Will Inequality Continue to Rise? Forecasting Income Inequality in the United States

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Abstract: Recently, an idea has emerged that "the rich are getting richer and the poor are getting poorer". Using historical data from the CPS, this paper performs pseudo-out-of-sample (2011-2014) and true out-of-sample (2015-2017) forecasts for eight measures of income inequality. While measures of human capital attainment and labor force participation often enhance performing models, the out-of-sample forecasts differ between models by <6% for all variables, and by <2% for 4/8 measures. Though the top 1% share of income may continue to rise (slowly) for households, the top 0.1% income share and inequality within the top 1% are predicted to fall.

Keywords: Forecasting; Inequality; Wage Inequality
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1 Introduction

Efforts to explain trends in income inequality have increased as it has become a hot topic for policy debate. Moreover, recent works such as Piketty (2014) seek to predict future trends. As the literature on skill-biased technological change continues to evolve, economists debate levels, measures, income definitions, and appropriate data to reconcile estimates from existing studies.[1] Most have shown a trend of increasing inequality, since 1980, yet it has not been determined whether this trend will continue and if so, what model might best predict it? This paper answers these questions by choosing models to forecast several inequality measures and providing short-term forecasts.

In order to best predict inequality, we must begin with two major questions: what is the most appropriate measure, and what then are its determinants? Though seemingly straightforward, these questions are very difficult to answer. Many sources of data can be used to study the income distribution in the United States, including historical data from the Current Population Survey (CPS), Internal Revenue Service (IRS), American Community Survey (ACS), Survey of Consumer Finances (SCF) and decennial censuses. Once a data source is selected, establishing a consistent series proves to be a daunting exercise. Changes in questionnaires, income definitions, topcoding practices, treatment of transfers, and other factors are likely to affect estimates of inequality. Even once a consistent series can be produced, the choice of measure is vital.

The selection of the most appropriate inequality measure is often driven by data constraints and income definitions. Some survey datasets have detailed sources of income; others are administrative. Both are likely to suffer from bias and underreporting, particularly among top earners. We may choose to study wages or labor or market earnings, or income includ-

[1] Such studies include but certainly are not limited to Goldin and Katz (1998), Acemoglu (1998), Acemoglu (2002), Goldin and Katz (2008), Schultz (1975) and Moretti (2013).

ing (or excluding) transfers and capital gains. We may be able to observe these series for individuals, households, labor force participants, or tax units. In this paper, I will study two categories of income: (1) individual earnings - comprised of wages, self-employment, and farm income, and (2) household income - comprised of labor income (70% of total household income), capital income, and government transfers.

After choosing an income definition and a population, we are left with many choices for inequality measures including the popular Gini index, the general entropy measures, wage polarization, quintiles, and income shares, such as the top 1 percent. Although inequality is generally thought to be rising, the rate of its increase depends on the measure chosen. For instance, while calculations from the CPS show that in the past 35 years the Gini for individual labor market earnings has not changed and the Gini for household income has risen by 13% (See Table 1), calculations of Piketty and Saez (2003) using IRS data suggest that the income share of the top 1% has risen by 136%.

Both survey and administrative data have shown the stagnation of low and middle incomes, while top shares have increased rapidly (Piketty, 2014). Therefore, it is necessary to look at both top shares and income inequality overall. Thus, in this paper I will focus on three measures which capture the volatility of top incomes: the share of income accruing to the top 1%, the share of income accruing to the top 0.1%, the Gini index *within* the top 1%, and a measure of the overall distribution (Gini index). Additionally, I will look at the 90/10 income ratio (income share of the top 90%/bottom 10%) as a robustness measure of the overall distribution in the discussion section.

Once the data, measure, and population to study are selected, we can turn to the second big question: what determines inequality? Here, I group potential determinants into three major categories: human capital attainment, labor force structure, and macroeconomic indicators.

When considering human capital attainment, I consider percentages of the population who have completed high school or college in addition to the rate of return to education. In order to capture changes in inputs and outputs of the labor force, I consider female labor force participation and occupational and sectoral shifts related to skill biased technological change. Finally for macroeconomic indicators, I test the explanatory importance of business cycle measures including GDP growth, inflation, and unemployment.

In line with the seminal paper by Burkhauser et al. (2011), I use data from the CPS to forecast the following measures of inequality for individual earnings and household income (8 in total): the top 1% share, top 0.1% share, the Gini coefficient *within* the top 1%, and the overall Gini coefficient. Focusing on predicting short-run changes in income inequality, this paper complements the literature on determinants and predictions of long-run trends as well as studying the impacts of policy changes. Using a general-to-specific modeling approach and Impulse Indicator Saturation (IIS) to find structural breaks in the series, I use historical data to perform pseudo-out-of-sample forecasts for these measures of income inequality for 2011-2014 and true out-of-sample forecasts for 2015-2017.

I find that while metrics of human capital attainment and measures of labor force participation often lead to better performing forecasts in the test period, the out-of-sample forecasts differ between models by less than 6% for all variables, and by less than 2% for 4 out of 8 measures.[2] Often model selection is extremely sensitive to not only variable choice but lag length as well. In fact, for two measures, the "best" forecast model does not significantly outperform the naïve model when a bootstrapped White Reality Check is performed (White, 2000), implying adding outside variables does not lead to a better forecast. Moreover, results generally indicate the difficulty of producing an accurate inequality forecast, regardless of model chosen and subsequent challenges of assessing future trends.

[2] In section 6, results for the 90/10 measure for individuals and households are discussed as well.

This paper proceeds as follows. Sections 2 and 3 review literature on determinants of income inequality and describe the data. Section 4 outlines the model and methodology and Section 5 presents the results, discussed in Section 6. Section 7 concludes.

2 Determinants of Income Inequality

In order to predict which variables will produce the most accurate forecasts, it is helpful to begin with a survey of the extensive literature on inequality to motivate their selection. While there is general agreement on the rise in inequality over the past few decades in the U.S. as well as in other countries, there are multiple theories as to its cause. I begin with skill-biased technological change.

2.1 The Role of SBTC in Income Inequality

Skill-biased technological change (or SBTC) has been a popular topic of academic debate, making headlines in recent years. Popularized by Goldin and Katz (1998) and Acemoglu (1998), the discussion on the duration, role, and impact of technological change has evolved over the course of two decades.[3] Goldin and Katz (1998) studied industries from 1909-1929 to see the impact of technology on the wage structure, finding that the wage gap between those with high school diplomas and those with less education narrowed and then remained stable, rather than expanding. This leads to the following questions: what is different this time around? How does it affect income inequality? Will these trends continue?

Acemoglu (1998) sheds some light on this question by first documenting the increase in supply of skilled members of the labor force from 1970 onward and then breaking up its effect into the short-run and long-run. In the short-run (the 1970s), this increase in sup-

[3]Prior to their works, Schultz (1975) discussed the notion of allocative efficiency, which allowed high-skill workers (those with more education) to use technology more effectively in response to changes in expected returns, but also postulated the eventual catch-up of low-skill workers.

ply reduces the skill premium through a substitution effect (a movement down the relative demand curve). In the long-run, it induces SBTC and increases the skill premium (the demand curve shifts out) by inducing "faster upgrading of skill-complementary technologies". In recent decades, the introduction of new technologies has accelerated the skill bias, which can be represented as a college premium.

In a follow-up paper, Acemoglu (2002) expands on the theory that there has been an acceleration in the skill bias in the past few decades as a response to the increase in the skilled labor force, as compared to the past 60 years. However, he believes that the rate of overall progress has not increased sharply and we are not in the middle of a "technological revolution", but rather that the type of technology being developed has changed (Acemoglu, 2002). Additionally, he points out that average wages have stagnated, while low-skill wages have fallen in real terms since the 1970s. For the high-skilled, real wages have increased.

Goldin and Katz (2008) provide two explanations for the rise in inequality: demand side and supply side. On the demand side, continuously changing technology has kept moving forward to push up skill prices, rather than acting as a one-time shock. On the supply side, educational attainment has experienced a slowdown (esp. for males). They explain that although the relative supply of college educated people grew, it grew less quickly from 1980-2005 than in previous decades, believing this mechanism to be the driving force behind increasing inequality. This deceleration in human capital growth has meant that supply hasn't kept up with the demand, leading to a rising skill premium and thus inequality.[4]

Autor et al. (2006) show that the labor market has become polarized during recent decades. High-skill and low-skill jobs have grown while jobs in the middle of the skill distribution have

[4] Goldin and Katz (2008, p. 305) estimate empirically that demand (the speed up in skill bias) outpaces the growth in the supply of skills (3.75% vs. 2.3% from 1980-2005). An alternative explanation may lie in the allocative efficiency argument of Schultz (1975), discussed above.

been displaced. Additionally, Autor et al. (2008) argue against the “revisionist” view that growth in wage inequality in the 1980s was an “episode” due to a decline in the real minimum wage and labor force composition changes. While the minimum wage appears to have contributed to the rise of lower-tail inequality, it did not contribute to rises in the other quintiles.

Acemoglu and Autor (2011) further analyze the existence and causes of wage polarization. First identifying that though the college/high school wage gap has increased monotonically, the overall rise in earnings inequality has not been monotonic. Over time, occupation has increased in statistical importance in explaining wage differences across workers. Accordingly, I test the effectiveness of a skill premium (college wage/high school wage) measure for inequality forecasting. However, they offer a few cautions: there is no one-to-one mapping of skills and tasks, and the response of technology can be endogenous to labor market conditions. This may have an impact on the predictive quality of the skill-premium.

2.2 Human Capital and the Changing Labor Force Structure

Given the clear importance of education in the SBTC theory, educational attainment variables are important to consider. To be employed in a high-skill job, it is often necessary to acquire a high level of human capital, usually by way of a college education. Using census data from the postwar period for adult males, Chiswick and Mincer (1981) sought to explain and project earnings inequality (measured by the variance) with a human capital earnings function. They found that the most important determinant was the rate of return to education (then predicted to be constant), along with changes in the distribution of age and employment. As aforementioned, I will look at the return to education via the skill premium as a predictive variable along with labor force participation (discussed below).

Lindley and Machin (2014) look at spatial dimensions of labor market inequality in the U.S. (1980-2010) and conclude that there is a persistent and rising wage gap between college graduates and high school graduates. Similarly, Florida and Mellander (2013) find that wage inequality is associated with SBTC and city size by looking at 350 metro areas using the 2010 ACS. Consistent with these studies, I look at changes in shares of the population with bachelors degrees and high school diplomas.

To capture the effects of this increased educational attainment on the labor force, Foote and Ryan (2015) studied the evolution of low-skill, middle-skill, and high-skill jobs, with particular attention to trends during the Great Recession. They classify jobs as high-skill (non-routine cognitive skills-managers, professionals, and technicians), middle-skill (routine-manual and routine-cognitive) and low-skill (non-routine manual). They found that middle-skill jobs are cyclical and have been lost, because they are replaceable - a structural shift which is unlikely to reverse (Foote and Ryan, 2015). Additionally, low-skill jobs have not been, and won't be, cyclical in the future, while high-skill jobs have become more cyclical recently. Accordingly, I have included their constructed measures of high-skill, middle-skill, and low-skill levels of employment as well as ratios of the above groups.[5]

A related factor suggested by the SBTC framework is the evolution of services in the economy. Given that the share of U.S. labor hours in service occupations grew by 30% from 1980 to 2005 (Autor and Dorn, 2013), there is reason to believe it will be an important determinant of inequality. Beaudry et al. (2014) also claim that there has been a "reversal" of employment patterns in 2000 due to changes within-cohorts and therefore high-skill workers are doing low-skill jobs. This is occupational downgrading without a decrease in wages. Therefore, I will test the share of services in GDP as an explanatory variable.

In order to properly observe the impact of changes in the labor force, we must consider female labor force participation. During the 20th century, female labor force participation

[5]See appendix for more details.

rates tripled. Beaudry et al. (2014) argue that an important factor in the growth observed in the 1980s and 1990s was the increased labor force participation of women. Recently, Acemoglu et al. (2004) have shown that as female labor force participation has increased it may have affected the direction of technological change and reduced the wage differential. Women tend to work in jobs which benefit more from the technological advances than men do - less routine, low-skilled labor. Specifically, women who entered the labor force were closer substitutes for men with high school degrees than for men with less or more education.[6]

Accordingly, their model shows that a 10% increase in female labor supply lowers male wages by 2.5-4% for those with high school diplomas, 1-2.5% for those with bachelors degrees, and 1.5-2.5% for those who completed 8th grade, for a total reduction of 3-5%. Male earnings inequality is expected to increase and women's wages have been growing relative to men's, reducing the wage gap (Acemoglu et al., 2004). Moreover, this effect may be particularly important given the stronger impact on wages and unemployment that recessions have had historically (particularly the Great Recession) for men vs. women (Wall, 2009).[7]

2.3 Macroeconomic Influences

Another set of potentially significant factors is changes in the macroeconomy, particularly given that the pseudo-out-of-sample period includes the aftermath of the Great Recession. Though there is a large debate in the literature regarding the relationship of growth in GDP and income inequality, it is natural to consider the impact of changes in the business cycle.[8]

[6] This relationship may also be two-directional. Improved technology used in home production was shown to significantly increase female labor force participation in the postwar period (Greenwood et al., 2005).

[7] While another natural variable to test may be demographic change, particularly with regards to the baby boomers, the working age population series for this time period is not stationary, even after second differencing, and loses economic meaning if further differenced. Moreover, while Almas et al. (2011) find that controlling for age slightly mitigates the sharpness of inequality trends for Norweigan males (1967-2000), Blinder and Esaki (1978) did not find a strong impact of changes in the demographic distribution on the earnings profile. A priori, it is unclear what the effect of demographic change on inequality may be. It was also not found to be a useful predictor in Gindelsky (2015).

[8] GDP and GDP per capita are 99% correlated in the U.S. in recent decades. GDP per capita was found to serve the same purpose as a predictive variable as GDP in Gindelsky (2015) and therefore will not be tested separately in this exercise.

For many countries, government expenditure as a share of GDP has been found to be an inequality determinant (Barro, 2000). It's important to note that government expenditure may also be used to mitigate (or aggravate) rises in inequality. Increased growth or government expenditure may be seen in effects of outcomes such as decreases in unemployment (which are unlikely to affect incomes uniformly) on inequality.

Testing CPS data for 1947-1974, Blinder and Esaki (1978) find that unemployment has a strong effect on the bottom two income quintiles, but not on the middle class. Moreover, the effect is regressive, taking 0.3% of national income away from the bottom 40% and redistributing it to the top 20% for every percentage point increase in unemployment. Studying the Great Recession, using the Consumer Expenditure Survey (CES), Fisher et al. (2014) found that bottom and middle quintiles saw decreases in employment income, as labor income is the biggest component of overall income. They conclude that inequality didn't rise as much as it could have were there not unemployment benefit extensions. However, studying disposable household income in the UK (1958-1974), Jantti and Jenkins (2010) found no effect of unemployment on inequality due to the nonlinear nature of macroeconomic variables and inequality, i.e. higher inflation is associated with only *slightly* higher inequality.

Looking at OECD countries, Afonso et al. (2010) find that 1 percentage point higher of unemployment is associated with a decrease of $275 in per capita income for the poorest quintile of households. They also find that an increase in per capita income of $1 is associated with an increase of 41 cents of income of the poorest quintile. Moreover, efficient public spending (especially redistribution), which is associated with higher GDP per capita, results in lower income inequality for developed countries. Therefore, I will test the predictive power of unemployment overall, in addition to male unemployment (more cyclical).

Another natural factor to consider is the effect of inflation on inequality. Albanesi (2007) shows that the cross-country correlation of inflation and inequality as measured by the top 40%/bottom 60%, or the Gini, is 0.85 and 0.70 respectively for OECD countries. However, this relationship is difficult to quantify and larger inequality may lead to higher inflation because the relative vulnerability of households in the bottom quintiles to inflation also weakens their bargaining position. In their U.K. study, Jantti and Jenkins (2010) found no effect of inflation on inequality - the same result Blinder and Esaki (1978) found for the U.S. Rather, they say it acts as a "slightly progressive tax". In this case, inflation may reduce inequality by hurting top quintiles more than bottom quintiles. Accordingly, it is difficult to say a priori whether macroeconomic indicators will be useful in the prediction of inequality.

3 Data

The annual March Supplement of the Current Population Survey for earnings years 1975-2014 (survey years 1976-2015) is used to calculate all inequality series for individual earnings and household income.[9] As discussed above 1980 represents a significant turning point in the series. Gindelsky (2015) demonstrates that utilizing post-1980 data leads to either statistically indifferent models or even lower forecast errors as compared with a longer time series. Individual earnings are calculated by summing wages, self-employment income, and farm income, while household income is the sum of all reported sources of income by household. All series are calculated using consistent top codes, under the most recent system (swaps)[10]. Adjustments were made in all series to account for the structural break from 1992-1993,

[9] Unless otherwise specified, all years mentioned refer to the year in which income was earned, rather than the year in which the survey was completed (one year later).

[10] There have been several different methods of topcoding over the length of the series. The most recent method, a rank proximity swapping procedure, in which all values greater than or equal to the topcode are swapped with other values within a bounded interval. Thus, the new system allows for public use data which better represent internal data and allow for more accurate income inequality calculations. There are also other systems of adjustment to produce consistent series such as Larrimore et al. (2008) which use cell means, applied in Gindelsky (2015). See Appendix for more details

which results from a change in CPS data collection methods (Burkhauser et al., 2011).[11] An additional change in the survey instrument occurred from 2014-2015. In 2014, the ASEC implemented a split panel design to test a redesigned set of income questions for 1/3 of the sample, affecting 2013 earnings (see DeNavas-Walt and Proctor (2015) and Semega and Welniak (2015) for more details on this procedure). Given the results of this test, this new design was implemented for all participants in 2015. In this paper, I use only the traditional sample in 2014. Thus, we must be cautious in interpreting results from 2014-2015 (earnings years 2013-2014), as some part of the observed slight increase in the Gini may be due to questionnaire changes, particularly affecting bottom quintiles (Semega and Welniak, 2015).

Attention must also be drawn to 2007 (survey year 2008) for several series, pronouncedly for the individual earnings. There is a drop in income inequality and subsequent rebound in 2008 for both individuals and households (see App. Table A2). The reason for this drop appears to be a decrease in the number of individuals reporting top earnings in this year. It is unclear whether this observed decline is possibly due to a decrease in earnings preceding the official start of the Great Recession, an increase in potential underreporting in 2008, or another factor. There is no similar drop found when calculating the Gini using the American Community Survey and Census Bureau published figures confirm this break.

A number of explanatory variables were considered to choose a model which best fits historical data, and subsequently a forecast. Based on the literature as reviewed above, I have chosen to group inequality determinants into three broad groups: human capital attainment, labor force indicators and macroeconomic indicators. To this effect, I considered the following variables for each group:[12]

[11] Without an adjustment, CPS data show a very large jump in inequality in that year. For more information on adjustment procedures, please see Appendix.

[12] Ratios of aforementioned variables will be denoted *var1/var2*. Please see the appendix for more information on the sources and calculations of these variables.

- Human Capital Attainment Variables
  - Percent of Population 25+ Years Who have Completed College (*col*)
  - Percent of Female Population 25+ Years Who have Completed College (*col_fem*)
  - Percent of Population 25+ Years Who have Completed High School (*hs*)
  - Percent of Female Population 25+ Years Who have Completed High School (*hs_fem*)
  - Skill Premium (College Wage/High School Wage) (*skill_prem*)
- Labor Force Structure Variables
  - High-Skill Employment (Non-routine Cognitive)[13] (*hskill*)
  - Middle-Skill Employment I (Routine Cognitive) (*mskill1*)
  - Middle-Skill Employment II (Routine Manual) (*mskill2*)
  - Low-Skill Employment (Non-routine Manual) (*lskill*)
  - Share of Services in GDP (*serv/gdp*)
  - Labor Force Participation (*lfpr*)
  - Female Labor Force Participation (*fem_lfpr*)
- Macroeconomic Variables
  - Real GDP (*gdp*)
  - Government Expenditure as a Share of GDP (*gov/gdp*)
  - Inflation (*infl*)
  - Unemployment (*unemp*)
  - Male Unemployment (*m_unemp*)

[13] as in Foote and Ryan (2015), see Appendix

4 Model and Forecasting Methodology

After collecting data for these three groups, I predict inequality using a general model which reflects hypothesized determinants of inequality discussed above using an Autoregressive Distributed Lag model (ARDL).[14]

$$y_t = \beta_0 + \sum_{i=1}^{q} \beta_i y_{t-i} + \sum_{i=1}^{q} \sum_{j=1}^{n_1} \gamma_{ij} x_{t-i,j} + \sum_{i=1}^{q} \sum_{k=1}^{n_2} \delta_{ik} w_{t-i,k} + \sum_{i=1}^{q} \sum_{l=1}^{n_3} \phi_{il} z_{t-i,l} + \epsilon_t \qquad (1)$$

where $q < t$, y is one of four inequality measures (the top 1% share, top 0.1% share, Gini coefficient *within* the top 1%, and Gini overall for individuals or households), and x, w, and z are variables from the Human Capital Attainment (n_1), Labor Force Structure (n_2), and Macroeconomic variable (n_3) sets respectively.

Prior to conducting the analysis, I test all the series to ensure that they are stationary. Although the series are not stationary in levels, each first-differenced series used is stationary, except female labor force participation which was second-differenced (See Table 1 for descriptive statistics and Table 2 for p-values of inequality series). Thus the specification below is estimated and converted back to levels to forecast the series.

$$\triangle y_t = \beta_0 + \sum_{i=1}^{m} \triangle \beta_i y_{t-i} + \sum_{i=1}^{m} \sum_{j=1}^{n_1} \triangle \gamma_{ij} x_{t-i,j} + \sum_{i=1}^{m} \sum_{k=1}^{n_2} \triangle \delta_{ik} w_{t-i,k} + \sum_{i=1}^{m} \sum_{l=1}^{n_3} \triangle \phi_{il} z_{t-i,l} + \epsilon_t \qquad (2)$$

where $m < q - 1$. Moving from this general model, my next step is to find the simplest, most parsimonious model, which conveys (encompasses) all the information of a more complicated model (Hoover and Perez, 1999). Often naïve approaches outperform more complicated models limiting additional gains from more-complicated forecasts (Clemen and Guerard, 1989). In this case, the validity of this simpler model can then be tested by comparing its Root

[14] This structure is suggested by many of the works cited above. Other model forms were tested, but found to have lower predictive power.

Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) to those of other models, with the lower error indicating a more predictive model.

I consider combinations of $\triangle x$, $\triangle w$ and $\triangle z$ (from above models) in addition to lags of $\triangle y$. I hope to retain only the variables that should be included and avoid the pitfalls of both overspecification and misspecification, as well as selecting a noncongruent representation - that is one which does not appropriately reflect the dataset (Campos et al., 2005).

Empirically, I use an automated model-selection algorithm which searches along multiple paths to estimate a General Unrestricted Model (GUM) based on the criteria described above. As a first step, I run an AR model to determine which lags of the dependent variable are most significant (at a 5% level). I also test for any structural breaks occurring at any point in the sample, with any duration/magnitude series using Impulse Indicator Saturation (Ericsson, 2012). The target significance level for these structural breaks chosen was 1%.[15] In the second stage, I estimate a GUM again, keeping the previously selected significant lags of the dependent variable and structural breaks found using IIS, and now including explanatory variables. The resulting model includes only the most significant variables, which are chosen after dropping sets of insignificant variables, starting with their longest lag. The target significance level chosen for this paper was 5%.

After examining which variables are selected as best fitting the data for each historical period, I compare the Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) of the forecasts to see which model is most accurate. As it is often the case that the models which best fit the in-sample data are not those that best forecast, I will focus on the models which provide the best inequality forecast for 2011-2014. I then test whether the chosen models outperform naïve approaches with the Diebold-Mariano test as well as the

[15]Estimation performed using Autometrics in Oxmetrics (Doornik, 2007). Following Castle et al. (2012), I force an intercept in the models to ensure that Autometrics performs well.

White Reality Check (White, 2000). After selecting the best pseudo-out-of-sample forecast, I then use this model to calculate true out-of-sample forecasts for 2015-2017. In order to check the robustness of these models, I also test a pseudo-out-of-sample period of 2010-2013 and compare the model selected for each inequality measure.

5 Results

When examining income inequality trends, we begin by looking at the series over time. We first note that time trends differ markedly among variables. To estimate the trends from 1980-2014, I run a simple specification for a given measure y and a dichotomous variable for each structural break (i) found by IIS: $\triangle y_t = \beta_0 + \sum_{i=1}^{m} str.break_i + \epsilon_t$ (Results in Table 1). The regression results confirm what we can observe graphically in Fig. 1 and 2; there are no significant upward/downward trends for the majority of measures, excepting household income inequality which has been rising steadily. In fact, the top 0.1% share has shown a small, but insignificant decline for individuals and households, and inequality within the top 1% appears to be falling as well.[16] Fig. 1 and 2 show series over the sample period for individual earnings and household income respectively with shaded bars indicating recessions.

Turning to our forecast results, Fig. 3 and 4 show historical data for 2006-2014 (red line with square markers), the best forecasts for the 2011-2014 (solid blue line)[17] and 2010-2013 (dotted pink line) test periods from 2011-2014 (both of these lines continue for the projection in the true-out-of-sample period 2015-2017), and naïve forecast for 2015-2017 (dashed green line). Each forecast also contains confidence interval fans, which represent a 95% confidence interval in the lightest area, with confidence levels decreasing as the color becomes darker. We begin with individual earnings.

[16] Regression results for all models are located in App. Tables A5 and A6.

[17] This line is extended back to 2006 to show the model fit before the pseudo-out-of-sample test period

5.1 Individual Earnings

At first glance, there appear to be no consistent patterns among the results. The share of labor income reported by the top 1% of earners rose sharply in 1985 in anticipation of the Tax Reform Act of 1986 and then continued rising in the early 1990s, before falling in the 2000s. It shows great volatility, particularly around business cycles (See Fig. 1). In choosing the best-fitting model, various human capital attainment and labor force structure variables were selected. IIS identified significant structural breaks in 1985 and 2007. Indeed, the model with the lowest forecast error includes the second lag of the top 1% share, high skill employment, college attainment, and female labor force participation, though only female labor force participation is significant. This model is a significant improvement over the naïve model (AR3 + Constant + d85 + d07), by the RMSE and MAE criteria, according to the Diebold-Mariano test and White Reality Check. The best model selected for the 2010-2013 pseudo-out-of-sample period includes inflation and college attainment, though neither is significant. Models for both periods as well as the naïve model forecast a small rise in the next few years (See Fig. 1a and App. Table A7). The out-of-sample forecast from the best model only differs from the naïve model by 1.5% on average from 2015-2017.

Examining an even narrower slice of the income distribution, the share of labor income earned by the top 0.1% of earners, we see a substantially different trend. Falling significantly in every period with some volatility tied to business cycles, the top 0.1% share has returned to its 1980 level of 2.5%, after its 1985 jump to 4.8% (See Fig. 1). In choosing the best-fitting model, various human capital attainment and labor force structure variables were selected along with unemployment. IIS identified significant structural breaks in 1985 and 1987. However, the best model includes only the ratio of middle-skill employment II (routine manual) to low-skill employment and it is insignificant. This model does not have higher explanatory power than a naïve model, but has much better predictive power according to the aforementioned criteria (See Fig. 1b and App. Table A8). However, the best model for the 2010-2013 pseudo-out-of-sample period includes government expenditure as a share of gdp and the skill premium, though they are insignificant. All out-of-sample forecasts predict that the top 0.1% share will continue to fall.

There has also been discussion in the literature of inequality *within* the top 1%. Accordingly, I estimate a Gini coefficient among them. Inequality within the top 1% shows a steady decline, with the exception of the 1985 jump (See Fig. 1). In choosing the best-fitting model, various human capital attainment and labor force structure variables and log GDP were selected. IIS identified significant structural breaks in 1981 and 1985. The best model for both pseudo-out-of-sample periods includes the ratio of middle-skill employment I (routine cognitive) to low-skill employment, though it is insignificant in both. Despite the choice of the same model, the forecast error is significantly lower for the 2010-2013 pseudo-out-of-sample period (See Fig. 1c and App. Table A9). All models predict a fall.

Studying the distribution overall rather than focusing on the top share by using the Gini Coefficient, we see that labor earnings inequality declined in the 90s while staying relatively constant in the following period (excepting 2007). Overall, there is little volatility (See Fig. 1). In choosing the best-fitting model, various human capital attainment and labor force structure variables were selected along with the first two lags of the Gini. IIS identified significant structural breaks in 2007 and 2008. Similar to results for the top 0.1% share, the best model includes middle-skill employment II (routine manual) (1st lag sig.) in addition to the two lags of the Gini (2nd lag sig.). The best model for the 2010-2013 pseudo-out-of-sample period also includes inflation (insig.) and labor force participation (sig.). Interestingly, the best models for the two periods as well as the naïve model have the same explanatory power and forecast a very small decline (See Fig. 1d and App. Table A10). The average difference between the best model for 2011-2014 and the naïve approach is only -0.4%.

5.2 Household Income

As with individual earnings, we begin with the income of the top 1% of households from labor and non-labor sources. Much like the trend in the share of the top 1% of earners, the income share of the top 1% of households shows a rise with great volatility (See Fig. 2). In choosing the best-fitting model, various human capital attainment and labor force structure variables were selected as well as unemployment and inflation. IIS identified significant structural breaks in 2002 and 2007. The best model includes labor force participation (2nd lag sig.) and inflation (3rd lag sig.). However, even this model does not significantly outperform the following best naïve model by RMSE according to the White Reality Check.[18]

$$\triangle\widehat{Top}1_t = 0.110 - 0.321\triangle Top1_{t-2} + 0.207\triangle Top1_{t-3} - 0.179\triangle Top1_{t-4} - 1.01d2002 - 1.318d2007$$

Conversely, the best 2010-2013 pseudo-out-of-sample period model includes 2 lags of log GDP (insig.) and the Diebold-Mariano fails to reject according to the MAE criterion, while the White Reality Check fails to reject by the RMSE criterion but does reject at the 1% level by the MAE. The average difference between the best 2011-2014 forecast and naïve forecast is 1.1% across the years and all forecasts show a slight decline. Though the 2015 forecasts differ across models, forecasts converge by 2017 (See Fig. 2a and App. Table A7).

As with individuals, the income share of the top 0.1% of households has been declining steadily since the jump in 1985 (See Fig. 2). In choosing the best-fitting model, various human capital attainment and labor force structure variables were selected as well as inflation. IIS identified significant structural breaks in 1985 and 1987. The best model includes the ratio of middle-skill employment I (routine cognitive) to low-skill employment, services as a share of GDP, and female college attainment, though none are significant. The best model

[18]According to the MAE criterion, ths model outperforms at the 1% sig. level

significantly outperforms the naïve model (See Fig. 2b and App. Table A8). The best model for the 2010-2013 period includes high-skill employment, though insignificant. All models forecast a decline, though the best model for 2011-2014 forecasts the largest decline.

Next, we study inequality within the top 1% of households, which follow the same pattern as the top 1% of individual earners: a jump in 1985, preceded and followed by declines (See Fig. 2). In choosing the best-fitting model, various human capital attainment and labor force structure variables were selected as well as inflation. IIS identified a significant structural break in 1985. The best model for both the 2011-2014 and 2010-2013 pseudo-out-of-sample periods includes low-skill employment and female labor force participation, though neither is significant in either model. However, the best model for the most recent period does not outperform the following naïve model by either RMSE or MAE according to Diebold-Mariano or White Reality Check:

$$\triangle \widehat{Ginioftop1}_t = -0.036 - 5.36 d1981 + 5.09 d1985 + \epsilon_t$$

The best models for 2011-2014 and 2010-2013 models predict a fall and the naïve model shows almost no change; the three track closely for 2015 and 2016, distancing themselves in 2017 (See Fig. 2c and App. Table A9).

Finally, examining the household income distribution overall using the Gini coefficient, we see a steady increase in inequality (See Fig. 2). Various human capital attainment and labor force structure variables were selected as well as government expenditures as a share of GDP. IIS identified a significant structural break in 2007. As with the top 0.1%, the best model includes the ratio of middle-skill employment I (routine cognitive) to low-skill employment, services as a share of GDP, and female college attainment, though only female college attainment is significant at a 10% level. Although the best model is significantly better than the naïve model, the average difference between the two models is only 0.2%. Conversely, the model for the 2010-2013 pseudo-out-of-sample period includes the ratio of high skill employment to middle skill employment II (routine manual) and government expenditures as a share of GDP, all insignificant. Though this model has a lower forecast error when considering the 2010-2013 period (See Fig. 2d and App. Table A10), when applied to a 2011-2014 model pseudo-out-of-sample, it performs less well. All models predict a rise.

5.3 Robustness

In addition to conducting the aforementioned analysis for 2010-2013, additional robustness tests were done for 2009-2012 and 2003-2006. The former period chosen tests the effects of the modeling approach on the immediate aftermath of the Great Recession and the latter tests whether different explanatory variables will be selected without incorporating the recession as many have suggested pre-recessionary trends may resume in the future. In Table 4, we can see the results. There is little consistency in the variables chosen for the best model in each period though the general pattern of labor force participation indicators and human capital attainment variables being important predictors holds. The forecast error is higher for the best models in these pseudo-out-of-sample periods.

A further question may arise: how *good* are the true-out-of-sample forecasts for 2015-2017? And which models are more accurate - the best or the naïve? To answer this, we can examine the 2014 prediction with the 2010-2013 models. The predicted values for 2014 from 2010-2013 models differed from the actual value by 2.3% on average for the best models and 2.8% for the naïve models. The most accurate predictions were: top 1% individuals (best model > by 1%, naïve by 3%), gini individual (best model < by 0.6%, naïve by 0.2%), gini household (best model < by 0.8%, naïve by 0.5%) and top 1 gini indiv (best model < by 0.1%, naïve by 0.6%). These same variables are the ones with the lowest MAPE for the

2011-2014 pseudo-out-of-sample forecasts and appear to be the ones we can predict best - whether with naïve models or explanatory variables. For the other four variables, the 2010-2013 models over/under predict the 2014 value by 3%-11%. It may well be that explanatory variables I have not considered would produce more accurate forecasts for the others.

6 Discussion

There are several conclusions we can draw from the results above. First, the best predictors of inequality in the short-run are largely indicators of human capital attainment and labor force structure, in line with the idea of skill-biased technological change being the motivating factor for changes in income inequality in the past few-decades. However, there is no one explanatory variable that is prevalent above all. For example, both overall labor force participation and female labor force participation are significant in various models. Both levels of high skill employment and ratios of middle skill to low skill employment have been predictive as well. This suggests that while tracking SBTC can play an important role in inequality predictions, we must be careful about which variables impacted by technological change lead to the most accurate forecasts. In robustness testing, often substituting one Foote and Ryan (2015) employment variable for another (e.g., share of high-skill employment vs. share of low-skill employment) led to much worse forecast performance.

Accordingly, we may reach a second important conclusion: model selection in a General-to-Specific modeling approach does not always yield robust results. Adding or subtracting a lag of a variable can change the forecast error in a way which does not preserve the forecast accuracy ranking. Autometrics is a useful tool for identifying many variables that do indeed have high predictive power, but best-fitting specifications that it selects often do not result in the lowest forecast error. Indeed, sometimes the best forecasting model is not statistically significantly different from a naïve model (such as for the top 1% share (households) and top 1 Gini (households)). Moreover, the 95% confidence intervals for the forecasts (error fans) demonstrate their wide potential range. It becomes very difficult to claim forecast accuracy.

One possible source of measurement error in calculating top shares stems from the fact that CPS data (and survey data in general) underestimate top shares as compared with administrative data (IRS) (Burkhauser et al., 2012). To this effect, I use the same model estimation technique for a p90/p10 series (income share of the top 90%/bottom 10%), much less affected by top incomes, for individual earnings and household income in the 2011-2014 and 2010-2013 pseudo-out-of-sample test periods. The results are generally consistent with results for the top income shares; individual earnings (household income) predictions differ from naïve models by -0.8%(-2.6%)[19] respectively for the pseudo-out-of-sample period. The results are shown in Table 3.[20] Explanatory variables chosen include labor force participation, middle skill employment, and the ratio of government spending to GDP. For household income, the best model with much lower forecast error predicts a decline while the naïve model predicts an increase, which is more likely given the patterns in thee data. However, the naïve models have significantly higher forecast errors for both measures.

Third, tax policy changes have a very important impact on inequality trends for both individuals and households but are difficult to include in existing models. Though in this analysis we are considering only pre-tax sources of income, policies such as these significantly influence individual forward-looking behavior as well as reporting. Structural breaks identified by IIS result from both ex-ante and ex-post responses. For example, the Tax Reform Act of 1986 (enacted in 1986, but announced in 1984) which affected top shares is visible in increases from 1986-1987. It is not very noticeable when considering the Gini coefficient of the entire distribution. The short-run effects of this bill were due to a shifting from the

[19] As in Table 3, the percent difference between the values for 2015 (5.29 vs. 5.35) is 1.1%, for 2016 (5.35 vs. 5.40) is 0.9% and for 2017 (5.42 vs. 5.45) is 0.5%. Thus the average difference is 0.8% for individuals, and correspondingly 2.6% for households.

[20] The series for households is significantly affected by the CPS redesign and thus tested only the 2010-2013 sample. As discussed earlier, since only the *traditional design* observations were used for 2013, there is no effect of survey redesign on these estimates.

soon-to-be higher taxed corporate income to the now lower taxed personal income as well as a subsequent increase in the capital gains tax. Thus, in the short-run (1 year jump) reporting of wage and self-employment income increased, rather than an actual increase in incomes (Piketty et al., 2014). Some ex-ante response by top earners demonstrates the importance and difficulty of accounting for these tax changes. Other structural breaks are less easily understood. Although there is a significant increase from 1984-1985 for several series, consistent with results from internal data, there is not a readily available explanation for this yet.

While short-run responses can be seen in 1 year changes, medium-run responses (5yrs) and longer-run responses are harder to predict and may depend on subsequent policies. For example, the 2013 increase in top tax rates was announced in 2012 and so there was some retiming, which inflated top income shares in 2012 and depressed them in 2013 (Saez, 2015). We can see this pattern with top 1% (individual) and top 0.1% (individual), top 1% (household), and top 1 Gini (individuals and households). Furthermore, we must consider the effects of business cycles, where rises and falls in inequality usually even out. Although these can be thought of as short-run or medium-run effects in most cases, things may be different in the case of the Great Recession. Inequality levels in 2014 are consistently lower than in 2011 and mostly still haven't recovered to 2008, except for the Gini (household). It is also difficult to predict data anomalies such as the sharp decline and rebound of 2007-2008 (discussed above).

Finally, if we consider true-out-of-sample forecasts (2015-2017), we may gain some insights into medium-run inequality trends. For both individuals and households, the share of the top 1% is projected to rise a little though the share of the top 0.1% inequality is predicted to fall. In keeping with these results, inequality within the top 1% is predicted to fall as well. The greatest difference between results for individuals and households lies in the overall income distribution. The individual Gini is expected to remain constant, while the household Gini is predicted to keep rising (consistent with its significant trend). As the major source of household income, trends in individual earnings are very important to examine and predict. Furthermore, individual earnings suffer from less measurement error and underreporting than other sources of income.[21] Household income inequality is likely to rise due to other factors such as possibly assortative mating, increased female labor force participation, particularly among educated women in higher income households, and increase in single-parent households, rather than the definition of income for households vs. individual earnings. If household income is restricted to only earnings, as for individuals, the upward trend remains robust. Overall, the best model for 2011-2014, the naïve model for 2011-2014, and the best model for 2010-2013 produce results that trend in the same direction for 2015-2017.

7 Conclusions

Using data from the CPS, this paper forecasts eight inequality measures for 2015-2017: the top 1% share, top 0.1% share, the Gini coefficient *within* the top 1% and the overall Gini coefficient. I find that while metrics of human capital attainment and measures of labor force participation often lead to better performing forecasts in the pseudo-out-of-sample period (2011-2014), the out-of-sample forecasts differ between models by less than 6% for all variables, and by less than 2% for 4 out of 8 measures. Often model selection is extremely sensitive to not only variable choice but lag length as well. In fact, for the top 1% income share of households, and the inequality (Gini) within the top 1% of households, the "best" forecast model does not significantly outperform the naïve model when a bootstrapped White Reality Check is performed. For all variables, forecasts fall within fairly wide error bands, making it difficult to draw conclusions about future trends. While some of this may be due to measurement error (particularly with regards to incomes) in the series, analysis of the p90/p10 ratio which shows similar patterns, indicates that it is not the root cause. Surveys such as the Survey of Consumer Finances (Federal Reserve Board) which seek to oversample

[21] As evidence of this, when comparing aggregate wages in the CPS to aggregate wages in the National Income Product Accounts (NIPA), the CPS aggregate is only at most 5% lower on an annual basis from 1979-2012 (Hardy et al., 2016).

top earners and thus more accurately measure top shares, are not conducted annually- a necessity for a time series analysis.[22] Future forecasting work may use administrative data, such as from the IRS, with the caveats that the unit of observation is a tax unit, not a household, and there are additional restrictions on the definition of income, which has important implications for inequality measurement and comparability across series.

Both model fit and forecast performance are significantly influenced by policy changes, especially tax policy, which have short to medium-run effects and are difficult to predict. Although such events may influence inequality levels due to changes in income reporting, they are unlikely to influence trends, as shown by the historical data for both top income shares as well as *within* the set of top earners. Nevertheless, it is clear that household inequality has been rising overall and will probably continue to do so[23]; income inequality within the top 1% continues to decline. These findings highlight the differences in the conversation about income inequality, which shows less conclusive trends, as compared with wealth inequality, which has been shown uniformly to be steadily increasing since the 1980s.[24]

As an addition to the literature which seek to explain income inequality trends as well as on model selection in forecasting, this paper seeks to nail down which of these explanatory variables really does produce the best short-run forecasts. Thus it complements the literature on determinants and predictions for long-run trends as well as studying the impacts of policy changes. However, as with many macroeconomic indicators, we must be

[22]The SCF also excludes the Forbes 400 by design and even when income definitions are held as constant as possible is still not entirely reconcilable with IRS data. Moreover, as pointed out by Bricker et al. (2015), it is likely that inequality levels and growth rates derived from administrative data are biased upward due to the methodology employed.

[23]Many theories have arisen regarding this rise, particularly regarding the role of assortative mating. This theory postulates that individuals "marry their like" (Greenwood et al., 2014) - those with similar characteristics, particularly education. However, while Greenwood et al. (2014) find that inequality would have fallen if husbands and wives were matched randomly, Eika et al. (2014) find that trends in assortative mating have little impact on inequality *trends* when studying 1980-2007, and rather the return to education and increases in college attendance (particularly among women) are the leading factors.

[24]For a recent discussion on wealth inequality vs. income inequality and share comparison, see Saez and Zucman (2015).

aware that long-run trends are significantly different from short-run swings. When comparing multiple pseudo-out-of-sample periods - pre, during, and post recession - we see that the Great Recession has disrupted inequality patterns for a significant amount of time; the best models for the pseudo-out-of-sample 2003-2006 period have high forecast errors and do not predict current years very well, suggesting a more structural change may be taking place.

As inequality discussion continues to expand, it is likely that more attention will be devoted to not only the causes of inequality, but also forecasts, and potential future policies. Results from this analysis imply that to predict inequality in the short-run, we should pay significant attention to past trends in the series and effects of policies which affect the income distribution more so than structural changes in the economy, which are likely to have a longer-run effect on trends. However, we must also be cautious in interpreting these changes as they may possibly be due to a re-timing of income or level shift, rather than significantly altering the long-run trend. This analysis represents a first step, but leaves many questions unanswered.

8 Tables and Figures

8.1 Tables

Table 1: Descriptive Statistics for Inequality Measures
Individuals and Households (1980-2014)

	△Indiv. Top 1%	△Indiv. Top 0.1%	△Indiv. Top 1% Gini	△Indiv. Gini	△Hh. Top 1%	△Hh. Top 0.1%	△Hh. Top 1% Gini	△Hh. Gini
Mean	0.017	-0.026	-0.127	-0.04	0.025	-0.013	-0.233	0.160
Std. Dev	0.525	0.589	3.82	0.468	0.424	0.303	2.056	0.311
Min	-1.26	-1.01	-3.96	-1.18	-1.04	-0.70	-5.40	-0.73
Max	1.46	3.04	20.19	1.21	0.910	1.06	5.05	0.81
1980*	8.68	2.25	23.87	49.48	6.77	2.01	24.58	42.37
2014*	9.97	2.35	27.45	48.86	7.96	1.59	22.72	48.06
Structural Breaks (IIS)	1985, 2007	1985, 1987	1985	2007, 2008	2002, 2007	1985, 1987	1981 1985	2007

Source: Own calculations from 1975-2014 CPS, March Supplement.

* represents levels in these years, rather than differences.

Table 2: Stationarity of Series, 1980-2014
P-values for Dickey-Fuller Unit Root Test (1980-2014)

△Indiv. Top 1%	△Indiv. Top 0.1%	△Indiv. Top 1% Gini	△Indiv. Gini	△Hh. Top 1%	△Hh. Top 0.1%	△Hh. Top 1% Gini	△Hh. Gini
Series in Levels							
0.164	0.087	0.197	0.253	0.185	0.194	0.363	0.637
Series First-Differenced							
0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: All explanatory variable series were stationary once first-differenced as well, except labor force participation and female labor force participation, which were double differenced. *Source*: Own calculations from 1975-2014 CPS, March Supplement.

Table 3: 90/10 Ratio
Out-of-Sample Forecast Comparison

Year	Individuals Best Model 2011-2014	Individuals Naïve Model 2011-2014	Households Best Model 2010-2013	Households Naïve Model 2010-2013
2012 (actual)	5.40	5.40	11.95	11.95
2013 (actual)	5.42	5.42	12.10	12.10
2014 (actual)	5.30	5.30	12.92	12.92
2015 (forecast)	5.29	5.35	12.89	12.92
2016 (forecast)	5.35	5.40	12.64	13.03
2017 (forecast)	5.42	5.45	12.58	13.14
RMSE	0.039	0.270	0.073	0.250
MAPE	0.632	4.631	0.582	1.877
Adj. R^2	0.265	0.240	0.247	0.220

Source: Own calculations from 1975-2014 CPS, March Supplement.

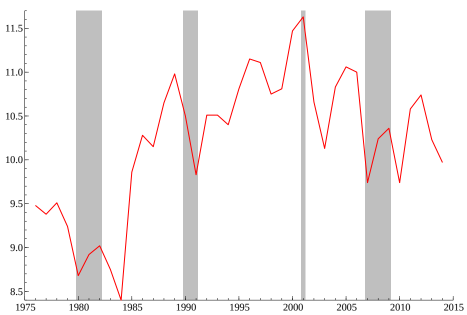
Table 4: Explanatory vars for different Pseudo-Out-of-Sample periods

Measure	2011-2014	2010-2013	2009-2012	2003-2006
		Individuals		
Top 1%	hskill,col, fem_lfpr	col,infl	hskill/lskill	unemp,hs/col
Top 0.1%	mskill2/lskill	gov/gdp,skill_prem	hs_col_fem	mskill1/lskill, hs_col_fem
Gini of Top 1%	mskill1/lskill	mskill1/lskill	hskill/lskill,lfpr	hskill
Gini	mskill2	mskill2,infl,lfpr	fem_lfpr,infl, hs_col_fem	unemp
		Households		
Top 1%	lfpr, infl	gdp	gov/gdp,lfpr	mskill1
Top 0.1%	mskill1/ls,serv/gdp, col_fem	hskill	–	fem_lfpr
Gini of Top 1%	lskill,fem_lfpr	lskill,fem_lfpr	hskill/lskill, fem_lfpr	fem_lfpr, hs_col_fem
Gini	mskill1/ls,serv/gdp, col_fem	hskill/mskill2, gov/gdp	lfpr,gov/gdp	mskill2/lskill

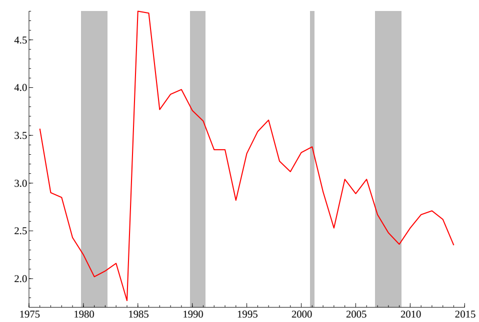
Source: Own calculations from 1975-2014 CPS, March Supplement.

8.2 Figures

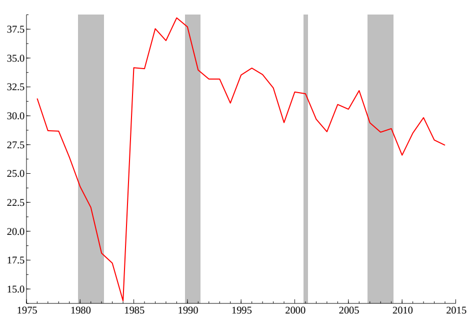
Figure 1: Individual Earnings Series



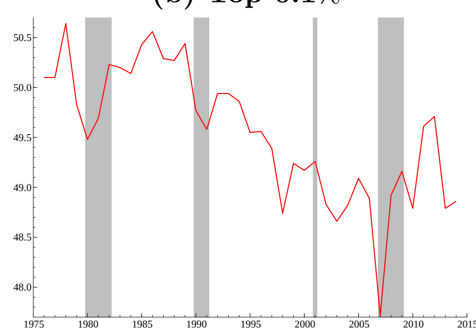
(a) Top 1%



(b) Top 0.1%

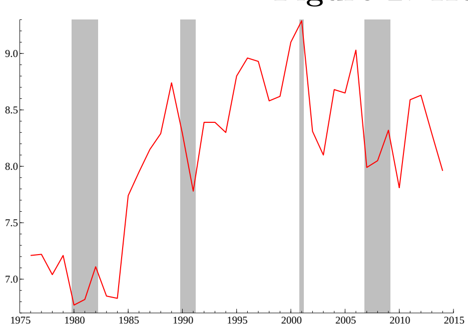


(c) Gini of Top 1%

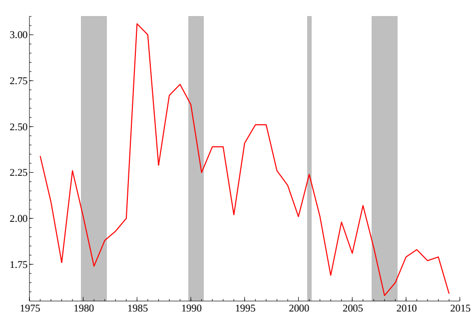


(d) Gini Index

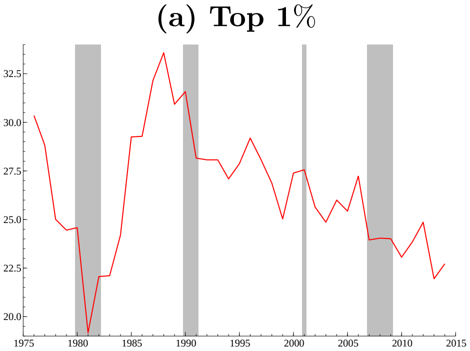
Figure 2: Household Income Series



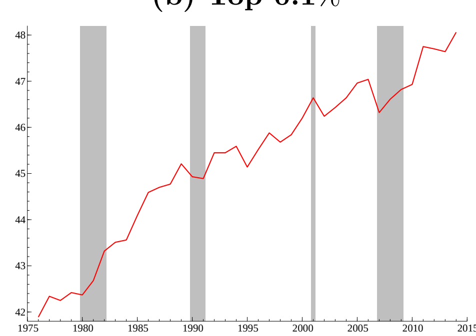
(a) Top 1%



(b) Top 0.1%



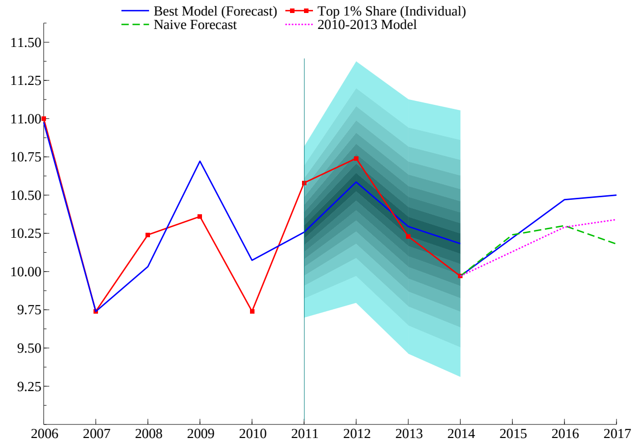
(c) Gini of Top 1%



(d) Gini Index

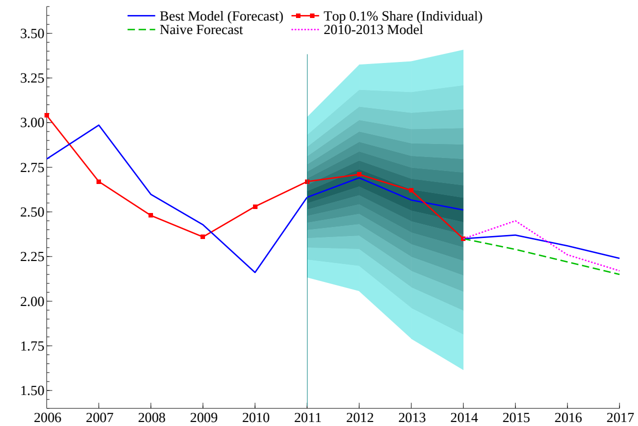
Source: Own calculations from 1975-2014 CPS, March Supplement.

Figure 3: Individual Earnings Forecasts



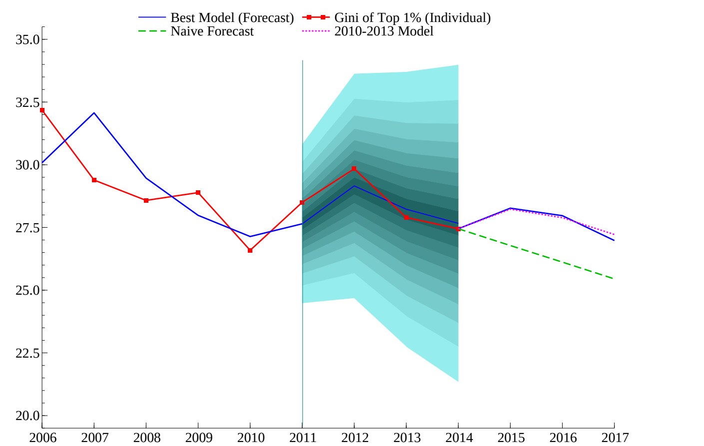
Best model: $\triangle\widehat{Top1}_t = 0.55 + 1.7d1985 - 1.50d2007$
$-0.53 \triangle Top1_{t-2} + 0.50 \triangle \triangle fem\_lfpr_{t-3} - 6.48 \triangle hskill_{t-2}$
$+0.16 \triangle hskill_{t-3} - 0.21 \triangle col_{t-1} - 0.54 \triangle col_{t-2} + \epsilon_t$
RMSE: 0.211, MAPE: 1.816

(a) Top 1%



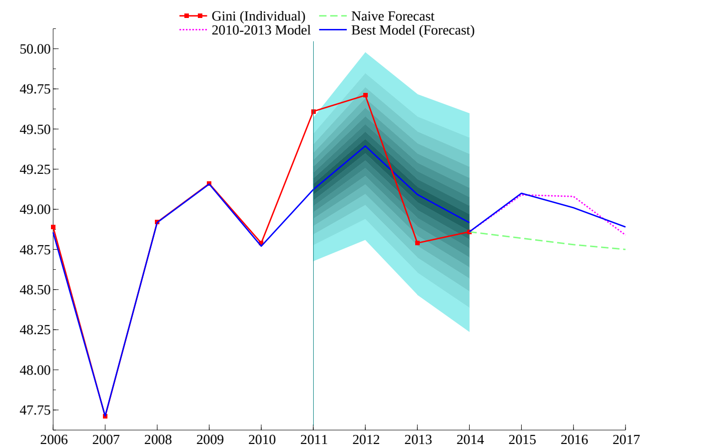
Best model: $\triangle\widehat{Top0.1}_t = -0.04 + 2.8d1985$
$-0.97d1987 + 15.24 \triangle \frac{mskill2}{lskill}_{t-1} - 17.78 \triangle \frac{mskill2}{lskill}_{t-2} + \epsilon_t$
RMSE: 0.096, MAPE: 3.228

(b) Top 0.1%



Best model: $\triangle\widehat{Top1Gini}_t = -0.69 + 19.00d1985$
$+207.85 \triangle \frac{mskill1}{lskill}_{t-1} - 258.27 \triangle \frac{mskill1}{lskill}_{t-2} - 184.89 \triangle \frac{mskill1}{lskill}_{t-3} + \epsilon_t$
RMSE: 0.581, MAPE: 1.810

(c) Gini of Top 1%

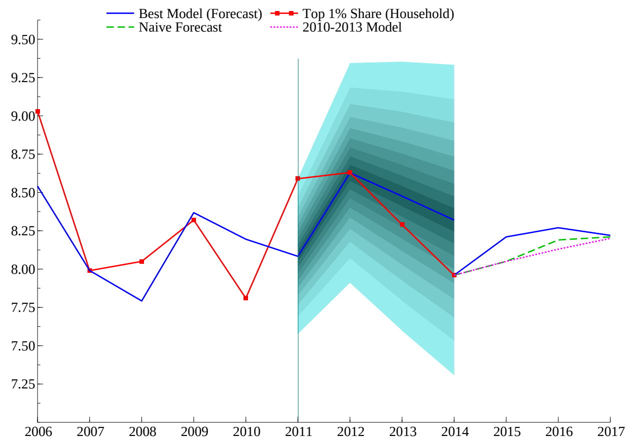


Best model: $\triangle\widehat{Gini}_t = 1.70 - 1.50d2007 + 0.50d2008 - 0.53 \triangle Gini_{t-1} +$
$0.55 \triangle Gini_{t-2} - 6.48 \triangle mskill2_{t-1} + 0.16 \triangle mskill2_{t-2} + \epsilon_t$
RMSE: 0.328, MAPE: 0.588

(d) Gini Index

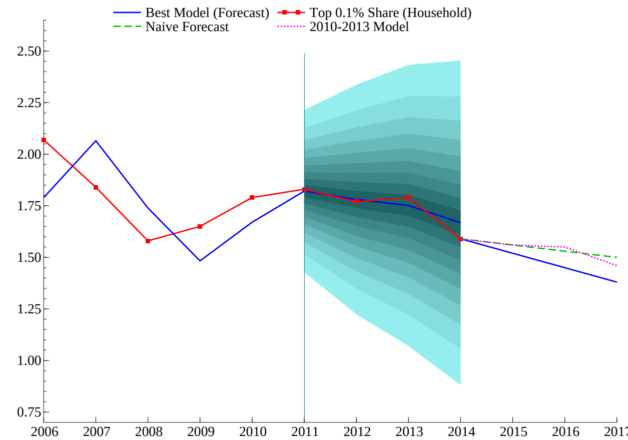
Source: Own calculations from 1975-2014 CPS, March Supplement.
Notes: Error fans represent 95% confidence intervals.

Figure 4: Household Income Forecasts



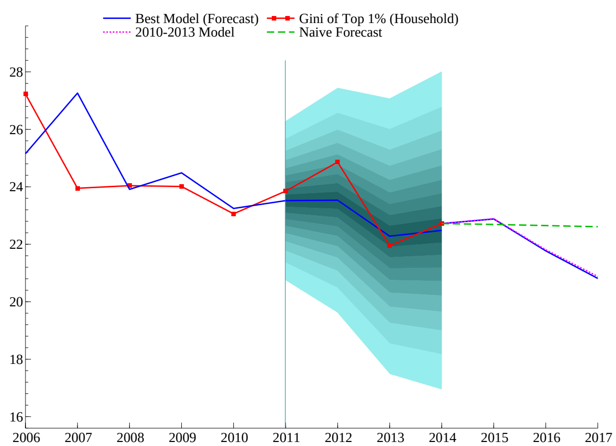
Best model: $\triangle\widehat{Top}1_t = 0.07 + -0.91d2002 - 1.03d2007 + 0.15\triangle\triangle lfpr_{t-1}$
$-0.55\triangle\triangle lfpr_{t-2} + 0.23\triangle infl_{t-2} - 10.02\triangle infl_{t-3} + \epsilon_t$
RMSE: 0.291, MAPE: 3.038

(a) Top 1%



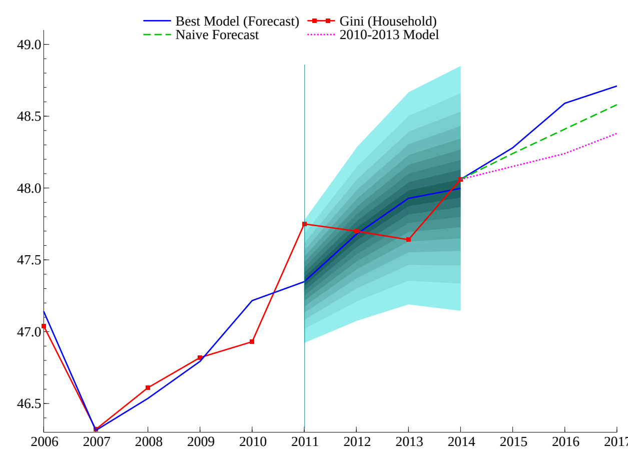
Best Model: $\triangle\widehat{Top}0.1_t = 0.08 + 1.13d1985 - 0.75d1987 + 3.97\triangle\frac{mskill1}{mskill2}_{t-1} + 0.42$
$\triangle\frac{mskill1}{mskill2}_{t-2} - 0.15\triangle col\_fem_{t-1} - 0.05\triangle col\_fem_{t-2} + 1.18\triangle serv/gdp_{t-2} + \epsilon_t$
RMSE: 0.044, MAPE: 2.025

(b) Top 0.1%



Best model: $\triangle\widehat{Top1Gini}_t = -0.73 - 5.78d1981 + 3.83d1985 + 36.89\triangle lskill_{t-2} -$
$1.23\triangle\triangle fem\_lfpr_{t-2} - 0.27\triangle\triangle fem\_lfpr_{t-3} + 0.63\triangle\triangle fem\_lfpr_{t-4} + \epsilon_t$
RMSE: 0.713, MAPE: 2.320

(c) Gini of Top 1%



Best model: $\triangle\widehat{Gini}_t = 0.01 - 0.91d2007 + 6.10\triangle serv/gdp_{t-2}$
$-38.90\triangle\frac{mskill1}{lskill}_{t-3} + 0.28\triangle col\_fem_{t-3} + \epsilon_t$
RMSE: 0.249, MAPE: 0.406

(d) Gini Index

Source: Own calculations from 1975-2014 CPS, March Supplement.
Notes: Error fans represent 95% confidence intervals.

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9 Appendix

9.1 Inequality Measures

Available data: 1961-2014 (survey years 1962-2015)

There have been several different methods of topcoding over the length of the series. The most recent method, a rank proximity swapping procedure, in which all values greater than or equal to the topcode are swapped with other values within a bounded interval. Thus, the new system allows for public use data which better represent internal data and allow for more accurate income inequality calculations. Although this system was only implemented in 2011, a crosswalk for creation of a consistent series is available here: *http://www.census.gov/housing/extract_toc/data/*. This crosswalk is available for values from 1975 forward and thus the CPI data considered is 1975-2014.

To address the structural break from 1992-1993 caused by a change in the questionnaire, the resulting values for each variable are scaled up so as to eliminate the difference from 1992-1993, following a strategy used by Atkinson et al. (2011). As the table below demonstrates, there would be a sharp increase in top income shares, not due to economic phenomena.

Table A1: 1992-1993 Jump

	Top 1% Indiv.	Top 0.1% Indiv.	Gini of Top1% Indiv.	Gini Indiv.	Top 1% Hh.	Top 0.1% Hh.	Gini of Top1% Hh.	Gini Hh.
1992	7.37	1.35	18.07	47.56	6.43	1.05	14.27	43.42
1993	10.51	3.35	33.18	49.94	8.39	2.39	28.07	45.45
Percent Change								
	42.7%	148.5%	83.7%	5.0%	30.5%	127.7%	96.6%	4.7%

Source: Own calculations from 1975-2014 CPS, March Supplement.

There is an additional break which occurs in 2007 but as this is a one-year blip as opposed to a questionnaire change which continues forward, an indicator variable was added. For survey years 1975-1986 (and 2015), microdata from the census FTP is used with self-made data

Table A2: Individual and Household Gini for 2005-2010

Earnings Year	Individual Earnings Gini	Household Income Gini
2005	49.09	46.96
2006	48.89	47.04
2007	47.71	46.32
2008	48.92	46.61
2009	49.16	46.82
2010	48.79	46.93

Source: Own calculations from 1975-2014 CPS, March Supplement.

dictionaries and NBER data dictionaries are used for survey years 1987-2014. For individual earnings, wages, self employment income, and farm income are aggregated. For household income, the following sources of income are summed: ern-val, se-val, frm-val, ws-val, alm-val, fin-val, csp-val, dis-val1, dis-val2, div-val, ed-val, int-val, oi-val, rnt-val, ret-val1, ret-val2, sur-val1, and sur-val2. Swapped values are available for all topcoded variables.

Table A3: Adjusted Data

Earnings Year	Top 1% Indiv.	Top 0.1% Indiv.	Gini of Top 1% Indiv.	Gini Indiv.	Top 1% Hh.	Top 0.1% Hh.	Gini of Top 1% Hh.	Gini Hh.
1975	9.29	3.34	32.4	50.76	6.99	2.28	31.81	41.81
1976	9.48	3.57	31.5	50.10	7.21	2.34	30.35	41.89
1977	9.38	2.90	28.71	50.10	7.22	2.09	28.82	42.34
1978	9.51	2.85	28.67	50.64	7.04	1.76	25.01	42.25
1979	9.24	2.43	26.41	49.83	7.21	2.26	24.45	42.42
1980	8.69	2.25	23.87	49.48	6.77	2.01	24.58	42.37
1981	8.92	2.02	22.06	49.69	6.82	1.74	19.17	42.68
1982	9.02	2.08	18.10	50.23	7.11	1.88	22.06	43.32
1983	8.75	2.16	17.24	50.20	6.85	1.93	22.11	43.51
1984	8.40	1.77	13.97	50.14	6.83	2.00	24.20	43.56
1985	9.86	4.80	34.16	50.43	7.74	3.06	29.25	44.09
1986	10.28	4.78	34.08	50.56	7.95	3.00	29.28	44.59
1987	10.15	3.77	37.54	50.29	8.15	2.29	32.15	44.70
1988	10.65	3.93	36.51	50.27	8.29	2.67	33.58	44.77
1989	10.98	3.98	38.48	50.44	8.74	2.73	30.93	45.21
1990	10.50	3.76	37.70	49.77	8.29	2.62	31.58	44.93
1991	9.83	3.65	33.96	49.58	7.78	2.25	28.16	44.89
1992	10.51	3.35	33.18	49.94	8.39	2.39	28.07	45.45
1993	10.51	3.35	33.18	49.94	8.39	2.39	28.07	45.45
1994	10.40	2.82	31.10	49.86	8.30	2.02	27.09	45.59
1995	10.81	3.31	33.53	49.55	8.80	2.41	27.87	45.14
1996	11.15	3.54	34.13	49.56	8.96	2.51	29.19	45.52
1997	11.11	3.66	33.57	49.39	8.93	2.51	28.08	45.88
1998	10.75	3.23	32.41	48.74	8.58	2.26	26.87	45.68
1999	10.81	3.12	29.41	49.24	8.62	2.18	25.03	45.84
2000	11.47	3.32	32.06	49.17	9.10	2.01	27.39	46.20
2001	11.63	3.38	31.91	49.26	9.29	2.24	27.56	46.64
2002	10.66	2.91	29.70	48.83	8.31	2.01	25.64	46.24
2003	10.13	2.53	28.62	48.66	8.10	1.69	24.86	46.43
2004	10.83	3.04	30.98	48.82	8.68	1.98	26.00	46.64
2005	11.06	2.89	30.57	49.09	8.65	1.81	25.43	46.96
2006	11.00	3.04	32.18	48.89	9.03	2.07	27.23	47.04
2007	9.74	2.67	29.39	47.71	7.99	1.84	23.95	46.32
2008	10.24	2.48	28.58	48.92	8.05	1.58	24.04	46.61
2009	10.36	2.36	28.89	49.16	8.32	1.65	24.01	46.82
2010	9.74	2.53	26.59	48.79	7.81	1.79	23.06	46.93
2011	10.58	2.67	28.50	49.61	8.59	1.83	23.85	47.75
2012	10.74	2.71	29.84	49.71	8.63	1.77	24.86	47.70
2013	10.23	2.62	27.90	48.79	8.29	1.79	21.95	47.64
2014	9.97	2.35	27.45	48.86	7.96	1.59	22.72	48.06

Source: Own calculations from 1975-2014 CPS, March Supplement.

Table A4: Raw Data (Unadjusted)

Earnings Year	Top 1% Indiv.	Top 0.1% Indiv.	Gini of Top 1% Indiv.	Gini Indiv.	Top 1% Hh.	Top 0.1% Hh.	Gini of Top 1% Hh.	Gini Hh.
1975	6.75	1.34	17.64	48.34	5.36	1.00	16.18	39.94
1976	6.88	1.44	17.15	47.72	5.53	1.03	15.44	40.02
1977	6.81	1.17	15.63	47.71	5.54	0.92	14.66	40.45
1978	6.91	1.15	15.61	48.22	5.40	0.77	12.72	40.36
1979	6.71	0.98	14.38	47.45	5.53	0.99	12.44	40.52
1980	6.31	0.91	13.00	47.12	5.19	0.88	12.50	40.48
1981	6.48	0.81	12.01	47.32	5.23	0.77	9.75	40.77
1982	6.55	0.84	9.86	47.84	5.45	0.82	11.22	41.39
1983	6.35	0.87	9.39	47.81	5.25	0.85	11.24	41.57
1984	6.11	0.71	7.61	47.75	5.24	0.88	12.30	41.61
1985	7.16	1.93	18.60	48.03	5.94	1.34	14.87	42.12
1986	7.47	1.92	18.56	48.15	6.10	1.32	14.89	42.60
1987	7.37	1.52	20.44	47.89	6.25	1.01	16.35	42.70
1988	7.74	1.58	19.88	47.88	6.36	1.17	17.08	42.77
1989	7.98	1.60	20.95	48.04	6.70	1.20	15.73	43.19
1990	7.63	1.51	20.53	47.40	6.35	1.15	16.06	42.93
1991	7.14	1.47	18.49	47.22	5.96	0.99	14.32	42.88
1992	7.64	1.35	18.07	47.56	6.43	1.05	14.27	43.42
1993	10.51	3.35	33.18	49.94	8.39	2.39	28.07	45.45
1994	10.40	2.82	31.10	49.86	8.3	02.02	27.09	45.59
1995	10.81	3.31	33.53	49.55	8.80	2.41	27.87	45.14
1996	11.15	3.54	34.13	49.56	8.96	2.51	29.19	45.52
1997	11.11	3.66	33.57	49.39	8.93	2.51	28.08	45.88
1998	10.75	3.23	32.41	48.74	8.58	2.26	26.87	45.68
1999	10.81	3.12	29.41	49.24	8.62	2.18	25.03	45.84
2000	11.47	3.32	32.06	49.17	9.10	2.01	27.39	46.20
2001	11.63	3.38	31.91	49.26	9.29	2.24	27.56	46.64
2002	10.66	2.91	29.70	48.83	8.31	2.01	25.64	46.24
2003	10.13	2.53	28.62	48.66	8.10	1.69	24.86	46.43
2004	10.83	3.04	30.98	48.82	8.68	1.98	26.00	46.64
2005	11.06	2.89	30.57	49.09	8.65	1.81	25.43	46.96
2006	11.00	3.04	32.18	48.89	9.03	2.07	27.23	47.04
2007	9.74	2.67	29.39	47.71	7.99	1.84	23.95	46.32
2008	10.24	2.48	28.58	48.92	8.05	1.58	24.04	46.61
2009	10.36	2.36	28.89	49.16	8.32	1.65	24.01	46.82
2010	9.74	2.53	26.59	48.79	7.81	1.79	23.06	46.93
2011	10.58	2.67	28.50	49.61	8.59	1.83	23.85	47.75
2012	10.74	2.71	29.84	49.71	8.63	1.77	24.86	47.70
2013	10.23	2.62	27.90	48.79	8.29	1.79	21.95	47.64
2014	9.97	2.35	27.45	48.86	7.96	1.59	22.72	48.06

Source: Own calculations from 1975-2014 CPS, March Supplement.

Table A5: Model Summary: Individual Earnings

dTop 1%		dTop 0.1%		dGini of Top 1%		dGini	
dTop 1 L2	-0.53***	dMskill2 L1	15.2	dMskill1 L1	207.8	dGini L1	-0.15
	(0.12)	/lskill	(16.0)	/lskill	(150.5)		(0.14)
d2fem_lfpr L3	0.50***	dMskill2 L2	-17.8	dMskill1 L2	-258.3	dGini L2	-0.37***
	(0.19)	/lskill	(23.4)	/lskill	(188.3)		(0.12)
dhskill L2	-6.48	Constant	-0.06	dMskill1 L3	-184.9	dMskill2 L1	-0.90
	(5.65)		(0.06)	/lskill	(169.5)		(1.69)
dhskill L3	0.16	d1985	2.84***	Constant	-0.694*	dMskill2 L2	-3.55
	(5.52)		(0.40)		(0.389)		(2.05)
dcol L1	-0.21	d1987	-0.97***	d1985	19.0**	Constant	-0.04
	(0.25)		(0.28)		(2.171)		(0.05)
dcol L2	-0.54*					d2007	-0.97***
	(0.29)						(0.28)
Constant	0.55**					d2008	1.05***
	(0.22)						(0.32)
d1985	1.70***						
	(0.41)						
d2007	-1.50***						
	(0.38)						
Adj-R2	0.63	Adj-R2	0.82	Adj-R2	0.79	Adj-R2	0.60

Source: Own calculations from 1975-2014 CPS, March Supplement.

Table A6: Model Summary: Household Income

dTop 1%		dTop 0.1%		dGini of Top 1%		dGini	
d2lfpr L1	0.15	dMskill1 L1	3.97	dLskill L2	36.9	dMskill L3	-38.9
	(0.24)	/Mskill2	(25.2)		(30.6)	/lskill	(24.9)
d2lfpr L2	-0.55*	/Mskill1 L2	0.42	d2fem_lfpr L2	-1.23	dcol_fem L3	0.28
	(0.25)	dMskill2	(34.1)		(1.02)		(0.15)
dinfl L2	0.23	dcol_fem L1	-0.15	d2fem_lfpr L3	-0.27	dServ/gdp L2	6.10
	(4.03)		(0.14)		(1.16)		(6.21)
dinfl L3	-10.0***	dcol_fem L2	-0.05	d2fem_lfpr L4	0.63	Constant	0.01
	(3.81)		(0.15)		(0.95)		(0.10)
Constant	0.07	dServ/gdp L2	1.18	Constant	-0.73	d2007	-0.91***
	(0.06)		(6.32)		(0.68)		(0.27)
d2002	-0.091***	Constant	0.08	d1981	-5.78***		
	(0.32)		(0.14)		(1.91)		
d2007	-1.03**	d1985	1.13***	d1985	3.83*		
	(0.34)		(0.36)		(1.95)		
		d1987	-0.75***				
			(0.25)				
Adj-R2	0.52	Adj-R2	0.44	Adj-R2	0.36	Adj-R2	0.31

Source: Own calculations from 1975-2014 CPS, March Supplement.

Table A7: Top 1% Out-of-Sample Forecast Comparison

Year	Indiv. Best Model 2011-2014	Indiv. Naïve Model 2011-2014	Indiv Best Model 2010-2013	Hh. Best Model 2011-2014	Hh. Naïve Model 2011-2014	Hh. Best Model 2010-2013
2014 (actual)	9.970	9.970	9.970	7.96	7.96	7.96
2015 (forecast)	10.22	10.24	10.13	8.21	8.05	8.05
2016 (forecast)	10.47	10.30	10.29	8.27	8.19	8.13
2017 (forecast)	10.50	10.18	10.34	8.22	8.21	8.20
RMSE	0.211	0.517	0.235	0.291	0.377	0.265
MAPE	1.816	4.008	2.161	3.038	3.917	3.111
Adj. R^2	0.628	0.537	0.498	0.517	0.435	0.370

Source: Own calculations from 1975-2014 CPS, March Supplement.

Table A8: Top 0.1% Out-of-Sample Forecast Comparison

Year	Indiv. Best Model 2011-2014	Indiv. Naïve Model 2011-2014	Indiv Best Model 2010-2013	Hh. Best Model 2011-2014	Hh. Naïve Model 2011-2014	Hh. Best Model 2010-2013
2014 (actual)	2.35	2.35	2.35	1.59	1.59	1.59
2015 (forecast)	2.37	2.29	2.45	1.52	1.56	1.56
2016 (forecast)	2.31	2.22	2.26	1.45	1.53	1.55
2017 (forecast)	2.24	2.15	2.17	1.38	1.50	1.46
RMSE	0.096	0.240	0.229	0.044	0.072	0.063
MAPE	3.228	8.487	8.471	2.025	4.013	3.095
Adj. R^2	0.820	0.826	0.819	0.435	0.507	0.505

Source: Own calculations from 1975-2014 CPS, March Supplement.

Table A9: Top 1% Gini Out-of-Sample Forecast Comparison

Year	Indiv. Best Model 2011-2014	Indiv. Naïve Model 2011-2014	Indiv Best Model 2010-2013	Hh. Best Model 2011-2014	Hh. Naïve Model 2011-2014	Hh. Best Model 2010-2013
2014 (actual)	27.45	27.45	27.45	22.72	22.72	22.72
2015 (forecast)	28.27	26.78	28.23	22.88	22.69	22.89
2016 (forecast)	27.97	26.12	27.89	21.77	22.65	21.81
2017 (forecast)	26.98	25.45	27.22	20.81	22.61	20.88
RMSE	0.581	3.5729	0.745	0.713	1.143	0.636
MAPE	1.810	12.281	2.000	2.320	4.105	2.128
Adj. R^2	0.793	0.782	0.790	0.361	0.370	0.352

Source: Own calculations from 1975-2014 CPS, March Supplement.

Table A10: Gini Out-of-Sample Forecast Comparison

Year	Indiv. Best Model 2011-2014	Indiv. Naïve Model 2011-2014	Indiv Best Model 2010-2013	Hh. Best Model 2011-2014	Hh. Naïve Model 2011-2014	Hh. Best Model 2010-2013
2014 (actual)	48.86	48.86	48.86	48.06	48.06	48.06
2015 (forecast)	49.10	48.82	49.09	48.28	48.24	48.15
2016 (forecast)	49.01	48.78	49.08	48.59	48.41	48.24
2017 (forecast)	48.89	48.75	48.84	48.71	48.58	48.38
RMSE	0.328	0.673	0.306	0.249	0.451	0.148
MAPE	0.588	1.078	0.495	0.406	0.881	0.255
Adj. R^2	0.597	0.573	0.640	0.312	0.245	0.240

Source: Own calculations from 1975-2014 CPS, March Supplement.

9.2 Explanatory Variables

Human Capital Attainment Variables

The source for variables below is Table A-2 of Census CPS Historical Time Series Tables.

- Percent of Population 25+ Years Who have Completed College (1958+)
- Percent of Female Population 25+ Years Who have Completed College (1958+)
- Percent of Population 25+ Years Who have Completed High School (1958+)
- Percent of Female Population 25+ Years Who have Completed High School (1958+)

The source for **Skill premium (college wage/high school wage) (1976+)** comes from estimation of a human capital earnings function for the sample described above in the CPS with earnings coded as described above, for those ages 25-64, who were full-time workers. Weekly earnings were regressed on a dummy for college education, experience, and demographic controls for those with either a high school education or a college education. The coefficient on *college* was then taken for the skill premium.

Labor Force Structure Variables

Sources for variables below comes from Foote and Ryan (2015, Table 1). They are logged numbers of those employed in high-skill, middle-skill (I and II) and low-skill professions as defined by them. Using 2010 groups: High skill = professional occupations (managers, professionals, and technicians); Middle skill I = office & administrative occupations, sales; Middle skill II = production occupations, transportation, construction; Low skill = service occupations. The series have been helpfully updated by Richard Ryan. Each value used is the first quarter of the year, seasonally adjusted.

- High-Skill Employment (Nonroutine Cognitive) (1947+):
- Middle-Skill Employment I (Routine Cognitive) (1947+)
- Middle-Skill Employment II (Routine Manual) (1947+)
- Low-Skill Employment (Nonroutine Manual) (1947+)

Labor Force Participation (1947+) and **Female Labor Force Participation** (1947+) are from the Bureau of Labor Statistics and **Services as a Share of GDP** (1930+) comes from the Bureau of Economic Analysis.

<u>Macroeconomic Variables</u>

Real GDP (1930+) and **Government Expenditure as a Share of GDP (1930+)** come from the Bureau of Economic Analysis while **Inflation (1914+)**, **Unemployment (1947+)**, and **Male Unemployment (1947+)** are from the BLS.