since occupation information was not coded for all years of the panel, we impute occupations to observations from these years using information from other years. To do this, we assign to each observation the occupation from the closest year in which an occupation is observed. If there is a tie, we take the occupation from the earlier year.

Marginal tax rates and tax liabilities in this study were calculated using the comprehensive income tax calculator program described in Bakija (2008), and include both state and federal income taxes and Social Security and Medicare payroll taxes. The calculator incorporates such details as the minimum and alternative minimum taxes, maximum tax on personal service income, and income averaging in the years when these were applicable.[15] Marginal tax rates were calculated by incrementing wages and salaries by ten cents, calculating the marginal increase in taxes owed, and dividing that by the ten cents.[16]

For the estimation using the panel file, several cuts were made. All dependent filers and all taxpayers under the age of 25 were dropped from the panel sample, as were married taxpayers who filed separately and taxpayers with missing data on state of residence. To remove returns with internally inconsistent data, we dropped from the panel any returns where the federal income tax liability reported on the return was not sufficiently close to federal income tax liability figured by the tax calculator.[17] Since we

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[15] For some returns in 1979-95 panel, we used an iterative process to back out certain items needed for income averaging and AMT computations from the reported liabilities for those taxes.

[16] Taxes incorporated into our marginal tax rate variable include both federal and state personal income taxes as well as federal Social Security and Medicare payroll taxes. Let *mtr* be the marginal personal income tax rate computed as described above, and *ssmtr* be the combined employer and employee payroll tax computed as described above. Our marginal tax rate variable is (mtr + ssmtr)/[1 + (ssmtr/2)]. This represents the marginal increase in tax liability caused by earning another dollar of wage and salary income *including* the employer payroll tax contribution. For consistency, we add employer social security contributions to our income variable when we use it in the econometric analysis, but not in the descriptive statistics.

[17] Specifically, we cut observations if the federal tax liability before credits and minimum taxes computed by the tax calculator differs from the amount reported in the dataset by more than $10,000. Also note that before doing this, we made extensive efforts to resolve internal

use information from two year lags and one year lead, we exclude any observations for which any of these leads or lags are missing.

We sometimes need to impute occupations across years for an individual, and we wish to avoid incorrectly imputing an occupation to someone who is no longer working. So we drop returns where the primary taxpayer (who is male 90 percent of the time in our panel sample) is likely to be out of the labor force. In addition to dropping people whose occupation codes indicate they are not working in the years we have occupation codes, we also drop from the panel sample returns where the primary taxpayer is aged 65 or above. Returns with income excluding capital gains, or sum of salary income and business income, less than $10,000 are also dropped. Retirement and labor force participation are one margin along which behavior may respond to taxes, so our estimates will not reflect that particular kind of behavioral response.

We then drop anyone with an occupation that either tends not to earn a high income or which represents a very small share of top income earners (including farmers and ranchers, pilots, government workers, teachers, social workers, blue collar workers, and miscellaneous service professions). This is done because we are trying to explain why top income shares are rising, and because we want the people in our sample who experienced little or no change in tax rates to be a good control group (in the sense of providing an accurate counterfactual) for the high-income people who experienced large changes in tax rates. We choose to drop people from the sample based on occupation rather than income (except for the very low $10,000 threshold) because selecting the sample on income can be a source of bias when there is mean-reversion. Under a selection rule based on income, people with positive transitory shocks to income will be more likely to be selected and will subsequently experience income declines, while people with negative transitory shocks to income (who therefore subsequently experience increases in income) are less likely to be selected. Our data confirm that

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inconsistencies in the data by inferring values of problematic variables from information available elsewhere on the return.

occupation (as we have defined it) tends to be far more stable over time than income, so using occupation for selection is far less likely to produce this problem.

The final panel estimation sample comprises 244,909 observations. Sample statistics are presented in Appendix Table A.4. As evidence of the large number of high income taxpayers represented in this sample the mean amount of income (excluding capital gains) is $1.1 million. Over 80 percent of the sample is married, with the mean age of the primary filer being 46. Executives make up 15.0 percent of the sample, with managers comprising 13.1 percent and those working in finance comprising 10.6 percent. Numbers and shares of observations in the panel sample used for estimation that fall into each quantile are shown in appendix table A.5. Twenty percent of the panel estimation sample, or 50,127 tax returns, are in the top 0.1 percent of the income distribution.

Occupations and Incomes of High Income Taxpayers

Table 1 reports the percentages of primary taxpayers that are in each occupation among the top 0.1 percent of income earners, from the 2004 cross-sectional tax data, and compares it to estimates of the same thing by Kaplan and Rauh (2009) that were based on extrapolations from publicly-available data. For comparability with Kaplan and Rauh, in this table we rank taxpayers by income including capital gains. In the tax data, occupation is known for all but 0.7 percent of these taxpayers. In comparison, Kaplan and Rauh, using data from a variety of different sources, are able to identify occupations for about 17.4 percent of this income group. It also appears that the shares of occupations that Kaplan and Rauh study comprise a greater share in the tax data than was found in their paper. In the tax data, 18.4 percent of the top 0.1 percent of the income distribution had financial professions (including financial executives, managers, and supervisors), 6.2 percent were lawyers, and 3.1 percent were in the arts, media or sports, while in their data sources, Kaplan and Rauh were able to identify 10.3 percent of the top 0.1 percent of the income distribution coming from financial professions, 2.4

percent employed in law firms, and 0.9 percent having an occupation in arts, media or sports.

Kaplan and Rauh were able to identify 3.8 percent of the top 0.1 percent of income as top non-financial executives in publicly traded firms. Based on this, they argued that executives represent too small of a share of top income earners for corporate governance issues and stock options to be a good explanation for rising top income shares. Our tax data does not contain information about the ownership structure of the firm for which the taxpayer works, but over 40.8 percent of the top 0.1 percent report their occupation as being an executive, manager, or supervisor of a firm in a non-financial industry, and 28.6 percent report being an executive. Undoubtedly, many of these executives work for closely-held businesses rather than large publicly traded firms. To investigate this issue, we attempt an approximate division of executives, managers, and supervisors into "salaried" versus "closely held business" categories. An executive, manager or supervisor is assigned to the "closley held business" category if the sum of primary earner self-employment income, and partnership and S-corporation income for the return as a whole, exceeds wage and salary income on the return. Otherwise, the executive is assigned to the "salaried" category. Among managers and supervisors in the "salaried" category, wages and salaries represent 94 percent of combined labor and business income reported on the tax return; the corresponding figure for those in the "closely held business" category is only 12 percent, so this method of division appears to work well. We would expect that those in the "salaried" category are likely to be working for publicly-traded corporations, or at least large closely-held corporations. Salaried non-financial executives account for 15 percent of the top 0.1 percent, and salaried managers represent another 4.7 percent, for a total of about 20 percent. The vast difference between this and Kaplan and Rauh's 3.8 percent figure might be explained partly by non-publicly-traded firms, to the extent that executives and managers of these firms receive most of their income from wages and salaries. Some of the difference must also be due to the fact that Kaplan and Rauh only look at the top 5 executives at each firm, and some may be due to other income of executives and managers that is not disclosed in public documents but which is included on their tax returns. This suggests that corporate governance issues and stock options may be more important for explaining top income shares than Kaplan and Rauh suggested. Moreover, while principal-agent problems may be smaller in closely-held firms, they are not always absent, and executives and managers of closely held firms are sometimes compensated with stock options, so that financial market asset prices may be important for explaining their pay. Later in the paper, we demonstrate that the incomes of executives, managers, and supervisors in the top 0.1 percent of the income distribution are highly sensitive to stock prices (this has been demonstrated before for top executives at publicly traded firms by Eissa and Giertz, 2009). Together, executives, managers, and supervisors, and financial professionals account for 59.2 percent of the distribution of income (including capital gains) in 2004. Therefore, it seems that corporate governance issues and stock price movements may indeed play a large role in explaining the movement of top income shares, at least for the top 0.1 percent.

To examine the distribution of occupations across years, Table 2 presents the percentage of primary taxpayers in the top 1 percent of income that report each occupation in the years for which we have occupation data, and Table 3 repeats this exercise for the top 0.1 percent of primary taxpayers. From now on, we focus on income excluding capital gains. For many occupations, the share of the top percentile of taxpayers in each occupation remained relatively stable between 1979 and 2005, but for executives, financial professions, and real estate these shares changed noticably. The fraction of the top 1 percent that are non-financial executives, managers, and supervisors gradually declined, starting at 36 percent in 1979 and dropping to 31 percent by the end of the sample period. Salaried executives declined sharply from 21 percent of the top percentile in 1979 to 11.3 percent by 2005, while executives of closely held businesses rose from 1.8 percent to 4.8 percent of the top percentile. Both changes were sharpest between 1979 and 1993, which is consistent with the observation that TRA86 created an incentive to switch firms from C-corporation to S-corporation status. The share of the top 1 percent in financial professions has almost doubled from 7.7 percent in 1979 to 13.9

percent in 2005. The share of the top 1 percent in real estate related professions was stable between 1979 and 1997, and then grew from 1.8 percent in 1997 to 3.2 percent by 2005, no doubt reflecting the effect of increased housing prices on the incomes of these taxpayers.

Among taxpayers in the top 0.1 percent of the distribution of income, the share in executive, managerial and supervisory occupations drops from 48.1 percent in 1979 to 42.5 percent in 2005, which is similar to the decline for the top one percent as a whole. But the share in financial professions increases even more dramatically, from 11.0 percent to 18.0 percent, and the share in real estate increases from 1.8 percent in 1997 to 3.7 percent in 2005. By 2005, executives, managers, supervisors, and financial professionals accounted for 60.5 percent of the top 0.1 percent of the distribution of income excluding capital gains. Other occupations particularly well-represented in the top 0.1 percent as of 2005 include: lawyers (7.3 percent); medical professionals (5.9 percent); entrepreneurs not already counted elsewhere (3.0 percent); arts, media, and sports (3.0 percent); business operations, which includes professions such as management consultant and accountant (2.9 percent); and computer, mathematical, engineering and other technical professions (2.9 percent).

Tables 4 and 5 examine the occupations of spouses among those in the top 1 percent or top 0.1 percent. Comparisons of spousal occupations over time that involve the 1979 data should be interpreted with caution, because the IRS was evidently less successful at matching spouses to occupations in 1979 (when it was unable to do so for 30.7 percent of returns) than in later years (for instance, only 7 percent were unknown in 1993). Among those for whom an occupation was identified for the spouse, the largest occupation group is non-financial executives, managers, and supervisors; 12.0 percent of taxpayers in the top one percent had a spouse in this category in 2005. The share in this group increased over time, perhaps reflecting increased assortative mating. The share of spouses reporting their occupation being in a medical profession also increased, from 3.5 percent in 1979 to 7.6 percent in 1993, and then further to 8.2 percent in 2005.

Interestingly, the second largest occupation group for spouses in the top one percent of income in 1979 consisted of workers in blue collar or miscellaneous service occupations, at 7.9 percent, though this share declined to 6.4 percent by 2005, perhaps also reflecting increased assortative mating. Finally, the share of spouses in financial, real estate, and law professions increases through the period, from 3.5 percent in 1979 to 8.8 percent in 2005. Looking at the top 0.1 percent of taxpayers, similar patterns are found, though the share in medical professions does not appear to increase among this group. The most notable difference is that a much smaller share of spouses are working in paid employment in the top 0.1 percent. In 2005, 27.6 of taxpayers in the top 0.1 percent had a spouse working in an identified occupation, compared to 38.4 percent for the top one percent as a whole. Finally, 16.1 percent of taxpayers in the top 0.1 percent of the income distribution have a spouse who is an executive, manager, supervisor, or financial professional, suggesting that if anything, looking just at the occupation of the primary taxpayer may understate the importance of corporate governance issues and the stock market in explaining rising top income shares.

Tables 6 and 7 examine the share of national of income received by taxpayers who were in the top 1 percent (or top 0.1 percent) of the income distribution for each primary taxpayer occupation. Over the 1979 to 2005 period, the share of national income (excluding capital gains) going to the top 1 percent increased from 9.2 percent to 17.0 percent. Looking within occupations, although share of people in the top 1 percent employed as executives, managers, and supervisors declined, the share of national income going to members of this group increased substantially, from 3.7 percent to 6.4 percent between 1979 and 2005. The share of income received by financial professionals in the top 1 percent also increased dramatically, from 0.8 percent to 2.8 percent. The bottom panel of the table demonstrates that these two occupation groups alone explain a majority of the increase in the income share of the top 1 percent, explaining 60 percent of the increase between 1979 and 2005, and 61 percent of the increase between 1993 and 2005.

Table 7 shows that the share of income received by the top 0.1 percent of income recipients increased from 2.8 percent in 1979 to 7.3 percent in 2005. Again, the shares received by executives, managers, supervisors, and financial professionals increased markedly, with the increase in the share of income among these occupations accounting for 70 percent of the increase in the share of national income going to the top 0.1 percent of the income distribution between 1979 and 2005.

We next examine the extent to which mean real income in different occupations in a given top quantile of the income distribution would have evolved over the sample period if the occupational composition in the top quantiles had remained constant. This is done for three income groups – taxpayers in the top 1 percent but outside of the top 0.5 percent, taxpayers in the top 0.5 percent but outside the top 0.1 percent, and taxpayers within the top 0.1 percent. To do this, we calculate each occupation's share of each top quantile in 1979. We then identify, in subsequent years, the taxpayers of a given occupation that would have fallen within a particular quantile if that occupation's share of the quantile was the same in the subsequent year as it was in 1979.[18]

Tables 8, 9 and 10 examines the annual real growth rate of income (excluding capital gains) between selected years for tax units inside the top 1 percent but below the top 0.5 percent (p99 – p99.5), inside the top 0.5 percent but outside the top 0.1 percent (p99.5 – p99.9), and within the top one percent (p99.9), respectively. The key lessons of these tables are: (1) real income growth was high in almost all top-earning professions in all three income groupings; (2) despite that, there was substantial heterogeneity in income growth rates across professions; (3) there is substantial heterogeneity across occupations in the apparent degree of sensitivity of income to the business cycle and asset prices; and (4) there was major divergence over time between the incomes of the

[18] For example, lawyers represented 7.3 percent of tax units in the top 0.1 percent of the income distribution in 1979. In each subsequent year *t*, we calculate the number of lawyers that would be in the top 0.1 percent of the income distribution holding occupation composition constant as 0.001 * 0.073 * *N*, where *N* is the total number of tax units in the nation in year *t*, taken from Piketty and Saez (2003, updated 2008). We then sort all lawyers in descending order by income and count down until we get that number of lawyers. We repeat this procedure for each occupation and quantile.

highest paid people within each profession and others in that profession, even when we restrict our attention to people in the top one percent of the national income distribution.

The first three lessons are highlighted in Figures 4, 5, and 6. They graph, for each income quantile, mean real income between 1979 and 2005 for selected occupations (finance, real estate, executives, lawyers, medical professionals, and managers), again holding the occupational shares of the quantiles constant at their 1979 levels. The heterogeneity of income growth and sensitivity to the business cycle and asset prices across occupations is visible in all three figures, but most apparent in the top 0.1 percent.

Focusing on Figure 6, which shows the top 0.1 percent, one sees that among the professions shown in the graph, income grew much more for financial professionals and real estate related professions. Table 6 indicates that financial professionals in the top 0.1 percent experienced a 6.3 percent annual compound growth rate in real income between 1979 through 2005; the figure was 6.1 percent in real estate. Other professions not shown in the graph that experienced the fastest income growth 1979-2005 were business operations professionals (6.3 percent annual real growth), and arts, media, and sports (5.1 percent). Real income growth for non-financial executives and managers was also very strong, at annual rates of 4.2 percent and 4.6 percent, respectively. Lawyers and medical professionals in the top 0.1 percent experienced very healthy annual real income growth rates over this period (3.9 percent and 3.1 percent, respectively), but these growth rates were lower than for the other professions mentioned above, and Figure 6 demonstrates that over the 1979 to 2005 period as a whole, this led to massive divergence of average incomes across professions even among those within the top 0.1 percent.

Figure 6 also nicely illustrates the heterogeneity in apparent responsiveness to business cycles, the stock market, and other asset prices among different professions in the top 0.1 percent. Not surprisingly, incomes of financial professionals increase particularly dramatically during the stock market boom between 1993 and 2001, drop precipitously in 2002 and 2003, and then recover along with the stock market and the economy to new heights in 2004 and 2005. Also unsurprisingly, people in real estate experienced an extremely sharp increase in incomes between 2003 and 2005 as the housing market bubble took off. Executives and managers also exhibit substantial sensitivity to the business cycle and stock market, while the incomes of lawyers and especially medical professionals appear to be relatively insensitive to those factors.

The remaining lesson is that even within the top one percent of income earners, there has been a large amount of divergence in the incomes of people within the same profession. This point is highlighted in Table 11, which reports the ratio of the annual real growth rate among people in each profession in the top 0.1 percent of the national income distribution to the growth rate for taxpayers in the same profession in the 99^{th} to 99.5^{th} percentile range, again holding the occupational composition of the top quantiles constant. Most notably, the real income growth rate for non-financial executives in the top 0.1 percent was 7 times as large as for non-financial executives in the 99^{th} to 99.5^{th} percentile range. Farmers and ranchers were the only profession with convergence, and among the other professions aside from executives, the range of ratios went from 1.7 (for financial professionals) to 4.2 (for non-financial supervisors). The mean ratio was 2.4.

Discussion

What does all this imply for which explanations of increasing income inequality work best, and what does it imply for the taxable income elasticity literature? While an econometric analysis of these questions will be needed to provide a more convincing answer, at this stage the facts do seem consistent with certain observations.

First, the heterogeneity in income growth rates across professions within the top one percent, and the divergence in incomes within professions in the top one percent, both suggest that the causes of rising top income shares cannot *just*, or even primarily, be things that are changing in similar ways over time for everyone within the top one percent, such as federal marginal income tax rates. There is some variation in time paths of federal marginal income tax rates within the top one percent, especially before 1986, but since then most of the independent variation within the top one percent has come from factors, such as the AMT and state of residence, which are not simple increasing functions of income, and so can't explain why income grew so much faster at the top of the top 1 percent than at the bottom. Those facts, together with the very non-linear patterns of income growth exhibited in the data for some professions, suggest year dummies or linear time trends will do a poor job of controlling non-tax influences on income growth, so that more flexible methods are clearly called for.

Second, the fact that executives, managers, supervisors, and financial professionals can account for 70 percent of the increase in income going to the top 0.1 percent of the income distribution, the fact that financial professionals in the top 0.1 percent had substantially faster income growth than almost all other professions, and the fact that incomes of financial professionals, executives, and managers move in tandem with stock market prices during the period, suggest that some combination ofcorporate governance issues, the stock market, and entrepreneurship are probably very important parts of the explanation for rising top income shares. The fact that the incomes of top earners in fields such as medicine and law appear to be not very sensitive to stock market prices might make it possible to separately identify the effects of factors such as taxes from the influence of the stock market in data that has information on occupation. It will also help to use data that includes large non-linear movements both up and down in stock prices, as occurred with the bursting of the Internet bubble and subsequent recovery, as well as data that includes large changes in tax rates in both directions, in order to distinguish the effects of stock prices and taxes from the effects of other influences on income that are hard to measure and might be changing in a smooth fashion over time.

Third, the fact that top income shares are not rising in Continental Europe and Japan suggests that skill-biased technical change and globalization are probably not very good explanations for rising top income shares in the U.S. As previously suggested by Kaplan and Rauh, the fact that top earners in occupations where country-specific human capital is important, such as law, have been experiencing fast income growth further weakens globalization as an explanation for what is happening at the top of the income distribution. But unlike Kaplan and Rauh, we find that professions where high pay is associated with asset market prices (finance and real estate) and superstardom (arts, media, sports) had much faster income growth than lawyers, and were three of the four professions with the fastest income growth among those in the top 0.1 percent. This bolsters both the asset price and "superstar" theories.

It is unclear, however, whether occupations to which the superstar phenomenon applies comprise enough of the top of the distribution to account for much of what is going on. The superstar phenomenon could apply broadly in many different types of occupations. For instance, technology and globalization now enable the best management consultants to sell their services to a much broader audience, and notably their occupational category (business operations) experienced the fastest income growth of all in the top 0.1 percent between 1979 and 2005. But if superstars are so important, is hard to explain why superstars in Continental Europe and Japan have not been causing top income shares to rise there (perhaps social norms prevents this from ocurring).

Finally, given this set of facts, it is hard to think of any factor at all that might be particularly important in explaining growth and top income shares and that is evolving in a smooth linear way over time and would be captured well by a different linear time trend for each income class, except for perhaps social norms, which we arguably can't measure at all.

Preliminary Econometric Analysis

In this section of the paper, we turn to applying the lessons learned above to the estimation of the elasticity of gross income with respect to the net-of-tax share, as well as to other factors such as asset prices, using the 1987 to 2005 panel data on federal income tax returns described earlier. Our base econometric specification takes the following form:

$$
\begin{aligned}
y_{it} = {} & \alpha_i + \alpha_t + \\
& p99.9_{t-2} * (\beta_1 n_{it-1} + \beta_2 n_{it} + \beta_3 n_{it+1} + \beta_4 y_{t-1}) + \\
& p99p99.9_{t-2} * (\beta_5 n_{it-1} + \beta_6 n_{it} + \beta_7 n_{it+1} + \beta_8 y_{t-1}) + \\
& p90p99_{t-2} * (\beta_9 n_{it-1} + \beta_{10} n_{it} + \beta_{11} n_{it+1} + \beta_{12} y_{t-1}) + \qquad (1) \\
& p0p90_{t-2} * (\beta_{13} n_{it-1} + \beta_{14} n_{it} + \beta_{15} n_{it+1} + \beta_{16} y_{t-1}) + \\
& \mathbf{X}_{it}\gamma + \varepsilon_{it},
\end{aligned}
$$

where y_{it} is the log of gross income excluding capital gains, i indexes an individual taxpaying unit, and t indexes time. Once-lagged income is included in the specification to allow for mean reversion and other forms of income dynamics.[19] We allow for a year-specific fixed effect α_t by including year dummies in the specification, which will control for any factors influencing income that are changing in the same way for everyone in the sample over time. We also allow for time-invariant individual characteristics that may be associated with income and our regressors by allowing for an individual specific-fixed effect α_i.

The main explanatory variables of interest involve $n_{it,}$ which represents $ln(1-\tau_{it})$, the log of the net-of-tax-share, where τ_{it} is the taxpayer's marginal tax rate on wage and salary income (including both personal income taxes and payroll taxes). We include variables for n from time t-1 and time t+1 as well, to allow for the possibility of gradual adjustment to tax changes over time, as well as to control for the possibility of income shifting across years in response to anticipated changes in the future tax rate. Similar approaches to dealing with re-timing have been used in the empirical tax literature in general many times, but some of the most influential studies in the taxable income

[19] Once the data is first differenced, we are including the lagged change in income as one method of controlling for transitory fluctuations in income and mean-reversion – this is similar to the approach, for example, in Kopczuk (2005) and Heim (2009), though those papers also included lagged income as a regressor. We are aware that there could be problems with a lagged dependent variable in the presence of serial correlation of the error term. This complication has largely been ignored in the taxable income elasticity literature, but with the very recent exception of Holmlund and Soderstrom (2008), who applied an Arellano-Bond approach to estimate taxable income elasticities on Swedish data. We plan to address this issue to the extent possible in a future draft.

elasticity literature (e.g., Gruber and Saez 2002) have not allowed for retiming of income in response to anticipated tax changes. If re-timing of income is important, we should expect that coefficients on the future net-of-tax-share (n_{t+1}) variables will be negative – if you expect the net-of-tax-share next year to be lower, that means income received next year will face a higher tax burden, which creates an incentive to shift some income from next year to this year, increasing the amount of income reported today. The main quantity of interest for policy evaluation is the sum of the coefficients on n_{it-1}, n_{it}, and n_{it+1}. That sum represents the longer-term elasticity of gross income with respect to a *persistent* change in net-of-tax shares. Intuitively, it tells us what happens when n_{it-1}, n_{it}, and n_{it+1} are *all* increased by one percent, relative to a situation where all of them are lower by one percent; or in other words, this is the effect of a new steady state in the tax regime compared to the old steady state, after the effects of retiming across adjacent years have been worked out of the system. The coefficient on the current-net-of tax share represents the elasticity of income with respect to an increase in the current period net-of-tax share, holding the net-of-tax share constant in adjacent years. Thus, it estimates the response to a transitory one period change in tax rates. If the elasticity with respect to current net-of-tax share is larger than the persistent elasticity, it also suggests willingness to re-time income realization in response to anticipated differences between future and current tax rates.

The variables with names beginning with p are indicator variables for whether the taxpayer was in a particular quantile of the income distribution at time t-2. The top 0.1 percent (99.9th quantile) is $p99.9_{t-2}$; the 99th to 99.9th percentiles are represented by $p99p99.9_{t-2}$; the 90th to 99th percentiles are represented by $p90p99_{t-2}$, and the bottom 90 percent of the income distribution is represented by $p0p90_{t-2}$. This specification allows the elasticity of gross income with respect to the net-of-tax share to differ by one's starting position in the income distribution. That is, people at different income levels can have different degrees of responsiveness to incentives. It also allows the effect of lagged income to differ by starting position in the income distribution. Gruber and Saez (2002), Kopczuk (2005), and Heim (2008), among others, have controlled for mean reversion using variations on this theme, and have found that the degree of mean reversion differs substantially across income levels.

X is a vector of control variables. In addition to the usual demographic factors, we will include in **X** a set of occupation dummies as well as a rich set of interactions among job, industry, starting quantile of the income distribution, stock market prices (measured by the log inflation-adjusted S&P 500 index), housing prices (measured by the log inflation-adjusted state-specific OFHEO housing price index), and state unemployment rates. Further details on how we do this will be provided in the discussion of the estimates.

We remove, and thereby control for, the individual-specific fixed effects by first-differencing the data shown in equation (1) when we implement our estimation procedure. Finally ε_{it} is an error term. In the computation of standard errors, we allow for heteroskedasticity across individuals and correlation of errors across time within individuals by allowing for clustering of the errors by individual.

The net-of-tax shares are endogenous because changes in income can push taxpayers into different marginal tax rate brackets. For each of the three first-differences of n, we use a synthetic tax instrument based on the change in tax rates holding income and all other dollar-valued inputs to the tax calculator function constant in real terms. To calculate the instrument for n_{t+1} we assume that taxpayers know the federal and state tax law applying to them one year in advance, but that they do not know their future income.

Following most of the previous literature, all of our regressions are weighted by the product of a sampling weight and real income (where real income is truncated at $1 million to avoid giving outliers undo influence). Thus our regression estimates indicate the impact of taxes on the average dollar of income in the economy rather than the average person.

In sensitivity analyses, but not our "base" specification, we experiment with including a 6-piece spline in log income (excluding capital gains) from period t-2. Partly because our sample consists predominantly high-income people, and exclusively of people in high-income *occupations*, we set the kinks in the spline at the thresholds for the 90th, 95th, 99th, 99.5th, and 99.9th percentiles of the national income distribution in the relevant year. The purpose of the spline is to control for unmeasured factors that influence income and that are moving in different linear time trends at each point in the income distribution. In addition, the spline controls in a very flexible fashion for mean reversion. The coefficients on the spline variables are reported in such a way that each one represents the average change in income from t-1 to t associated with a 1 percent higher level of initial year t-2 income, among people who are in that particular quantile of the income distribution. Previous taxable income papers that have used a spline in lagged income have generally estimated negative coefficients on almost all segments of the spline, suggesting that the mean-reversion issue dominates (see, e.g., Gruber and Saez 2002).

The kink points we have chosen for the spline make for a significantly more demanding identification strategy than in previous taxable income elasticity papers that have used a spline. Those papers used a ten-piece spline defined by decile of the national income distribution. As a result, in those studies, the linear time trend in unobservables and degree of mean reversion are only allowed to differ in a linear fashion within the top decile. Given the evidence shown above that income growth has been faster the higher you go up in the distribution, even within the top 1%, it seems likely that a more non-linear relationship within the top decile might better capture any unmeasurable non-tax influences on income growth that might be correlated with changes in federal income tax rates. In recent decades, most of the interesting variation in federal income tax rates has occurred within the top decile. Allowing flexibly for different linear time trends within the top decile represents a very demanding identification strategy, and requires that tax rates change in different and non-linear manner over time for different people within the top decile. Fortunately, our 1987-2005 sample period includes both major federal tax increases (1990 and 1993) and major federal tax cuts (2001 and 2003) that had heterogeneous impacts across the income distribution. State taxes, complicated federal features such as the alternative minimum tax, and interactions between these also contribute valuable identifying variation. This approach does have some important costs, however. First, there is the well-known concern that a saturated model increases the noise-to-signal ratio in what is left of the independent variation in taxes, exacerbating bias caused by measurement error in the explanatory variables. Moreover, this strategy runs afoul of the point made by Chetty (2009) that in the face of even small costs to re-optimizing one's plans in response to a tax change, taxpayers will ignore small and subtle changes to their tax incentives, so that evidence based on such changes may give a very misleading prediction for the effects of a larger, more salient tax change.

Column (1) of Table 12 shows the estimates the elasticity of gross income with respect to the net-of-tax share from the "base specification." That is equation (1) with controls for demographic variables, occupation dummies, and a rich set of interactions among occupation, stock prices, starting quantile of the income distribution, unemployment rates, and housing prices, but which does not include a spline in the lagged level of log income. Focusing first on the estimates for the top 0.1 percent, we estimate a long-run elasticity of gross income with respect to a persistent change in net-of-tax share of 0.716, with a standard error of 0.265, suggesting a high degree of responsiveness to incentives for income-earning efforts (or income reporting) among those with the highest incomes, and a correspondingly large deadweight loss from imposing highly progressive tax rates on these taxpayers. Simulations in Giertz (2009, Table 5-6a) suggest that an elasticity of that magnitude would imply that the marginal deadweight loss from raising an additional dollar of government revenue through an increase in the top marginal tax rate (35 percent) would be between $2.03 and $6.57. Very small and statistically insignificant estimates of the coefficients on lag and lead net-of-tax shares, together with the fact that the coefficient on current net-of-tax share is not significantly larger than the long-run elasticity, suggest relatively little re-timing behavior among people in the top 0.1 percent, although the confidence interval around the future change is large.

Interestingly, the estimates for the rest of the top one percent (p99 – p99.9) are quite different. In that income range, there is strong evidence of re-timing of income realization in response to anticipated differences between current and future tax rates, but the long run elasticity is statistically insignificant and of the wrong sign. A one percent increase in next year's net-of-tax share, holding taxes in current and previous year constant, is estimated to reduce current income by 0.77 percent, consistent with people delaying the realization of income to take advantage of lower tax rates next year. Similarly, a one percent increase in this year's net-of-tax share, holding taxes in adjacent years constant, is estimated to increase this year's income by 0.297 percent, which is much larger than the persistent elasticity. For taxpayers in the 90th through 99th percentiles of the income distribution, there is similar but less pronounced evidence of re-timing behavior, and again a statistically insignificant and wrong-signed persistent elasticity. For taxpayers in the bottom 90 percent of the income distribution, all of the elasticity estimates are small and statistically insignificant, suggesting no responsiveness of income to taxation at all.

The second column of Table 12 shows estimates from a specification similar to our base specification, but which drops the variables that interact occupation, income quantiles, stock prices, unemployment, and housing prices. Occupation dummies are still included to allow for different time trends in unobservables for each occupation. This is also somewhat similar to the specification used in Auten, Carroll, and Gee (2008), with the major remaining differences being that their data only covered 1999-2005, and they did not control for net-of-tax shares in adjacent years. Focusing on the top 0.1 percent, the pattern of elasticity estimates is roughly similar to that in our base specification, but the point estimates are smaller to an economically meaningful degree. The point estimate for the persistent price elasticity is 0.448. Given the standard error of 0.228, we can no longer be very confident the estimate is statistically different from zero in this specification. Nonetheless, the difference from the base specification is economically important. Giertz (2009) suggests that the marginal deadweight loss from raising a dollar of revenue by increasing the top marginal rate for people in the top 0.1

percent would be $0.86 at an elasticity of 0.4, which is substantial but roughly four times smaller than an elasticity around 0.7 would imply. The estimates for people between the 99th to 99.9th percentiles and the 90th to 99th percentiles are more similar to those for the base specification, and estimates for the bottom 90 percent are still small and statistically insignificant. The estimates for the top 0.1 percent do suggest that efforts to control for factors like stock prices that can have different influences at different points in the income distribution and in different occupations can make an economically meaningful difference to the coefficient estimates.

Since it seems that the set of control variables matters, in Table 13 we return to the base specification and show the complete list of controls and coefficient estimates. The first four control variables are the lagged change in income interacted with quantile dummies. These estimates are negative and significant, and become more negative the higher up in the income distribution you go. This suggests that mean reversion is important, and is particularly important at the upper reaches of the income distribution. Demographic controls include age, age squared, an indicator variable for the primary taxpayer being male, an indicator variable for marriage, number of children at home, and number of other dependents. Older taxpayers are estimated to have slower income growth, returns with male primary taxpayers have higher income growth, married taxpayers have lower income growth, and children and other dependents have little effect.

The next set of variables shown in Table 13 is the set of occupation indicators, with medical professionals being the excluded category (so the coefficients show the income growth for each occupation relative to medical professionals). Holding other factors constant, executives are estimated to have 4 percent per year faster income growth than doctors, financial professionals 2.5 percent faster growth, lawyers 2.3 percent faster growth, real estate related professions 4 percent faster growth, and entrepreneurs 4.3 percent faster growth, while supervisors have 1.6 percent slower growth. Other occupations are estimated to have income growth not statistically significant in its difference from doctors' income growth.

After that, the remaining variables reflect interactions between occupation, income quantile, asset prices, and unemployment. All income quantiles are defined based on year t-2 income to avoid endogeneity.

The first of these variables, exstk90 through exstk999, represent coefficients on an indicator variable for being a non-financial executive, manager, or supervisor, interacted with the first-differenced log real S&P 500 stock price index, interacted with indicators for each of six quantiles of the income distribution. The indicator represents people who are in the quantile represented by the number in the variable name, but not in the next higher quantile. Consistent with descriptive statistics reported in Eissa and Giertz (2009), we find that the pay of executives (and managers and supervisors) is not very responsive to the stock market for those below the top 0.1 percent of the income distribution, but that income is indeed highly responsive to stock market prices for executives, managers, and supervisors in the top 0.1 percent. A 1 percent increase in real stock prices is estimated to increase pay of top earning executives, managers and supervisors by a statistically significant 0.3 percent.

The next set of variables, techstk90 through techstk99, are defined similarly to the exstk variables, but for people whose occupation involves computers, engineering, and other technical pursuits, and whose industry is not finance, together with people in other occupations whose industry is computers or telecommunications. For this group, there is similarly no estimated responsiveness at the lower income quantiles, but there is much larger sensitivity to stock prices at the 99.5th and 99.9th percentiles. For people in this group who are between the 99.5th and 99.9th percentiles of the income distribution, a one percent increase in stock market prices increases income by 0.446 percent, and for members of this group in the top 0.1 percent of the income distribution, a one percent increase in stock prices increases income by 1.77 percent, with both estimates being highly statistically significant.

The next variables, finstk90 through finstk999, are analgous to the previous two variable sets, but for people in financial professions or whose industry is finance. Here, stock prices have significant impacts for everyone in the top percentile. The point estimates are 0.362 for p99 to p99.5, 0.253 for p99.5 to p99.9, and 0.505 for p99.9 and above.

The othstk90 through othstk999 variables interact stock price changes with income quantiles for people who are not in the executive / manager / supervisor, tech, or finance categories used above. Interestingly, the estimated effects of changes in stock prices are small and even negative for these people in most quantiles. The only statistically significant coefficient is -0.115 for those between the 95th and 99th percentiles. So the bottom line is that (income excluding capital gains) is indeed very sensitive to stock prices among the very highest-earning executives / managers / supervisors, financial professionals, and especially tech workers, even after controlling for a rich set of covariates. This is perhaps not surprising, but the estimates shown above in Table 13 suggest that it may be important to control for this phenomenon if you want to get unbiased estimates of the responsiveness of very-high-income people to taxes, and with the exception of a few papers examining executive compensation data (e.g., Eissa and Giertz 2009), the taxable income elasticity literature has not done so.

The next set of variables, each beginning with "dunemp," represent the change in the taxapayer's state unemployment rate, interacted with dummy variables for each occupation and each income quantile. There is little conclusive evidence of differences in sensitivity to business cycles across occupations, although the confidence intervals are wide. The only statistically significant estimate is -1.982 for people in skilled sales positions. By contrast, there is very strong evidence that the income of people in the top 0.1 percent of the income distribution is much more sensitive to the business cycle than are people who are in highly-paid professions but whose incomes do not put them near the top of the distribution. A one percent increase in the state unemployment rate is estimated to reduce incomes of people in the top 0.1 percentile by 3.585 percent, which is statistically significant and much larger than point estimates for all other quantiles except p99.5 to p99.9. Thus, a general sensitivity to business cycles among the highest earners survives even after controlling for fluctuations in the stock market that are highly correlated with the business cycle.

A final set of controls *rehousepr0* through *rehousepr999* consists of an indicator for being in a real estate profession or being in the real estate or construction industries, interacted with the change in the log inflation-adjusted OFHEO constant-quality state specific housing price index, interacted with income quantiles. The coefficient point estimates for most quantiles are positive and in the 0.3 to 0.5 range, but with large standard errors. Interestingly, the only statistically significant positive effect is for people below the 90th percentile, although the point estimate at 0.253 is not different from that for most other quantiles. The point estimate for the top 0.1 percent is negative but statistically significant, which seems at odds with Figure 6, but may be explained that we are including a much broader category of people here, anyone who works in any type of job in the real estate and construction industries, which may be too broad a categorization to pick up an effect. We also control for the effect of a change in state house price index on people in all other occupations and industries with *othhousepr*, but estimate a small and statistically insignificant impact.

In column (1) of Table 14, we experiment with adding to our base specification the six-piece spline in year t-2 log income (excluding capital gains) that we described earlier. Estimated elasticities for people below the top 0.1 percent do not change very much relative to the base specification without spline (shown back in Table 12), but estimates for the top 0.1 percent do change dramatically. The elasticity of gross income with respect to a persistent change in net-of-tax share is now a wrong-signed -0.27 and statistically insignificant, whereas the -0.591 point estimate on future change in net-of-tax share suggests a large degree of re-timing, both of which sharply contrast with the estimates from the base specification. This is a very saturated model, and because of signal-to-noise ratio reasons and the Chetty argument noted above, it is not necessarily better than the base specification, despite being more robust to omitted variable bias and mean reversion in incomes. Moreover, columns (2) and (3) of Table 14 demonstrate that saturation may not be the problem. Column two shows estimates for the base specification with spline added, but subtracting the variables that interact occupation and quantile with stock prices, house prices, and unemployment. Column three further drops occupation dummies. If anything, the reversal of conclusions relative to the base specification from Table 12 is even more dramatic, with large and stastistically significant evidence of re-timing in response to anticipated future tax changes, and large negative (but statistically insignificant) persistent elasticities.

Table 15 shows the coefficients on the control variables from the specification in column (1) of Table 14 (the base specification plus spline). The coefficients on the lagged changes in income are still negative and significant, and slightly larger in absolute value than before. The coefficients on the splines are large and negative for the top 0.1 percent and the bottom 90 percent, and relatively small for those in between. For the top 0.1 percent, the point estimate suggests that a one percent higher income in year t-2 is associated with an 0.137 percent reduction in income growth between t-1 and t. The coefficient for the bottom 90 percent is -0.144 and significant. This may suggest that lagged changes in income are insufficient to control for mean reversion at either end of the income distribution.

The strong impact of adding a very flexible spline in lagged income to the specification suggests several points. First, it reduces our confidence in the conclusion that the decisions of high-income people about how much income to earn and report are highly responsive to tax rates. Second, it suggests that further research efforts should focus very heavily on more robust methods for dealing with income dynamics, perhaps borrowing techniques for this purpose from the macroeconometrics literature to the extent they can be applied to moderately short panels. Third, the estimates in column (3) of Table 14 suggest that previous studies that have controlled for occupation dummies (Auten and Carroll, 1999, and Auten Carroll and Gee, 2008) might have come to very different conclusions had they controlled for a spline in lagged income, together with controlling for adjacent year net-of-tax shares and allowing for parameter heterogeneity across income classes. It is clear that occupation dummies do not control for the same thing that a spline in lagged income controls for. Fourth, it suggests that controlling for a spline in lagged income that is very flexible at the upper reaches of the income distribution has dramatic impacts on the estimates. At this point it is unclear whether this is because the flexible spline is removing all of our identification (which is not obviously true, because tax rates did not follow a linear time trend during the sample period), or because estimates are highly sensitive to the method of controlling for income dynamics. The previous literature has only controlled for decile-based splines, which restrict the effects of lag income to be similar across the top decile, and our estimates show that lagged income in fact has very diverse effects on income growth among people at different points in the top decile.

In Table 16, we demonstrate that our efforts to allow for income shifting across adjacent years in response to anticipated changes in future tax rates have important effects on the estimates, so that research that does not take that factor into account may come to misleading conclusions. Column (1) of Table 16 estimates a variant of our base specification that omits lag and lead changes in the net-of-tax share. The estimate for the top 0.1 percent is largely unchanged, but the estimate for p99 to p99.9 changes from insignificant and negative to positive 0.272 with a standard error of 0.116. Thus a researcher estimating this model might conclude that people in this income range exhibit a moderate but economically significant behavioral responsiveness to tax rates, but our estimates above suggest that would be a spurious inference. The moderate positive elasticity estimated here appears to be driven by factors such as the well-documented shifting of income from 1993 forward into 1992 in anticipation that the newly elected Clinton administration would raise the top marginal tax rate, which is apparent from Figure 1. Column (2) of Table 16 indicates that it is not just the spline that eliminates the large and significant gross income elasticity estimate for the top 0.1 perecent, but rather the combination of the spline with appropriate controls for adjacent-year income shifting. When we fail to control for income shifting across years, adding the spline does reduce the point estimate substantially, from 0.787 to 0.286, but the estimate is still economically and statistically significant, in contrast to a similar specification but with lags and leads of the net-of-tax share shown above in column (1) of Table 14, which finds an estimate of the persistent elasticity of *negative* 0.27.

Finally, column (1) of Table 17 shows what happens when the base specification is modified to constrain the elasticity with respect to net-of-tax shares to be constant across all income levels. In this specification, the persistent elasticity is -0.017 with a standard error of 0.13, although there is statistically significant evidence of moderate re-timing behavior. But as our estimates above showed, this masks significant heterogeneity across income levels. The second column of Table 17 modifies the base specification by constraining elasticities to be constant across income classes, and also adds a spline and drops the interactions between jobs, quantiles, stock prices, housing prices, and unemployment, to show that the problem is not a saturated model. Similarly to column (1), in this specification, the elasticity of gross income with respect to the net-of-tax share is wrong-signed and insignificant, but there is still statistically significant evidence of re-timing of income in response to taxes.

Conclusion

In this paper, we have presented for the first time complete information on the occupations of very high-income people, and on how the incomes of top earners in different occupations have grown over time. Our findings suggest that the incomes of executives, managers, supervisors, and financial professionals can account for 60 percent of the increase in the share of national income going to the top percentile of the income distribution between 1979 and 2005. We also demonstrate significant heterogeneity in income growth across and within occupations among people in the top percentile of the income distribution, suggesting that factors that changed in the same way over time for all high-income people are probably not the main cause of increasing inequality at the top. The incomes of executives, managers, financial professionals, and technology professionals who are in the top 0.1 percent of the income distribution are found to be very sensitive to stock market fluctuations. Most of our evidence points towards an important role for financial market asset prices and possibly corporate governance and entrepreneurship in explaining the dramatic rise in top income shares. In an econometric specification that controls in a flexible way for the factors that our descriptive statistics suggest are important, we find that a one percent increase in the net of tax share is associated with an 0.7 percent reduction in incomes earned by people in the top 0.1 percent of the income distribution, which would imply that if we were to raise top marginal tax rates further on these taxpayers, the increase in deadweight loss would be substantially larger than the increase in revenue raised. However, we find essentially no evidence at all of any responsiveness of people below the top 0.1 percent, and we find that the estimate for the top 0.1 percent can be reduced to wrongly signed and statistically insignificant if reasonable alternative methods for address the dynamics of income are applied. This suggests that further research on this topic should emphasize better and more robust econometric modeling of the income dynamics process.

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Table 1 -- Percentage of primary taxpayers in top 0.1 percent of the distribution of income (including capital gains) that are in each occupation in 2004: tax return data compared to Kaplan and Rauh

	Tax return data	Kaplan and Rauh Estimate
Executives, managers, supervisors (non-finance)	40.8	
Top non-financial executives, publicly traded firms		3.8
Executive, non-finance, salaried	15.0	
Executive, non-finance, closely held business	13.6	
Manager, non-finance, salaried	4.7	
Manager, non-finance, closely held business	4.6	
Supervisor, non-finance, salaried	1.3	
Supervisor, non-finance, closely held business	1.7	
Financial professions, including management	18.4	10.3
Not working or deceased	6.3	
Lawyers	6.2	2.4
Real estate	4.7	
Medical	4.4	
Entrepreneur not elsewhere classified	3.6	
Arts, media, sports	3.1	0.9
Computer, math, engineering, technical (nonfinance)	3.0	
Other	2.6	
Business operations (nonfinance)	2.2	
Skilled sales (except finance or real estate)	1.9	
Professors and scientists	1.1	
Farmers & ranchers	1.0	
Unknown	0.7	82.6

Source: authors' tabulations of Statistics of Income individual income tax return data and Kaplan and Rauh (2007).

Table 2 -- Percentage of primary taxpayers in top one percent of the distribution of income (excluding capital gains) that are in each occupation

	1979	1993	1997	1999	2001	2002	2003	2004	2005
Executives, managers, supervisors (non-finance)	36.0	33.6	34.5	34.1	31.6	31.3	30.3	30.4	31.0
Medical	16.8	20.4	17.9	15.1	16.5	17.2	17.7	16.7	15.7
Financial professions, including management	7.7	10.6	11.9	13.1	13.5	13.2	13.1	13.6	13.9
Lawyers	7.0	8.9	7.7	7.3	8.3	8.5	8.9	8.8	8.4
Computer, math, engineering, technical (nonfinance)	3.8	3.3	4.2	5.5	5.1	4.9	5.4	4.6	4.6
Not working or deceased	5.2	3.3	4.0	4.2	3.8	4.1	3.5	3.9	4.3
Skilled sales (except finance or real estate)	4.6	4.1	4.5	4.3	4.2	4.1	4.1	4.1	4.2
Blue collar or miscellaneous service	4.2	3.2	3.2	3.2	3.0	3.3	3.2	3.6	3.8
Real estate	1.9	1.4	1.8	2.6	2.6	2.9	2.6	3.1	3.2
Business operations (nonfinance)	2.4	2.2	2.6	2.8	3.3	3.0	2.8	3.3	3.0
Entrepreneur not elsewhere classified	2.7	2.1	2.1	2.1	2.1	1.7	2.1	1.9	2.3
Professors and scientists	1.3	1.8	1.6	1.4	1.8	1.8	1.9	1.8	1.8
Arts, media, sports	1.6	2.0	1.7	2.1	2.0	1.7	2.0	1.7	1.6
Unknown	1.6	1.3	1.0	0.9	0.9	1.0	1.3	1.1	0.9
Government, teachers, social services	0.8	0.9	0.5	0.8	0.5	0.8	0.7	0.8	0.8
Farmers & ranchers	1.8	0.1	0.6	0.4	0.4	0.3	0.4	0.5	0.5
Pilots	0.7	0.8	0.3	0.3	0.4	0.3	0.3	0.2	0.2
Addendum: detail on executives, managers, and supervisors									
Executive, non-finance, salaried	21.0	15.2	15.5	14.0	13.4	12.6	12.0	11.6	11.3
Executive, non-finance, closely held business	1.8	3.5	4.8	4.8	4.5	4.6	4.3	4.7	4.8
Manager, non-finance, salaried	6.6	8.1	8.2	9.0	7.8	7.4	7.8	7.4	7.3
Manager, non-finance, closely held business	1.8	2.1	3.1	3.2	3.1	3.4	3.3	3.7	4.2
Supervisor, non-finance, salaried	2.5	3.1	1.7	1.7	1.6	2.1	1.7	1.7	1.9
Supervisor, non-finance, closely held business	2.3	1.6	1.2	1.3	1.1	1.3	1.2	1.4	1.6
Total executives, managers, supervisors, and finance	52.7	54.0	52.4	49.1	48.1	48.5	48.0	47.1	46.7

Source: authors' tabulations of Statistics of Income individual income tax return data.

Table 3 -- Percentage of primary taxpayers in top 0.1 percent of the distribution of income (excluding capital gains) that are in each occupation

	1979	1993	1997	1999	2001	2002	2003	2004	2005
Executives, managers, supervisors (non-finance)	48.1	45.7	48.4	47.1	42.6	40.6	40.5	40.9	42.5
Financial professions, including management	11.0	14.1	14.7	16.4	19.1	19.0	17.8	18.7	18.0
Lawyers	7.3	6.5	6.3	5.9	7.1	8.2	8.8	8.0	7.3
Medical	7.9	13.3	6.8	4.4	5.2	6.8	7.6	6.3	5.9
Not working or deceased	5.4	2.5	3.5	3.8	4.0	3.7	3.7	3.8	3.8
Real estate	1.8	1.3	1.8	2.1	2.5	2.9	3.0	3.3	3.7
Entrepreneur not elsewhere classified	3.9	3.0	2.8	2.7	2.8	2.9	3.2	3.0	3.0
Arts, media, sports	2.2	3.3	3.5	3.5	3.3	3.6	3.4	3.3	3.0
Business operations (nonfinance)	1.5	1.7	2.3	2.2	2.7	2.7	2.2	2.7	2.9
Computer, math, engineering, technical (nonfinance)	2.3	2.3	3.1	4.7	4.0	3.0	3.1	3.0	2.9
Other known occupation	2.9	2.1	2.2	2.6	2.5	2.5	2.4	2.5	2.7
Skilled sales (except finance or real estate)	2.2	2.9	2.9	2.6	2.4	2.3	2.3	2.3	2.3
Professors and scientists	0.8	0.8	0.7	0.8	0.9	0.9	0.9	0.9	0.9
Farmers & ranchers	1.4	0.2	0.5	0.5	0.5	0.5	0.5	0.5	0.6
Unknown	1.4	0.5	0.5	0.9	0.7	0.6	0.8	0.7	0.5
Addendum: detail on executives, managers, and supervisors									
Executive, non-finance, salaried	32.0	21.8	19.4	18.0	15.4	13.9	14.3	14.5	14.0
Executive, non-finance, closely held business	5.3	12.8	15.7	15.2	13.7	14.2	13.7	14.3	15.6
Manager, non-finance, salaried	4.9	4.1	5.5	6.2	5.4	4.5	4.7	4.1	4.0
Manager, non-finance, closely held business	2.5	3.5	4.8	4.8	5.1	4.9	5.0	5.0	5.8
Supervisor, non-finance, salaried	1.6	1.4	1.0	1.2	1.2	1.1	0.9	1.1	1.0
Supervisor, non-finance, closely held business	1.8	2.0	1.9	1.8	1.8	1.9	1.9	2.0	2.2
Addendum: executives, managers, supervisors, finance	59.0	59.7	63.1	63.5	61.6	59.6	58.4	59.6	60.5

Source: authors' tabulations of Statistics of Income individual income tax return data.

Table 4 -- Percentage of tax units in top one percent of distribution of income (excluding capital gains), by occupation of spouse

	1979	1993	1997	1999	2001	2002	2003	2004	2005
Taxpayer is not married; no spouse	9.5	10.5	11.1	12.5	12.3	11.9	12.0	12.2	12.5
Not working or deceased	26.3	34.1	32.8	31.2	31.4	31.0	30.7	31.7	31.6
Unknown	30.7	7.0	6.3	5.8	5.8	5.4	5.5	5.5	5.6
Spouse in known employment	25.1	37.3	37.3	37.9	38.2	39.5	39.7	38.5	38.4
Executives, managers, and supervisors, non-finance	8.5	11.1	12.4	12.6	12.3	12.2	12.2	12.1	12.0
Medical	3.5	7.6	7.8	6.5	7.7	9.0	8.2	8.5	8.2
Blue collar or miscellaneous service	7.9	7.3	6.9	7.2	6.5	6.8	6.6	6.6	6.4
Government, teachers, social services	4.0	5.7	4.9	5.6	5.4	5.3	5.7	5.0	5.2
Financial professions, including management	1.5	3.1	3.2	3.5	3.6	3.6	3.9	3.5	3.7
Lawyers	0.5	2.0	2.0	2.0	2.6	2.8	3.0	2.8	2.8
Business operations (nonfinance)	1.1	1.7	2.0	2.5	2.6	2.5	2.3	2.3	2.5
Real estate	1.5	1.7	1.6	2.1	1.7	1.9	1.9	2.1	2.3
Arts, media, sports	2.0	2.5	2.6	2.7	2.6	2.5	2.3	2.1	2.2
Skilled sales (except finance or real estate)	0.8	2.4	2.5	2.2	2.2	2.1	2.3	2.2	2.0
Professors and scientists	1.1	2.0	1.7	1.5	1.4	1.4	1.5	1.5	1.4
Computer, math, engineering, technical (nonfinance)	0.3	0.9	1.3	1.6	1.5	1.1	1.3	1.2	1.1
Entrepreneur not elsewhere classified	0.7	0.3	0.5	0.6	0.3	0.4	0.5	0.5	0.5
Farmers & ranchers	0.2	0.1	0.2	0.2	0.2	0.1	0.1	0.1	0.1
Pilots	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0
Detail on executives, managers, and supervisors									
Executive, non-finance, salaried	3.0	3.2	2.7	2.8	2.8	2.6	2.4	2.3	2.2
Executive, non-finance, closely held business	1.0	0.7	0.9	0.9	0.9	0.9	0.8	0.9	0.9
Manager, non-finance, salaried	2.0	4.6	5.5	5.4	5.1	5.3	5.6	5.3	4.8
Manager, non-finance, closely held business	0.7	1.4	2.0	2.2	2.2	2.0	2.2	2.3	2.6
Supervisor, non-finance, salaried	1.2	0.9	1.1	0.8	0.8	0.9	0.8	0.9	0.9
Supervisor, non-finance, closely held business	0.5	0.4	0.3	0.5	0.4	0.5	0.5	0.5	0.5

Table 5 -- Percentage of tax units in top 0.1 percent of distribution of income (excluding capital gains), by occupation of spouse

	1979	1993	1997	1999	2001	2002	2003	2004	2005
Taxpayer is not married; no spouse	11.8	12.3	13.5	13.6	13.4	13.8	14.0	13.7	13.2
Unknown	34.8	8.4	7.8	7.9	8.2	7.7	7.5	7.7	7.3
Not working or deceased	25.7	39.8	39.9	38.6	39.7	38.5	37.9	38.7	39.3
Spouse in known employment	18.4	26.9	26.3	26.9	26.6	28.0	28.1	27.6	27.6
Executives, managers, and supervisors	8.8	12.4	12.3	12.8	11.9	11.9	12.3	12.2	12.5
Other	4.8	8.7	7.9	7.9	7.1	7.0	7.4	7.0	7.2
Medical	3.7	4.7	3.4	3.1	3.3	4.1	4.2	4.1	3.7
Financial professions, including management	2.8	2.9	3.3	3.3	3.6	3.7	3.6	3.6	3.6
Arts, media, sports	2.2	3.0	3.0	3.2	3.1	3.3	3.0	3.1	3.0
Lawyers	0.4	1.7	1.8	1.9	2.1	2.4	2.6	2.6	2.5
Business operations (nonfinance)	1.1	1.1	1.5	1.8	1.8	1.8	1.7	1.8	2.0
Real estate	1.0	1.2	1.3	1.5	1.4	1.7	1.9	1.8	1.9
Skilled sales (except finance or real estate)	0.6	1.7	1.8	1.7	1.6	1.6	1.6	1.5	1.4
Professors and scientists	0.4	0.9	1.0	1.0	1.0	1.0	0.9	0.9	1.0
Computer, math, engineering, technical (nonfinance)	0.2	0.5	0.7	1.0	0.9	0.7	0.7	0.7	0.7
Entrepreneur not elsewhere classified	1.3	0.5	0.7	0.6	0.5	0.6	0.6	0.7	0.7
Farmers & ranchers	0.5	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
Detail on executives, managers, and supervisors									
Executive, non-finance, salaried	4.0	3.8	3.1	2.8	2.4	2.7	2.4	2.3	2.3
Executive, non-finance, closely held business	0.9	2.2	2.6	2.7	2.6	2.5	2.7	2.7	2.9
Manager, non-finance, salaried	2.1	3.2	3.1	3.7	3.0	2.9	3.1	2.8	2.6
Manager, non-finance, closely held business	0.7	1.8	2.4	2.7	2.7	2.8	2.9	3.3	3.6
Supervisor, non-finance, salaried	0.7	0.9	0.5	0.5	0.7	0.4	0.6	0.6	0.5
Supervisor, non-finance, closely held business	0.4	0.5	0.5	0.5	0.6	0.7	0.6	0.6	0.7

Table 6 -- Percentage of national income (excluding capital gains) received by top 1 percent, and each primary taxpayer occupation in top 1 percent

	1979	1993	1997	1999	2001	2002	2003	2004	2005
Share of national income going to top 1 percent	9.18	12.70	14.43	15.41	15.17	14.64	14.99	16.17	16.97
Executives, managers, and supervisors (non-finance)	3.65	4.98	5.93	6.19	5.55	5.26	5.35	5.86	6.35
Financial professions, including management	0.82	1.55	1.96	2.32	2.53	2.34	2.35	2.67	2.77
Lawyers	0.61	1.00	0.96	0.98	1.13	1.13	1.22	1.25	1.22
Medical	1.29	2.19	1.88	1.58	1.77	1.90	1.96	1.91	1.85
Real estate	0.17	0.17	0.25	0.34	0.38	0.41	0.40	0.51	0.57
Skilled sales (except finance or real estate)	0.34	0.44	0.51	0.51	0.48	0.46	0.47	0.50	0.53
Arts, media, sports	0.17	0.34	0.38	0.44	0.43	0.42	0.45	0.44	0.42
Entrepreneur not elsewhere classified	0.31	0.33	0.36	0.38	0.38	0.34	0.38	0.40	0.47
Computer, math, engineering, technical (nonfinance)	0.31	0.35	0.51	0.78	0.67	0.56	0.62	0.57	0.60
Business operations (nonfinance)	0.18	0.25	0.35	0.39	0.45	0.40	0.37	0.47	0.48
Professors and scientists	0.10	0.18	0.17	0.17	0.21	0.19	0.21	0.22	0.23
Farmers & ranchers	0.16	0.02	0.08	0.07	0.07	0.05	0.06	0.07	0.08
Pilots	0.04	0.05	0.02	0.02	0.03	0.03	0.03	0.02	0.02
Government, teachers, social services	0.07	0.08	0.06	0.09	0.07	0.09	0.08	0.08	0.09
Blue collar or low-skill service	0.33	0.32	0.36	0.40	0.38	0.39	0.38	0.45	0.49
Not working or deceased	0.48	0.37	0.53	0.61	0.57	0.56	0.52	0.61	0.67
Unknown	0.15	0.10	0.11	0.13	0.11	0.11	0.14	0.14	0.12
Addendum: detail on executives, managers, supervisors									
Executive, non-finance, salaried	2.23	2.24	2.56	2.53	2.25	1.97	2.03	2.22	2.22
Executive, non-finance, closely held business	0.29	1.10	1.50	1.48	1.37	1.41	1.41	1.60	1.87
Manager, non-finance, salaried	0.54	0.79	0.95	1.19	0.95	0.86	0.91	0.92	0.92
Manager, non-finance, closely held business	0.19	0.33	0.53	0.55	0.56	0.57	0.58	0.66	0.80
Supervisor, non-finance, salaried	0.21	0.30	0.20	0.21	0.21	0.23	0.20	0.21	0.23
Supervisor, non-finance, closely held business	0.19	0.22	0.20	0.22	0.20	0.21	0.21	0.25	0.30
Total executives, managers, supervisors, and finance:	4.47	6.53	7.90	8.51	8.07	7.59	7.70	8.53	9.12
percent of increase since 1979 that they explain		59	65	65	60	57	56	58	60
percent of increase since 1993 that they explain			79	73	62	55	51	58	61

Table 7 -- Percentage of national income (excluding capital gains) received by top 0.1 percent, and each primary taxpayer occupation in top 0.1 percent

	1979	1993	1997	1999	2001	2002	2003	2004	2005
Share of national income going to top 0.1 percent	2.83	4.60	5.65	6.41	6.12	5.71	5.96	6.79	7.34
Executives, managers, and supervisors (non-finance)	1.37	2.32	2.96	3.16	2.73	2.51	2.63	3.05	3.42
Financial professions, including management	0.34	0.70	0.92	1.15	1.31	1.18	1.17	1.41	1.45
Lawyers	0.17	0.25	0.27	0.30	0.36	0.36	0.40	0.40	0.39
Medical	0.16	0.40	0.23	0.16	0.20	0.25	0.28	0.26	0.26
Real estate	0.05	0.05	0.08	0.11	0.14	0.15	0.16	0.21	0.25
Skilled sales (except finance or real estate)	0.05	0.11	0.12	0.13	0.11	0.10	0.11	0.12	0.14
Arts, media, sports	0.08	0.20	0.24	0.27	0.26	0.29	0.28	0.28	0.27
Entrepreneur not elsewhere classified	0.14	0.16	0.18	0.20	0.19	0.18	0.20	0.22	0.25
Computer, math, engineering, technical (nonfinance)	0.06	0.09	0.15	0.31	0.22	0.15	0.16	0.16	0.18
Business operations (nonfinance)	0.03	0.07	0.11	0.13	0.14	0.13	0.12	0.16	0.18
Professors and scientists	0.02	0.03	0.04	0.05	0.05	0.05	0.05	0.06	0.06
Farmers & ranchers	0.04	0.01	0.03	0.03	0.02	0.02	0.03	0.03	0.03
Not working or deceased	0.16	0.10	0.19	0.24	0.23	0.20	0.21	0.25	0.26
Unknown	0.06	0.02	0.03	0.05	0.04	0.03	0.04	0.04	0.03
Other	0.08	0.09	0.10	0.14	0.12	0.12	0.12	0.14	0.17
Detail on executives, managers, and supervisors (non-finance)									
Executive, non-finance, salaried	0.90	1.00	1.19	1.27	1.03	0.84	0.94	1.13	1.14
Executive, non-finance, closely held business	0.19	0.86	1.12	1.09	0.99	1.04	1.05	1.20	1.45
Manager, non-finance, salaried	0.12	0.15	0.25	0.39	0.27	0.21	0.22	0.23	0.24
Manager, non-finance, closely held business	0.08	0.16	0.25	0.26	0.27	0.26	0.28	0.31	0.39
Supervisor, non-finance, salaried	0.04	0.06	0.05	0.06	0.06	0.05	0.05	0.06	0.06
Supervisor, non-finance, closely held business	0.04	0.09	0.09	0.10	0.10	0.10	0.10	0.11	0.14
Total executives, managers, supervisors, and finance:	1.72	3.02	3.88	4.31	4.04	3.69	3.80	4.46	4.87
percent of increase since 1979 they explain		74	77	72	71	68	67	69	70
percent of increase since 1993 that they explain			82	71	67	60	57	66	67

Table 8 -- Average annual real growth rate of income excluding capital gains, by job of primary taxpayer, among tax units in the top 1 percent but outside the top 0.5 percent of the distribution, using constant year 1979 job shares, ranked by income growth 1979-2005

	1979-1993	1993-1999	1999-2002	2002-2005	1979-2005
Financial professions, including management	2.6	6.7	-1.3	4.4	3.3
Real estate	0.1	9.9	0.8	7.9	3.2
Business operations (nonfinance)	1.0	6.7	-0.1	4.5	2.6
Manager, non-finance	1.6	6.7	-3.7	4.0	2.4
Professors and scientists	2.2	2.1	-0.3	5.3	2.2
Lawyers	1.9	2.6	1.9	2.4	2.1
Arts, media, sports	1.9	6.2	-3.5	0.3	2.1
Computer, math, engineering, technical (nonfinance)	0.5	8.3	-4.3	2.6	1.9
Skilled sales (except finance or real estate)	1.0	4.6	-2.9	3.1	1.6
Medical	2.0	0.8	1.8	0.7	1.6
Entrepreneur not elsewhere classified	0.3	3.5	-4.8	8.6	1.3
Supervisor, non-finance	0.7	0.9	-0.2	3.0	0.9
Executive, non-finance	0.1	3.8	-3.4	0.6	0.6
Farmers & ranchers	-7.3	13.3	-1.1	3.6	-0.9

Table 9 -- Average annual real growth rate of income excluding capital gains, by job of primary taxpayer, among tax units in the top 0.5 percent but outside the top 0.1 percent of the distribution, using constant year 1979 job shares, ranked by income growth 1979-2005

	1979-1993	1993-1999	1999-2002	2002-2005	1979-2005
Real estate	0.7	10.3	1.4	11.4	4.1
Financial professions, including management	3.4	7.6	0.3	4.3	4.1
Business operations (nonfinance)	2.1	8.8	-0.7	7.8	3.9
Arts, media, sports	4.0	7.5	-2.2	0.5	3.6
Manager, non-finance	2.0	9.3	-5.0	5.5	3.2
Professors and scientists	2.7	3.2	-0.7	7.6	2.9
Lawyers	2.3	4.0	1.8	3.3	2.8
Computer, math, engineering, technical (nonfinance)	1.1	12.4	-9.6	4.8	2.7
Skilled sales (except finance or real estate)	2.3	4.8	-3.4	4.2	2.4
Medical	3.1	0.3	2.0	1.9	2.2
Entrepreneur not elsewhere classified	0.7	4.4	-0.8	7.5	2.1
Supervisor, non-finance	1.3	3.8	-2.9	6.3	1.9
Executive, non-finance	1.2	4.6	-5.2	3.4	1.5
Farmers & ranchers	-6.9	15.2	-4.0	8.9	-0.1

Table 10 -- Average annual real growth rate of income excluding capital gains, for each primary taxpayer job among tax units in the top 0.1 percent of the distribution, using constant year 1979 job shares, ranked by income growth

	1979-1993	1993-1999	1999-2002	2002-2005	1979-2005
Business operations (nonfinance)	5.2	11.2	-4.6	13.8	6.3
Real estate	1.6	12.1	5.3	17.2	6.1
Financial professions, including management	4.2	11.3	-2.8	9.7	5.6
Arts, media, sports	5.5	8.1	0.8	1.4	5.1
Manager, non-finance	3.1	13.3	-9.8	11.0	4.6
Professors and scientists	2.4	10.5	-4.0	12.3	4.6
Skilled sales (except finance or real estate)	4.4	7.7	-7.2	11.3	4.5
Computer, math, engineering, technical (nonfinance)	2.4	21.2	-19.4	8.7	4.3
Executive, non-finance	3.9	7.4	-6.9	11.6	4.2
Supervisor, non-finance	3.5	5.2	-2.3	9.4	3.9
Lawyers	3.1	7.1	-1.1	6.4	3.9
Medical	4.1	0.0	2.3	5.4	3.1
Entrepreneur not elsewhere classified	1.3	7.0	-4.9	11.3	3.0
Farmers & ranchers	-5.4	15.5	-4.0	11.1	1.1

Table 11 -- Divergence: ratio of 1979-2005 growth rate of real income (excluding capital gains) in the top 0.1 percent of income distribution, to growth rate at p99 to p99.5, by job, holding job shares in top percentiles constant at 1979 levels, 1979-2005

Occupation	Ratio
Executive, non-finance	7.0
Supervisor, non-finance	4.2
Skilled sales (except finance or real estate)	2.9
Business operations (nonfinance)	2.5
Arts, media, sports	2.5
Computer, math, engineering, technical (nonfinance)	2.2
Entrepreneur not elsewhere classified	2.2
Professors and scientists	2.0
Medical	2.0
Manager, non-finance	1.9
Real estate	1.9
Lawyers	1.8
Financial professions, including management	1.7
Farmers & ranchers	-1.2
Mean	2.4

Source: authors' tabulations from Statistics of Income individual income tax return data.

Table 12 -- Estimates of elasticity of income with respect to net-of-tax share: base specification, with and without interactions

	(1)	(2)
	Base specification, including job dummies and full set of controls	Including job dummies but excluding stock and house price and unemployment interactions
Top 0.1 percent		
lag change in log net-of-tax share	0.011	0.063
	(0.131)	(0.104)
current change in log net-of-tax share	0.785	0.587
	(0.130)**	(0.129)**
future change in log net-of-tax share	-0.081	-0.202
	(0.331)	(0.271)
persistent elasticity (sum of 3 coefficients above)	0.716	0.448
	(0.265)**	(0.228)
p99 - 99.9		
lag change in log net-of-tax share	0.140	0.189
	(0.108)	(0.104)
current change in log net-of-tax share	0.297	0.221
	(0.117)*	(0.118)
future change in log net-of-tax share	-0.772	-0.850
	(0.146)**	(0.128)**
persistent elasticity (sum of 3 coefficients above)	-0.335	-0.440
	(0.194)	(0.188)
p90 - p99		
lag change in log net-of-tax share	0.064	0.037
	(0.088)	(0.090)
current change in log net-of-tax share	-0.055	-0.048
	(0.118)	(0.118)
future change in log net-of-tax share	-0.424	-0.356
	(0.191)*	(0.187)
persistent elasticity (sum of 3 coefficients above)	-0.415	-0.367
	(0.324)	(0.324)
Bottom 90 percent		
lag change in log net-of-tax share	-0.089	-0.109
	(0.065)	(0.065)
current change in log net-of-tax share	0.031	0.023
	(0.094)	(0.093)
future change in log net-of-tax share	0.080	0.100
	(0.135)	(0.133)
persistent elasticity (sum of 3 coefficients above)	0.021	0.013
	(0.235)	(0.232)

Robust standard errors clustered by individual in parentheses.
* significant at 5 percent; ** significant at 1 percent

Table 13 -- Coefficients on control variables in base specification

(lag Δy) * p0p90	-0.147	exstk95	-0.009	dunemp_medical	0.927
	(0.015)**		(0.057)		(0.860)
(lag Δy) * p90p99	-0.239	exstk99	0.043	dunemp_realestate	-2.045
	(0.021)**		(0.091)		(1.885)
(lag Δy) * p99p99.9	-0.349	exstk995	0.070	dunemp_sales	-1.982
	(0.014)**		(0.082)		(0.861)*
(lag Δy) * p99.9	-0.318	exstk999	0.306	dunemp_mediasports	0.027
	(0.018)**		(0.107)**		(1.381)
age	-0.004	techstk90	-0.002	dunemp_entrep	-2.061
	(0.001)**		(0.042)		(1.412)
(age/100) squared	0.155	techstk95	0.083	dunemp_tech	-0.492
	(0.149)		(0.048)		(0.826)
male	0.018	techstk99	0.260	dunemp_profsc	-0.683
	(0.005)**		(0.296)		(0.896)
married	-0.013	techstk995	0.446	dunemp0	0.389
	(0.004)**		(0.159)**		(0.784)
children at home	-0.003	techstk999	1.772	dunemp90	0.478
	(0.002)		(0.339)**		(0.800)
other dependents	0.004	finstk90	0.034	dunemp95	-0.299
	(0.002)*		(0.133)		(0.794)
executive	0.040	finstk95	-0.146	dunemp99	-0.303
	(0.006)**		(0.088)		(1.014)
manager	0.004	finstk99	0.362	dunemp995	-1.535
	(0.005)		(0.137)**		(0.963)
supervisor	-0.016	finstk995	0.253	dunemp999	-3.585
	(0.005)**		(0.136)		(1.064)**
finance	0.025	finstk999	0.505	rehousepr0	0.253
	(0.006)**		(0.158)**		(0.101)*
lawyer	0.023	othstk90	-0.054	rehousepr90	0.242
	(0.006)**		(0.044)		(0.399)
realestate	0.040	othstk95	-0.115	rehousepr95	0.305
	(0.015)**		(0.052)*		(0.217)
sales	-0.007	othstk99	-0.001	rehousepr99	0.533
	(0.005)		(0.080)		(0.309)
mediasports	0.011	othstk995	-0.007	rehousepr995	0.344
	(0.011)		(0.067)		(0.289)
entrepreneur	0.043	othstk999	-0.113	rehousepr999	-0.224
	(0.011)**		(0.115)		(0.308)
technical	-0.025	dunemp_exmansup	-0.734	othhousepr	0.030
	(0.004)**		(0.822)		(0.031)
profscience	-0.007	dunemp_finance	0.050	Year dummies?	yes
	(0.005)		(0.938)		
exstk90	-0.052	dunemp_lawyer	-0.127		
	(0.048)		(1.027)		

Robust standard errors clustered by individual in parentheses.
* significant at 5 percent; ** significant at 1 percent

Table 14 -- Estimates of elasticity of income with respect to net-of-tax share: base specification supplemented with spline in lagged log income, with and without interactions and occupation

	(1)	(2)	(3)
	Base specification plus spline	Base specification plus spline, minus stock, house price, & unemployment interactions	Base specification plus spline, minus stock, house price, & unemployment interactions, minus job dummies
Top 0.1 percent			
lag change in log net-of-tax share	0.031	0.157	0.166
	(0.122)	(0.098)	(0.098)
current change in log net-of-tax share	0.291	0.114	0.105
	(0.130)*	(0.126)	(0.127)
future change in log net-of-tax share	-0.591	-0.854	-0.873
	(0.333)	(0.275)**	(0.271)**
persistent elasticity (sum of 3 coefficients above)	-0.270	-0.583	-0.602
	(0.290)	(0.253)	(0.250)
p99 - 99.9			
lag change in log net-of-tax share	0.145	0.200	0.206
	(0.110)	(0.105)	(0.105)
current change in log net-of-tax share	0.217	0.148	0.141
	(0.117)	(0.119)	(0.121)
future change in log net-of-tax share	-0.821	-0.894	-0.900
	(0.147)**	(0.129)**	(0.128)**
persistent elasticity (sum of 3 coefficients above)	-0.459	-0.547	-0.552
	(0.196)	(0.191)	(0.193)
p90 - p99			
lag change in log net-of-tax share	0.044	0.026	0.025
	(0.087)	(0.088)	(0.089)
current change in log net-of-tax share	-0.078	-0.078	-0.078
	(0.117)	(0.118)	(0.118)
future change in log net-of-tax share	-0.432	-0.395	-0.406
	(0.191)*	(0.187)*	(0.187)*
persistent elasticity (sum of 3 coefficients above)	-0.465	-0.446	-0.459
	(0.321)	(0.321)	(0.322)
below p90			
lag change in log net-of-tax share	-0.090	-0.114	-0.119
	(0.064)	(0.065)	(0.066)
current change in log net-of-tax share	0.033	0.027	0.025
	(0.092)	(0.091)	(0.092)
future change in log net-of-tax share	0.108	0.135	0.135
	(0.136)	(0.134)	(0.134)
persistent elasticity (sum of 3 coefficients above)	0.051	0.048	0.0403
	(0.236)	(0.234)	(0.236)

Robust standard errors clustered by individual in parentheses. * significant at 5 percent; ** significant at 1 percent

Table 15 -- Coefficients on control variables in base specification supplemented with spline in lagged income

(lag Δy) * p0p90	-0.215	sales	-0.014	othstk99	0.020
	(0.016)**		(0.005)**		(0.080)
(lag Δy) * p90p99	-0.240	mediasports	0.004	othstk995	0.029
	(0.021)**		(0.013)		(0.070)
(lag Δy) * p99p99.9	-0.355	entrepreneur	0.029	othstk999	0.050
	(0.014)**		(0.012)*		(0.111)
(lag Δy) * p99.9	-0.384	technical	-0.026	dunemp_exmansup	-0.710
	(0.019)**		(0.004)**		(0.806)
lnyspline1	-0.144	profscience	-0.014	dunemp_finance	-0.003
	(0.008)**		(0.005)*		(0.921)
lnyspline2	0.019	exstk90	0.011	dunemp_lawyer	-0.136
	(0.017)		(0.050)		(1.016)
lnyspline3	0.026	exstk95	0.024	dunemp_medical	0.785
	(0.012)*		(0.056)		(0.844)
lnyspline4	-0.024	exstk99	0.051	dunemp_realestate	-2.029
	(0.027)		(0.091)		(1.894)
lnyspline5	-0.059	exstk995	0.083	dunemp_sales	-1.839
	(0.011)**		(0.082)		(0.843)*
lnyspline6	-0.137	exstk999	0.410	dunemp_mediasports	0.278
	(0.010)**		(0.104)**		(1.390)
age	0.000	techstk90	0.044	dunemp_entrep	-2.175
	(0.001)		(0.043)		(1.440)
(age/100) squared	-0.274	techstk95	0.110	dunemp_tech	-0.540
	(0.159)		(0.048)*		(0.812)
male	0.036	techstk99	0.271	dunemp_profsc	-0.526
	(0.005)**		(0.296)		(0.881)
married	0.017	techstk995	0.434	dunemp0	0.238
	(0.005)**		(0.159)**		(0.766)
children at home	-0.008	techstk999	1.555	dunemp90	0.837
	(0.002)**		(0.360)**		(0.786)
other dependents	0.005	finstk90	0.077	dunemp95	-0.259
	(0.002)**		(0.133)		(0.791)
executive	0.052	finstk95	-0.123	dunemp99	-0.481
	(0.006)**		(0.088)		(0.997)
manager	-0.000	finstk99	0.373	dunemp995	-1.059
	(0.005)		(0.136)**		(0.958)
supervisor	-0.035	finstk995	0.242	dunemp999	-0.922
	(0.005)**		(0.137)		(1.028)
finance	0.030	finstk999	0.425		
	(0.006)**		(0.158)**		
lawyer	0.031	othstk90	0.013	Year dummies?	yes
	(0.006)**		(0.044)	House price variables	yes
realestate	0.033	othstk95	-0.077		
	(0.016)*		(0.053)		

Robust standard errors clustered by individual in parentheses.
* significant at 5 percent; ** significant at 1 percent

Table 16 -- Estimates of elasticity of income with respect to net-of-tax share: no lags and leads of net-of-tax share

	(1)	(2)
	Base specification	Base specification plus spline
Top 0.1 percent		
current change in log net-of-tax share	0.787	0.286
	(0.127)**	(0.128)*
p99 - 99.9		
current change in log net-of-tax share	0.272	0.200
	(0.116)*	(0.117)
p90 - p99		
current change in log net-of-tax share	-0.082	-0.092
	(0.098)	(0.098)
below p90		
current change in log net-of-tax share	0.072	-0.092
	(0.082)	(0.098)

Robust standard errors clustered by individual in parentheses.

* significant at 5 percent; ** significant at 1 percent

Table 17 -- Estimates of elasticity of income with respect to net-of-tax share: constraining elasticities to be constant across income classes

	(1)	(2)
	Base specification	Base specification plus spline, minus stock, house price, & unemployment interactions
lag change in log net-of-tax share	-0.004	0.001
	(0.048)	(0.049)
current change in log net-of-tax share	0.177	0.072
	(0.064)**	(0.064)
future change in log net-of-tax share	-0.190	-0.330
	(0.064)**	(0.063)**
persistent elasticity (sum of 3 coefficients above)	-0.017	-0.258
	(0.130)	(0.132)

Robust standard errors clustered by individual in parentheses.

* significant at 5 percent; ** significant at 1 percent

Table A.1 -- Job Classifications Used in This Paper, Part 1

	Job	Description	Relation to 2000 SOC and 1997 NAICS codes
1	**Executive, non-finance, salaried**	Executives, except those whose industry is finance , government, if wage and salary income >= business income (Schedule C self-employment of the taxpayer plus partnership and S-c,p,ation income of the return)	SOC=111000 , 111010; excludes executives with industry of finance (NAICS codes of 520000, 522100 - 525920, 525990, 551111) , government (921110 - 928120, and 521000 - 521110).
2	**Manager, non-finance, salaried**	Management occupations, except f, executives, financial managers, legislat,s, farmers, ranchers, agricultural managers, postmasters, and property and real estate managers, and those whose industry is finance , government; if wage and salary income >= business income.	SOC=110000, 111020, 112000 - 113020, 113040 -19120, 119150 - 119190, 131110, NAICS industry is not finance or government.
3	**Supervisor, non-finance, salaried**	Supervisors in any field except finance or government; if wage and salary income >= business income.	SOC codes 331000 - 331020, 351000 - 351011, 371011 - 371012, 391000 - 391010, 411000 - 411012, 431000 - 431010, 451010, 471000 - 471010, 491010, 511000, 511010; NAICS industry is not finance or government.
4	**Executive, non-finance, closely held business**	Same as 1, but business income > wage and salary income.	Same as 1, but business income > wage and salary income.
5	**Manager, non-finance, closely held business**	Same as 2, but business income > wage and salary income.	Same as 2, but business income > wage and salary income.
6	**Supervisor non-finance, closely held business**	Same as 3, but business income > wage and salary income.	Same as 3, but business income > wage and salary income.
7	**Financial professions**	Any financial SOC code, e.g., "financial managers," "financial specialists," "securities, commodities, and financial services sales agents," etc.; executives whose industry is finance, jobs 11 and 12 below (skilled sales; computer, engineering and technical) where industry is finance; taxpayers classified by the IRS as "investors"	SOC = 113030, 132000, 132030 - 132072, 132090, 413030, 920000; or job=11 or 12 below and NAICS industry is finance.
8	**Lawyers**	Lawyers, judges, legal occupations besides support	SOC = 230000 - 231020

Table A.1 -- Job Classifications Used in This Paper, Part 2

9	**Medical**	Medical doctors, surgeons, and other skilled medical professions	SOC = 291030, 291050, 291070, 291120 - 291130, 292000 - 299099.
10	**Real estate**	Property and real estate managers; appraisers and assesors of real estate; real estate brokers and agents	SOC = 119140, 132020, or 419020
11	**Skilled sales (except finance , real estate)**	Skilled sales positions; excludes anyone whose NAICS industry is finance, real estate, or construction	SOC = 413000 - 413020, 413090 - 419010, 419030 - 419099; NAICS industry is not finance; NAICS is not real estate or construction (525930, 531000-531310, 233000-235990).
12	**Arts, media, sports**	Arts, design, entertainment, sports, and media occupations, except blue-collar	SOC = 270000 - 273090, 274020.
13	**Entrepreneur not elsewhere classified**	Occupation is not assigned an SOC code, but taxpayer reports self-employment income on return.	No SOC code, but self-employment income > 0.
14	**Computer, math, engineering, technical (nonfinance)**	Computer and mathematical occupations; architects and engineers; technicians; excludes anyone whose industry is finance.	SOC = 150000 - 173031, 194000 - 194093; NAICS industry is not finance.
15	**Business operations (nonfinance)**	Nonfinancial business operations professions; for example accountants and management consultants.	SOC = 130000 - 131190
16	**Professors and scientists**	Professors and scientists	SOC = 190000 - 193099, 25100 - 251190
17	**Farmers & ranchers**	Farmers, ranchers, agricultural managers and supervisors	SOC = 119010 - 119012, 451010
18	**Pilots**	Aircraft pilots and navigators	SOC = 532010
19	**Government, teachers, social services**	Executives, managers and supervisors with NAICS industry = government; miscellaneous government workers; teachers; community and social services occupations	SOC = 251191- 259040, 210000 - 212090, 111030, 119130, 434030, 434060, 435050, 435052, 435053, 970000
20	**Blue collar , miscellaneous service**	All other SOC codes, which are generally blue collar jobs, or service jobs of relatively low skill-intensity.	All other SOC codes
21	**Not working , deceased**	Coded by IRS	Coded by IRS
22	**Unknown**		

Table A.2 -- Repeated cross section dataset sample statistics

	Mean	St. Dev.
Income	1,521,090	11,372,522
Income Excluding Capital Gains	834,491	6,321,352
Labor and Business Income	695,973	4,562,001
Wage and Salary Income	444,583	2,569,487
Have a Closely Held Business	0.255	0.436
Married	0.661	0.473
Observations	1,594,359	

Source: Authors' tabulations of Statistics of Income individual income tax return data from 1979, 1993, 1997, 1999, and 2001-2005.
Means are unweighted.

Table A.3 -- Occupation and industry of primary and secondary filers in repeated cross-section dataset

Occupation	Primary Fraction	Secondary Fraction	Industry	Primary Fraction	Secondary Fraction
Executive, salaried	8.97	2.2	Arts, media, sports	2.50	1.52
Manager, salaried	5.5	3.9	Finance	6.78	2.96
Supervisor, salaried	2.78	1.4	Management consulting	1.50	0.68
Executive, closely held business	4.78	1.34	Accounting	0.69	0.57
Manager, closely held business	2.59	1.99	Real estate and construction	8.62	3.37
Supervisor, closely held business	1.87	0.63	Law	1.55	0.82
Financial professions (non-managerial)	6.62	2.6	Health care	5.47	5.74
Lawyers	2.83	1.18	Computers and telecommunications	2.82	1.19
Medical	4.84	4.66	Government	4.19	4.61
Real estate	2.79	2.01	Other specified industry	43.14	24.84
Skilled sales (except finance or real estate)	2.54	1.62	Unknown, not working, or deceased	22.72	53.68
Arts, media, sports	1.91	2.49			
Entrepreneur not elsewhere classified	2.95	0.71			
Computer, math, engineering, technical (nonfinance)	3.73	1.03			
Business operations (nonfinance)	2.11	2.21			
Professors and scientists	1.14	0.99			
Farmers & ranchers	1.97	0.45			
Pilots	0.14	0.01			
Government, teachers, social services	3.12	5.61			
Blue collar or miscellaneous service	17.42	13.4			
Not working or deceased	10.82	37.94			
Unknown	8.56	11.63			

Source: Authors' tabulations of Statistics of Income individual income tax return data from 1979, 1993, 1997, 1999, and 2001-2005.

Table A.4 -- Sample statistics from 1987-2005 panel of tax returns, sample used for estimation

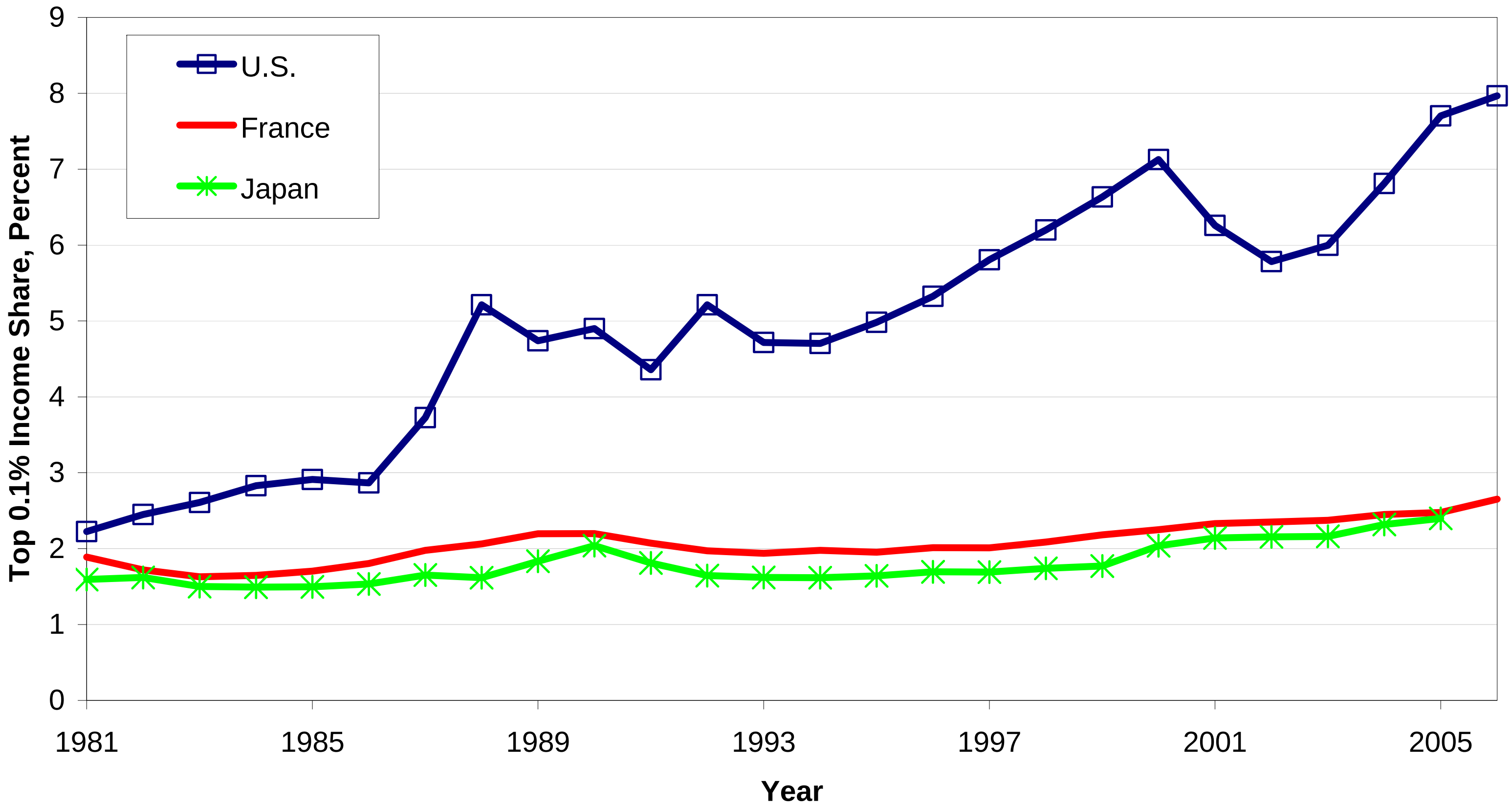
	Mean	St. Dev.
ln(Net ot Tax Share)	-0.499	0.123
Income Excluding Capital Gains	1,174,150	5,253,504
Age	46.583	9.331
Male	0.900	0.300
Married	0.805	0.396
Children at Home	0.496	0.805
Other Dependents	0.719	1.103
Executive	0.150	0.357
Manager	0.131	0.337
Supervisor	0.089	0.285
Finance	0.106	0.308
Lawyer	0.060	0.237
Real Estate	0.020	0.140
Skilled sales	0.057	0.233
Media and Sports	0.033	0.178
Entrepreneur	0.029	0.169
Technical	0.096	0.294
Professors and Scientists	0.046	0.210
ln(House Price)	11.933	0.377
ln(Real S&P 500)	6.644	0.361
State Unemployment Rate	0.060	0.014
Observations	244,909	

Source: Authors' tabulations of Statistics of Income individual income tax return data from 1987-96 Family Panel, 1997-98 CWHS Returns, and 1999-2005 Edited Panel.

Table A.5 -- Income Characteristics of Panel Estimation Sample

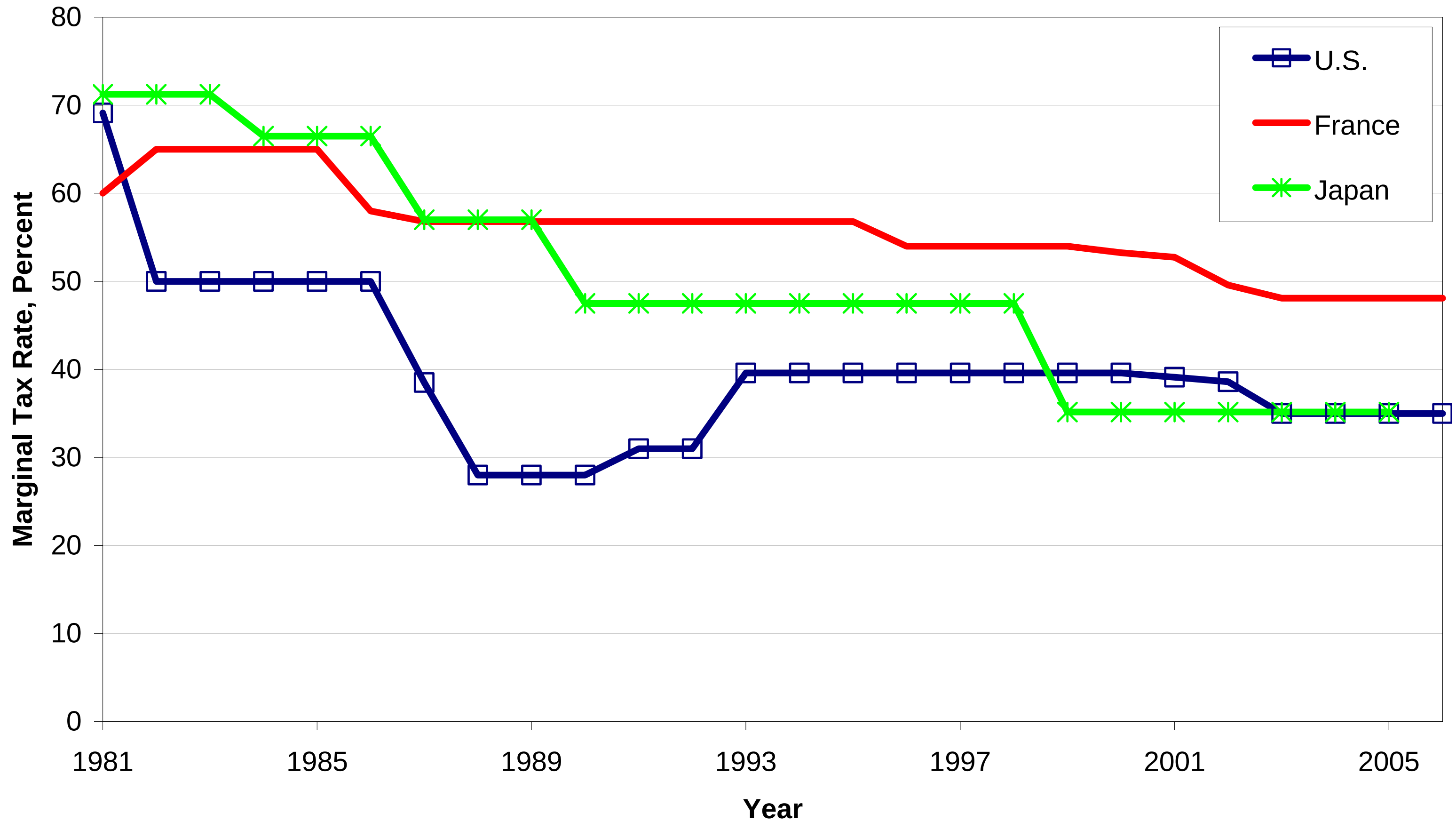
	Fraction of sample	Number of observations	Minimum income (excluding capital gains) in 2005, in thousands of constant year 2007 dollars
Below 90th percenitle of national income distribution	0.30	72,569	10
90th to 95th percentiles	0.10	25,438	94
95th to 99th percentiles	0.18	43,733	129
99th to 99.5th percentiles	0.06	15,787	295
99.5th to 99.9th percentiles	0.15	37,255	450
Top 0.1 percent	0.20	50,127	1,246

Figure 1 -- Percentage of national income (excluding capital gains) received by top 0.1% of income earners: United States, France, and Japan, 1981 - 2006



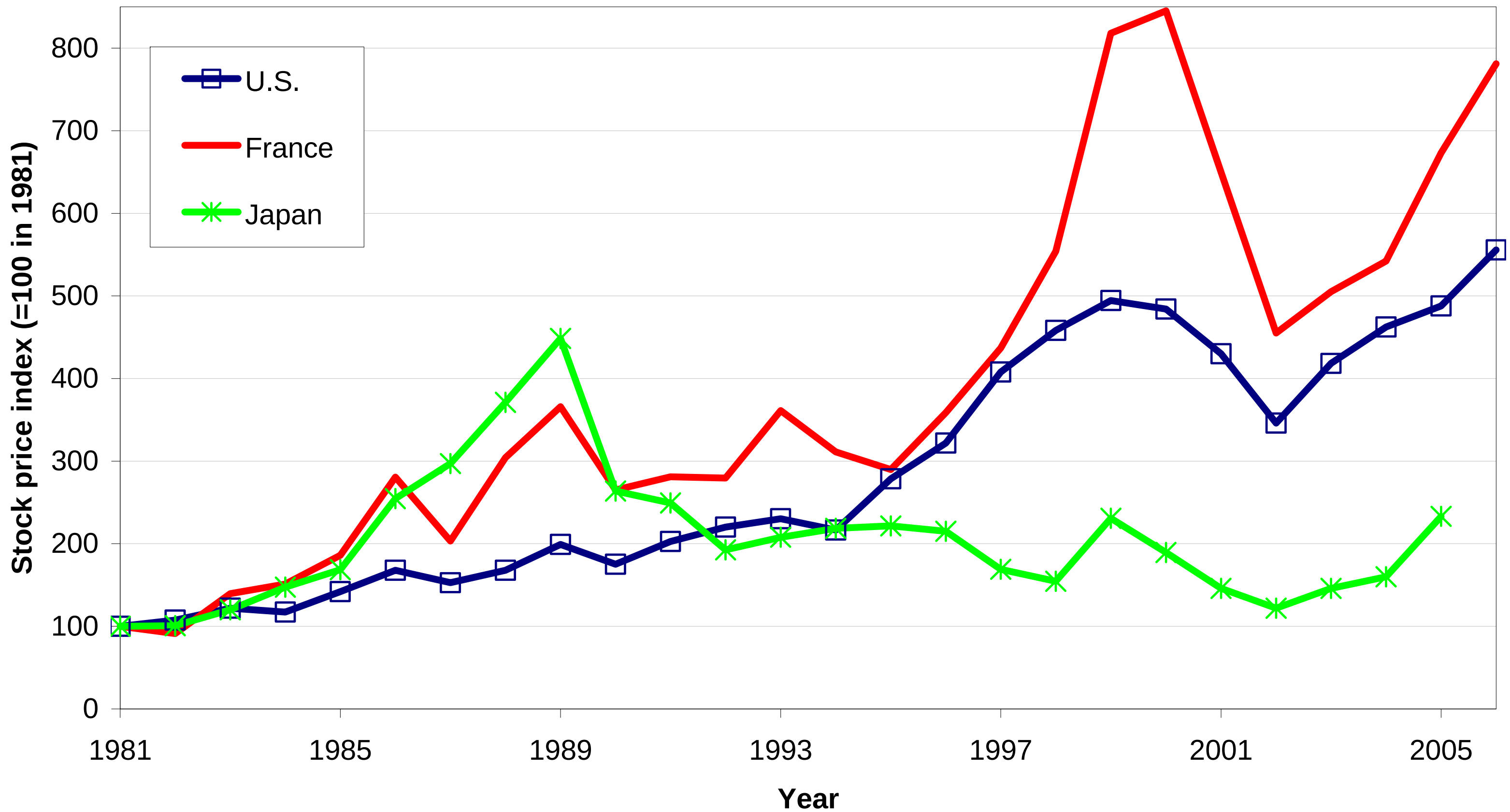
Source: Piketty and Saez (2003, updated in 2008 at <http://elsa.berkeley.edu/~saez/TabFig2006.xls>; Moriguchi and Saez (2008); Piketty (2003); Landais (2008); and upublished tables provided to the authors by Camille Landais.

Figure 2 -- Top marginal income tax rate: United States, France, and Japan, 1981 - 2006



Source: OECD (2009).

Figure 3 -- Index of average stock prices, adjusted for inflation: United States, France, and Japan, 1981 - 2006



Source: OECD (2009). Depicts the NYSE Composite index for the U.S., the TSE Topix All Shares index for Japan, and the Paris Stock Exchange SBF 250 index for France, each deflated using each country's consumer price index.

Figure 4 -- Mean income excluding capital gains in thousands of constant year 2007 dollars, top 1% but outside top 0.5% of distribution, by job of primary taxpayer, using constant 1979 job shares

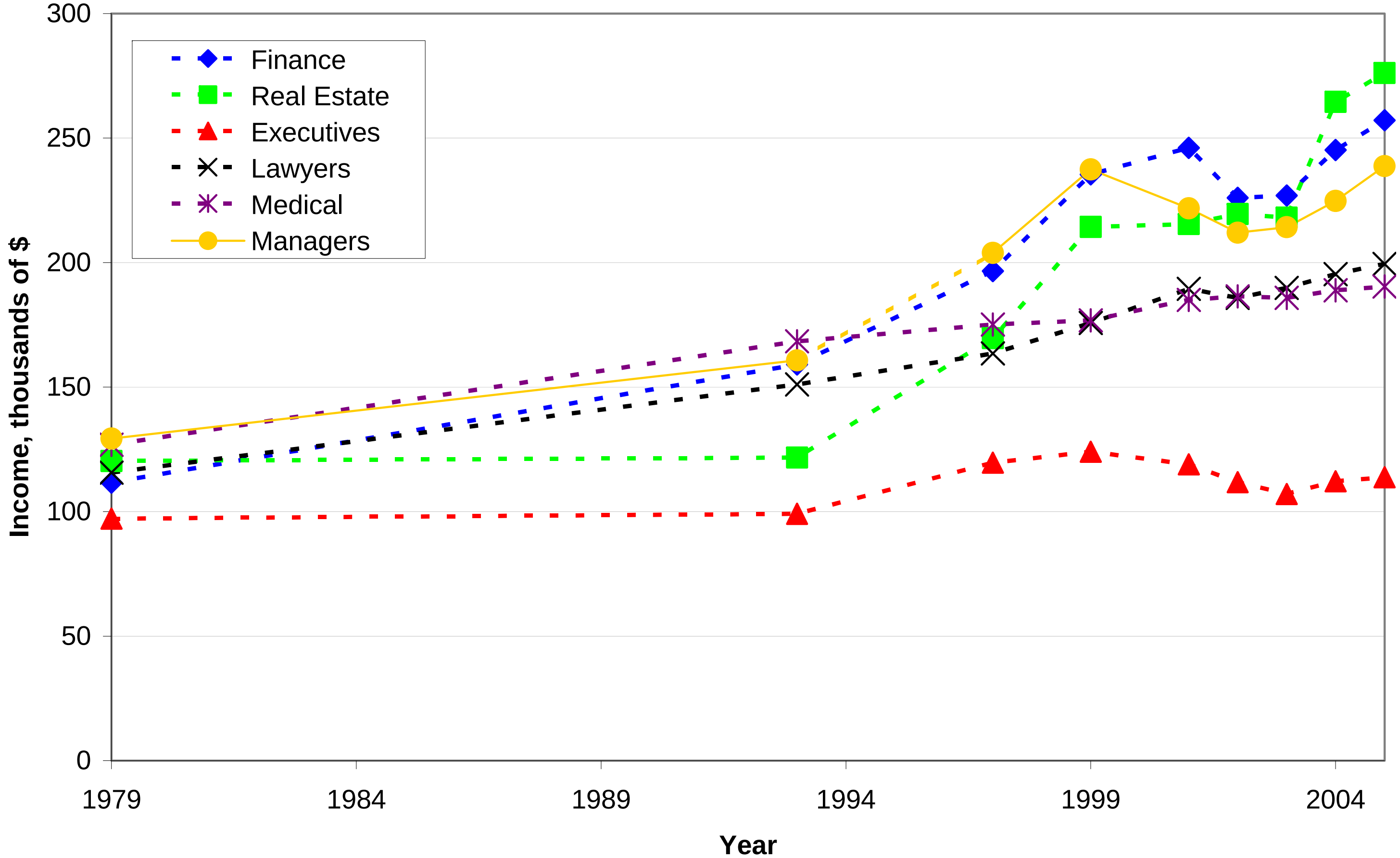


Figure 5 -- Mean income excluding capital gains in thousands of constant year 2007 dollars, top 0.5% but outside 0.1% of distribution, by job of primary taxpayer, using constant 1979 job shares

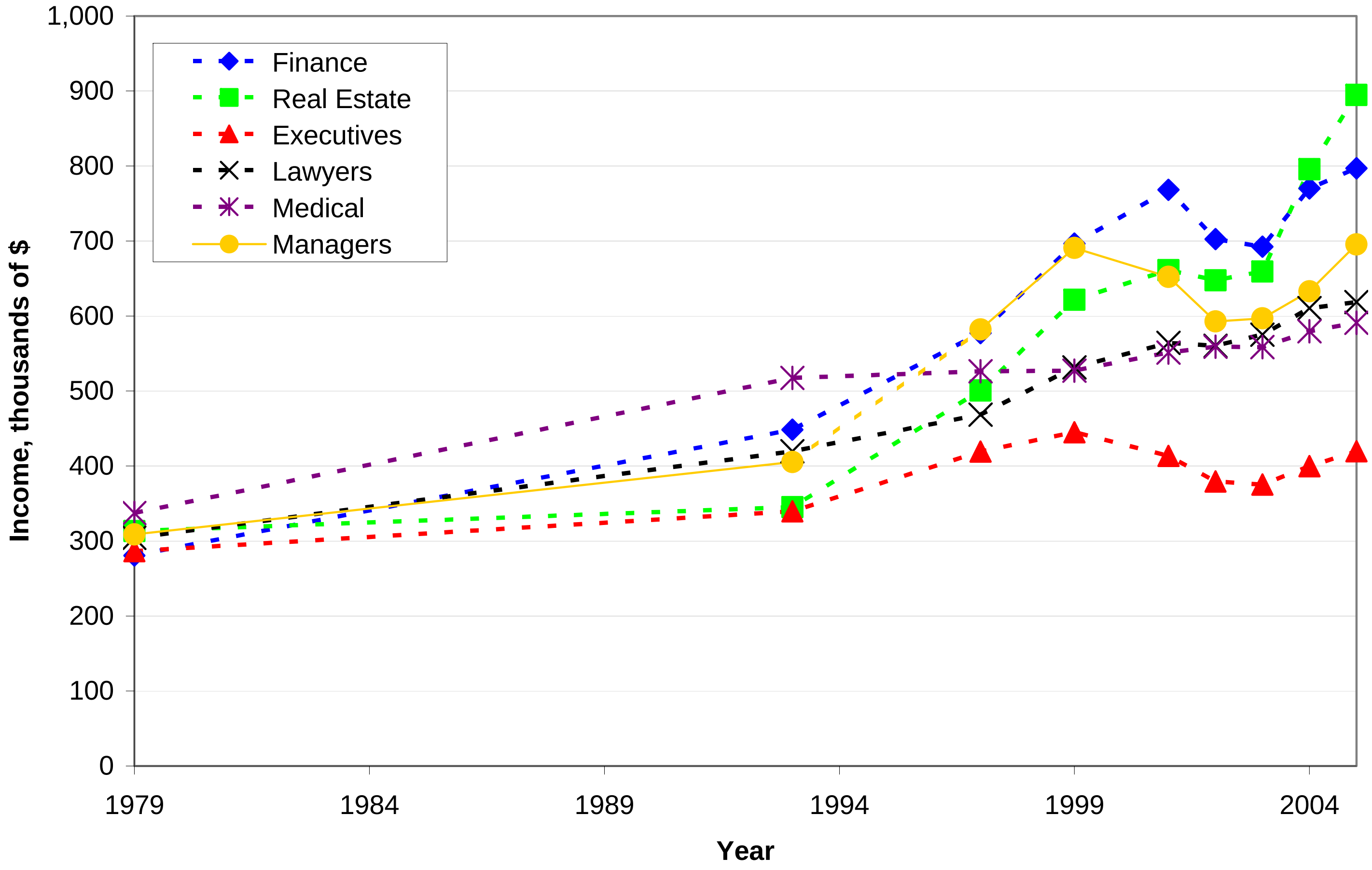


Figure 6 -- Mean income excluding capital gains in thousands of constant year 2007 dollars, top 0.1% of distribution, by job of primary taxpayer, using constant 1979 job shares