

# Modeling and 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 tax data from Piketty, Saez, and Zucman (2017) (updated in the World Wealth & Income Database) and internal microdata from the Current Population Survey (1975-2015), this paper models inequality and performs pseudo-out-of-sample (2012-2015) and true out-of-sample (2016-2018) forecasts for 5 income inequality measures. The lowest forecast errors from the best models are found for distributional metrics, as compared to top income shares. While macroeconomic indicators, human capital, and labor force metrics often enhance models, measures of skill biased technological change are not found to be robust predictors of inequality trends. Naïve approaches often outperform more complex models and forecasts differ between models by <4% for all variables.

**Keywords:** Forecasting; Inequality; Model;

**JEL classification:** D63; E27; J31

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Note: I obtained Special Sworn Status of the U.S. Census Bureau at the Suitland Research Data Center in 2015 in Washington, D.C. in order to conduct the research in this paper which uses internal CPS data. Research results and conclusions expressed are my own and do not necessarily reflect the views of the U.S. Census Bureau, the Bureau of Economic Analysis, or the Department of Commerce. The released data has been screened to ensure that no confidential data are disclosed.

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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, works such as Piketty (2014) seek to predict future trends. As the discussion on skill-biased technological change evolves, the focus has shifted to levels, measures, income definitions, and appropriate data to reconcile estimates from existing studies.<sup>1</sup> Most have shown a trend of increasing inequality since 1980; however, there is no consensus on which model best predicts both the level and the trend. This paper attempts to answer these questions by choosing models for several inequality measures and providing short-term forecasts.

To best predict inequality, we must determine the most appropriate measure and consequently its determinants. Existing studies of the United States use many data sources, 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. However, changes in questionnaires, income definitions, topcoding practices, treatment of transfers, and other factors are likely to affect estimates of inequality, making it difficult to establish a consistent series. Even once the 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. The choice of measure (wages, labor market earnings, or income including (or excluding) transfers and capital gains) and unit of analysis (individuals, households, or tax units) affects the conclusions. I analyze two sources of income: (1) Fiscal income for tax units (2) Personal income for equivalized households- comprised of labor (70% of total income), capital income, and government transfers.

Furthermore, the choice of inequality measure including the popular Gini index, the general entropy measures, wage polarization, quintiles, and income shares, such as the top 1 percent can significantly alter the conclusion. Although inequality is generally thought to be rising, the rate of its increase depends on the measure chosen. It is important to distinguish between changes in the income distribution itself and in a given measure. For instance, the Gini index is insensitive to changes in the top share (Osberg, 2017). While calculations from the CPS show that in the past 40 years the Gini for household income has risen by 20%, calculations of the fiscal income share for tax units using IRS data suggest that the income share of the top 1% has risen by 166%. This severe growth at the very top has prompted public outcry (Occupy Wall Street) and is a key factor in growing inequality overall, highlighting the role that structural change has played in the distribution (Atkinson, Piketty, and Saez, 2011; Piketty and Saez, 2003)

Both survey and administrative data illustrate the stagnation of low and middle incomes, juxtaposed with the rapid increase in top shares (Piketty, 2014), demonstrating the need to analyze both top shares and overall income inequality. In this paper, I will first focus on two measures of top incomes: the shares of income accruing to the top 1% and top 10%. Next, I will model and forecast

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<sup>1</sup>Such studies include but certainly are not limited to Goldin and Katz (1998), Acemoglu (1998), Acemoglu (2002), Goldin and Katz (2008) and Moretti (2013).

the Gini and Theil Indexes, and the 90/10 income ratio (income share of the top 90% to bottom 10%), to observe distributional impacts.

Using data from Piketty, Saez, and Zucman (2017) (calculated from IRS microdata), updated by the World Wealth and Income Database to 2015, I model and forecast the top 1% share and top 10% share for tax units (equally split into adults). Using data from the CPS, I calculate the 90/10 Ratio, the Gini coefficient, and the Theil Ratio for equivalized households (otherwise called size-adjusted household income). Next I apply a general-to-specific modeling approach and Impulse Indicator Saturation (IIS) to find structural breaks in the series and perform pseudo-out-of-sample inequality forecasts for 2012-2015 and true out-of-sample forecasts for 2016-2018.

Modeling trends in these measures, potential determinants can be grouped into three major categories, explored in the next section: 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. To capture changes in inputs and outputs of the labor force, I consider female labor force participation and occupational/sectoral shifts related to skill biased technological change (SBTC). Finally for macroeconomic indicators, I test the power of business cycle measures including GDP growth, inflation, and unemployment.

I find that the best models for the Gini Index and Theil Index (distributional measures) yield the lowest forecast errors. While macroeconomic indicators, metrics of human capital attainment, and labor force participation often lead to better performing forecasts in the test period, the out-of-sample forecasts only differ between models by <4% for all variables. Often model selection is extremely sensitive to not only variable choice but lag length as well. In fact, for top shares, the “best” forecast model is a naïve model, implying adding outside variables does not improve the forecast. Moreover, results generally indicate the difficulty of producing an accurate inequality forecast, regardless of model chosen and subsequent challenges of assessing future trends.

This paper provides a framework for predicting short-run changes in income inequality, attempting to enhance our understanding of which factors contribute to trends and how inequality evolves in response to policy changes. I argue that the ability to produce accurate forecasts of income shares at the right tail of the income distribution has important implications for more general work in income inequality. For example, trends in top incomes relate – both directly and indirectly – to changes in overall income inequality (Piketty and Saez, 2003). In light of the uneven recovery from the recent recession, predicting the divergence of income growth across top, middle, and low-income earners is particularly important (Saez, 2016). Relatedly, it is vital to predict top incomes in order to evaluate proposed redistributive tax policies and assess questions of “fairness” of the U.S. income distribution in a global context (Atkinson, Piketty, and Saez, 2011). Finally, the limited impact of SBTC found in predicting both top shares and overall inequality raises serious questions about its presently accepted role as the key driver of inequality trends; I argue that a re-examination of naïve approaches is merited.

This paper proceeds as follows. Sections 2 and 3 discuss 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

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 causal theories which motivate variable selection. 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. Initial findings indicated that in the short-run, an increase in the supply of skilled workers 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” (Acemoglu, 1998).

However, rather than leading to a “technological revolution” it’s possible that the type of technology being developed has changed in such a way that average real wages have stagnated, low-skill wages have fallen, and high-skill wages have increased since the 1970s (Acemoglu, 2002). A helpful job classification system to analyze these effects is suggested by Foote and Ryan (2015). 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 their ratios (e.g., high-skill to low-skill).<sup>2</sup>

These effects can also be decomposed into demand side and supply side explanations for rising inequality. 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) (Goldin and Katz, 2008). Although the relative supply of college educated people grew, it grew less quickly from 1980-2005 than in previous decades. 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.<sup>3</sup> 1980 therefore represents a significant turning point for wage inequality due to a decline in the real minimum wage and labor force changes contributing to the rise of lower-tail inequality rather than an “episode” (Autor, Katz, and Kearney, 2006). The labor market has become polarized as high-skill and low-skill jobs have grown as middle-skill jobs have been displaced. Occupation has increased in statistical importance in explaining wage differences, and though the college/high school wage gap has increased monotonically, the rise in earnings inequality has not been monotonic (Acemoglu and Autor, 2011).

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<sup>2</sup>See appendix for more details.

<sup>3</sup>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).

Since there is no one-to-one mapping of skills and tasks and technology responds to labor market conditions, it can be difficult to assess the precise nature of the impact of the skill premium on inequality. An additional possibility is within-cohort changes wherein high-skill workers do low-skill jobs - an occupational downgrading without a corresponding wage decrease (Beaudry, Green, and Sand, 2014)

## 2.2 Human Capital and the Changing Labor Force Structure

Given the clear importance of education in the SBTC theory, educational attainment metrics are important to consider. In addition to years of schooling, the rate of return to education could be an important determinant of earnings (Chiswick and Mincer, 1981). A persistent and rising wage gap between college graduates and high school graduates has been found since 1980, particularly when accounting for city size (Florida and Mellander, 2013; Lindley and Machin, 2014). 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 the share of services in employment will be an important determinant of inequality. Additionally, the share of women in the service sector has been growing as well.

Overall, during the 20th century, female labor force participation rates tripled. Beaudry, Green, and Sand (2014) argue that an important factor in the growth observed in the 1980s and 1990s was the increased labor force participation of women. Furthermore, examining the household-equivalized Gini using CPS data from 1980-2007, Larimore (2014) shows that male labor force participation is not the primary driver of long-term inequality growth, but rather female labor force participation is important, along with male earnings inequality. Recently, Acemoglu, Autor, and Lyle (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.<sup>4</sup> 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.<sup>5</sup> 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).<sup>6</sup>

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<sup>4</sup>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, Autor, and Lyle, 2004).

<sup>5</sup>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, Seshadri, and Yorukoglu, 2005).

<sup>6</sup>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, Havnes, and Mogstad (2011) find that controlling for age slightly mitigates the sharpness of inequality trends for Norwegian 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).

## 2.3 Macroeconomic Influences

Another set of potentially significant factors is changes in the macroeconomy, particularly given that the 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.<sup>7</sup> For many countries, government expenditure as a share of GDP has been found to be an inequality determinant (Barro, 2000). Government expenditure may also be used to mitigate (or aggravate) rises in inequality, particularly through effects on unemployment, which is unlikely to affect incomes uniformly. The effect on unemployment may be 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 (Blinder and Esaki, 1978). Unemployment benefits may mitigate the rise in income inequality slightly since labor income is the biggest component of overall income (Fisher, Johnson, and Smeeding, 2014).<sup>8</sup> Accordingly, it is difficult to say a priori how well macroeconomic indicators will predict inequality.

## 3 Data

There were two data sources used for inequality measures in this study. The first is Piketty, Saez, and Zucman (2017), updated to include 2015 in the World Wealth and Income Database. The top 1% and top 10% fiscal income shares include wages, pensions, business income, rents, interest, dividends, and capital gains.<sup>9</sup> These data are nationally representative data comprised of both labor and capital income for tax units. Unfortunately, within tax unit variation is not available and this income is equally split among adults in the unit.

The second source, the internal ASEC of the CPS for earnings years 1975-2015 (survey years 1976-2016), is used to calculate the 90/10 ratio, Gini index, and Theil index for equivalized households.<sup>10</sup> A major advantage of using the internal data as compared with public use data, is the increased accuracy and higher internal topcodes for sources of income which lead to more accurate distributional statistics.<sup>11</sup> Household equivalized incomes are calculated by taking total household income and dividing by the square root of the number of household members. 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. Household income is the sum of all reported sources of income by household. Adjustments were made in all CPS series to account for the structural break from 1992-1993, which results from a change in CPS data collection methods (Burkhauser et al.,

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<sup>7</sup>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.

<sup>8</sup>However, some non-U.S. studies have found little effect of unemployment on inequality. Janti and Jenkins (2010) found no effect of unemployment on inequality of disposable household income in the U.K. Afonso, Schuknecht, and Tanzi (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 in OECD countries.

<sup>9</sup>They correspond to Appendix Tables D9 and D10

<sup>10</sup>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).

<sup>11</sup>I obtained Special Sworn Status of the U.S. Census Bureau at the Suitland Research Data Center in 2015 in Washington, D.C. in order to conduct the research in this paper which uses internal CPS data.

2011).<sup>12</sup> 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. This paper uses only the traditional sample in 2014. Thus, we must be cautious in interpreting results from 2014-2015 (earnings years 2013-2014) due to questionnaire changes, particularly affecting bottom quintiles (Semega and Welniak, 2015).

A number of explanatory variables were considered to choose a model which best fits historical data, and subsequently a forecast. As discussed above, I have chosen to group inequality determinants into three broad groups: human capital attainment, labor force indicators and macroeconomic indicators. I considered the following variables for each group:<sup>13</sup>

- 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*)
- Labor Force Structure Variables
  - High-Skill Employment (Non-routine Cognitive)<sup>14</sup> (*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 Employment (*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*)

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<sup>12</sup>Without an adjustment, CPS data show a very large jump in inequality in that year. For more information on adjustment procedures, please see Appendix.

<sup>13</sup>Ratios of aforementioned variables will be denoted *var1/var2*. Please see the Appendix for more information.

<sup>14</sup>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).<sup>15</sup>

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

where  $q < t$ ,  $y$  is one of five inequality measures (the top 1% share, top 10% share, 90/10 Ratio, Gini coefficient, and Theil index) 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 series to ensure stationarity. 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).

\*INSERT TABLES 1 & 2 AROUND HERE\*

Thus the specification below is estimated and converted back to levels to forecast the series.

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

where  $m < q - 1$ . My next step is to find the 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). 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).<sup>16</sup> In the second stage, I estimate a GUM again, keeping the previously selected significant lags of the dependent variable 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%. Finally, 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%.

I consider combinations of  $\Delta x$ ,  $\Delta w$  and  $\Delta z$  (from above models) in addition to lags of  $\Delta y$ . I

<sup>15</sup>This structure is suggested by many of the works cited above. Other model forms were tested, but found to have lower predictive power.

<sup>16</sup>Estimation performed using Autometrics in Oxmetrics (Doornik, 2007). Following Castle, Doornik, and Hendry (2012), I force an intercept in the models to ensure that Autometrics performs well.



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, Ericsson, and Hendry, 2005). The validity of this simpler model can then be tested by comparing its Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) to those of other models, with the lower error indicating a more predictive model. 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 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 2016-2018. In order to check the robustness of these models, I also test a pseudo-out-of-sample period of 2003-2006 and compare the model selected for each measure.

## 5 Results

When examining income inequality trends, I begin by looking at the series over time. We first note that time trends differ markedly among variables. To estimate the trends from 1980-2015, I run a simple specification for a given measure  $y$  and a dichotomous variable for each structural break ( $i$ ) found by IIS:  $\Delta y_t = \beta_0 + \sum_{i=1}^m str.break_i + \epsilon_t$  (Results in Table 1). Shaded bars indicate recessions. The regression results confirm what we can observe graphically in Figure 1. All series show an increase in inequality, though the patterns vary substantially by series. All measures show that the most substantial rise in inequality occurred during the 1980s. However, patterns in the following decades vary distinctly by measure. These results demonstrate the importance of analyzing multiple inequality measures to obtain a clearer understanding of complex distributional changes.

\*\*INSERT FIGURE 1 AROUND HERE\*\*

Turning to the forecast results, Figure 2 shows historical data for 2006-2015 (red line with square markers), the best forecasts for the 2012-2015 (solid blue line)<sup>17</sup> and 2003-2006 (dotted pink line) test periods from 2012-2015 (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). The confidence interval fans represent a 95% confidence interval in the lightest area, with confidence levels decreasing as the color becomes darker. We begin with top shares.

\*\*INSERT FIGURE 2 AROUND HERE\*\*

### 5.1 Top Shares (PSZ)

Figures 2a and 2b show the models and forecasts for the Top 1% and Top 10% fiscal income shares. Turning to the model accuracy first, we see that the best models for the 2012-2015 pseudo-

<sup>17</sup>This line is extended back to 2006 to show the model fit before the pseudo-out-of-sample test period

out-of-sample periods are in fact, naïve models! The top 1% income share is modeled as an AR3 and the top 10% income share includes lags 2 and 3 as well. Both include dummies for 2002 and 2009, likely indicative of especially strong recessionary effects on these shares.<sup>18</sup> Thus in this case, there are no alternative “naïve” models plotted as the best models contain no other explanatory variables. In fact, these models do relatively well. The actual data (red line with square markers) falls well within the 95% confidence intervals of the forecast for both metrics and the Mean Absolute Percentage Error (MAPE) is 5% and 3% for the top 1% and top 10%, respectively.<sup>19</sup> The best models for 2003-2006 include human capital series as well as female labor force participation, but both predict that the shares will keep rising in the next few years.

## 5.2 Distributional Metrics (CPS)

Turning to inequality metrics which capture more of the distribution using internal CPS data for equivalized households, we begin with Figure 2c. The best model found includes female labor force participation, college attainment, and GDP (as well as a dummy for 2001). Though this model returned the lowest forecast error (MAPE=3%), it does not appear to fit particularly well in the test period, despite the inclusion of several explanatory variables. Though it fits well in the prior years, it underestimates the rise in this ratio from 2011 onward. When comparing the predictions of this model to the best naïve model, we see that this model predicts a further sharp rise, while the naïve model predicts little change and the 2003-2006 model actually predicts a slight decline. Thus it does not seem that this ratio can be very well predicted with our existing variables.<sup>20</sup>

However, both the Gini Index and the Theil Index are very well predicted by the chosen models, particularly during the pseudo-out-of-sample test period. The models are virtually on top of the chosen data, and the MAPE for both is under 1%. These two inequality measures which represent the whole distribution are very well predicted by labor force participation and unemployment for the Gini and a middle-skill employment ratio and services-to-employment ratio for the Theil. For the Gini, the out-of-sample predictions for the naïve model and 2003-2006 model are close to the chosen model but predict a slight rise, while the best model predicts a slight fall. For the Theil, the chosen and naïve models predicted no change while the 2003-2006 model predicts an increase (it is a naïve model, based on just a constant).

## 5.3 Robustness

As aforementioned, this analysis was repeated using data for 1980-2002 with a pseudo-out-of-sample test period of 2003-2006. This period was chosen to test whether the Great Recession affected outcomes significantly enough to alter trends permanently. It may be that pre-recessionary

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<sup>18</sup>IIS indicates 2001 to be a significant year for 3 of 5 measures. The effect may be either due to the 2001 US Tax Reform (Hotchkiss, Moore, and Rios-Avila, 2012), or the recession, or both.

<sup>19</sup>By comparing models using MAPE, we are able to normalize forecast accuracy. It is thus a more useful metric than RMSE in the case of multiple dependent variables with different scales, as in this exercise.

<sup>20</sup>The 90/10 ratio is a very specific snapshot of the income distribution which can vary substantially from year to year and is more likely to be noisy than other measures. Moreover, the data release restrictions require the ratio to be based on 22 observations. Burkhauser, Feng, and Jenkins (2009) find large differences for size-adjusted household income series when comparing the 90/10 ratio to the Gini using internal CPS data as well.

trends may resume in the future. In Table 3, we can compare the results of the two pseudo-out-of-sample periods side by side. 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 indeed lower for the 2003-2006 period (except for the Theil) than for the 2012-2015 pseudo-out-of-sample period, suggesting a distinct change has taken place in the income distribution.

**\*\*INSERT TABLE 3 AROUND HERE\*\***

Another question concerns the fitness of the internal CPS for estimating and forecasting top income shares. Although the internal CPS data is more representative of the distribution, it may not yield the same results as the forecast of the top shares using the IRS data. Therefore, I estimated the top 1% income share for individuals using the CPS data and conducted the same exercise. The results are in Table A9 and Figure A1. First, though the top 1% share in the CPS rose 30% from 1980 to 2001, since 2001 it has fallen 12%, contrary to the pattern in the Top 1 PSZ. The best predictors are low skill employment for 2013-2016 and the share of services in employment and log GDP for 2003-2006. The models have low MAPE ( $<2\%$ ) and both predict a decline in the top share but a naïve model predicts an increase. All in all, though the chosen models approximate the share well, they have little in common with models of the Top 1% PSZ. However, we cannot dismiss CPS data entirely. CPS data capture bottom incomes well, especially for non-filers, and thus are likely to be useful for distributional measures.

A further question may arise: how *good* are the true-out-of-sample forecasts for 2016-2018? And which chosen models are more accurate - the best or the naïve? As an illustrative exercise, I re-estimate the best models on 1980-2014 to predict 2015. The predicted values for 2015 by applying the 2012-2015 model to the 1980-2014 data differed from the actual value by 2.9% on average for the best models and 1.2% for the naïve models. The most accurate predictions were for the Gini (0.02% difference for the best model and 0.30% for the naïve model) and for the Theil (0.42% for the best model and 1.81% for the naïve model). For the other variables, the models over/under predict the 2014 value by 3%-6%. It may well be that explanatory variables I have not considered would produce more accurate forecasts for the others.

## **6 Discussion**

There are several insights we can draw from the results above. First, the inequality measures that we are best able to predict (lower forecast error as measured by MAPE) are the distributional metrics (Gini Index and Theil Index). This may be because they are less sensitive to more nuanced changes, particularly the Gini (Osberg, 2017). Second, 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 over the past few-decades. For example, overall labor force participation and female labor force participation, as well as services as a share of employment, are significant in various models as well as ratios of middle-skill and low-skill employment. Growth and unemployment overall as well as educational attainment (overall and for females) were also significant.

However, there is no one (or no group of) explanatory variable that is prevalent above all. While SBTC can still play an important role in inequality predictions, we must be careful about which variables impacted by technological change lead to the most accurate forecasts, if indeed any. 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. Moreover, Larimore (2014) decomposes the Gini for 1980-2007 to find that patterns of inequality during the 1980s differed substantially from the decades that followed and that contributing factors have changed over time, particularly with regards to non-labor income. These changing underlying processes can make it difficult to find determinants of inequality significant over the whole period.

Accordingly, we may reach a third 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 the selected best-fitting specifications often do not result in the lowest forecast error (Clark, 2004). Indeed, sometimes the best forecasting model is either a naïve model (such as for the top 1% and top 10% fiscal income shares) or else sometimes not statistically significantly different from a naïve model (Gini Index). Moreover, the 95% confidence intervals for the forecasts (error fans) demonstrate their wide potential range. It becomes very difficult to claim forecast accuracy for some variables.

There are several possible sources of measurement error. For the CPS, accurate reporting of incomes at the top constitutes one source, even in the internal data (Burkhauser et al., 2012). For the PSZ data derived from the IRS, omission of non-filers as well as tax evasion constitute others.<sup>21</sup> Another important source is methodological and definitional changes. For example the 1992-1993 jump in inequality shares in the CPS which necessitated an adjustment discussed earlier. Also, the CPS redesign may have affected inequality measures from 2013-2014.<sup>22</sup>

Moreover, tax policy changes have a very important impact on inequality trends but are difficult to include in existing models and anticipate for forecasting. Herauld and Azpitarte (2016) show that the direct effect of tax-transfer policy constitutes 1/2 of the observed increase in disposable income inequality in Australia from 1999-2008. However, their approach does not focus on behavioral responses (excepting labor supply). 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 can 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 1985-1987. The short-run effects of this bill were due to a shifting from the 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

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<sup>21</sup>Piketty, Saez, and Zucman (2017) do make an adjustment for non-filers using CPS data.

<sup>22</sup>When using the CPS to decompose the household-equivalized Gini, Larimore (2014) used the same adjustment.

incomes (Piketty, Saez, and Stancheva, 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 (e.g., IIS methodology indicates a structural break in 1998 for the Theil series).<sup>23</sup>

While short-run responses can be seen in 1 year changes (and often subsequent reversions), 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 re-timing, which inflated top income shares in 2012 and depressed them in 2013 (Saez, 2015). We can see this pattern clearly in each metric, except the 90/10, which does not include top earners. 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. Finally, if we consider true-out-of-sample forecasts (2016-2018), we may gain some insights into medium-run inequality trends. Top shares are projected to keep rising robustly based on the IRS data and distributional measures based on the CPS data show either a small rise or holding steady.

## 7 Conclusions

Using data from Piketty, Saez, and Zucman (2017) (calculated from IRS microdata), updated by the World Wealth and Income Database to 2015 and the CPS, this paper models and forecasts five inequality measures for 2016-2018: the top 1% share, the top 10% share, the 90/10 Ratio, the Gini index, and Theil index. I find that models for distributional metrics (the Gini Index and the Theil Index) have the lower forecast error (MAPE). Moreover, while macroeconomic indicators, metrics of human capital attainment and measures of labor force participation often lead to better performing forecasts in the pseudo-out-of-sample period (2012-2015), the out-of-sample forecasts differ between models by less than 4% for all variables. In fact, for the top 1% and top 10% shares, the “best” model is a naïve model, while for the Gini the best forecast model does not significantly outperform the naïve model when a bootstrapped White Reality Check is performed. For top shares, forecasts fall within fairly wide error bands, making it difficult to draw conclusions about future trends. Often model selection is extremely sensitive to not only variable choice but lag length as well. While some of this may be due to measurement error and nonfilers, analysis of the 90/p10 ratio which shows similar patterns, indicates that it is not the root cause.

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 top income shares. Therefore, we must be cautious in interpreting changes due to a re-timing of income or level shift, rather than significantly altering the long-run trend.<sup>24</sup> Nevertheless, it is clear that inequality at the top has been rising overall and will probably continue to do so.

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<sup>23</sup>Though this effect could be due to a 1997 tax reform, this year is not selected as significant for any other measures.

<sup>24</sup>For a recent discussion on wealth inequality vs. income inequality and share comparison, see Saez and Zucman (2015).

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. However, since naïve approaches are equivalent to or outperform more complex models, particularly for top shares, we need to re-examine the conclusions we can draw from the literature on determinants and predictions for long-run trends. We need to pay particular attention to the impacts of policy changes. However, as with many macroeconomic indicators, we must be aware that long-run trends (>5 years) are significantly different from short-run swings. When comparing the results to a pre-recession pseudo-out-of-sample period, 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 lower forecast errors, suggesting a more structural change may be taking place.

However, the limited power of SBTC indicators in forecasting accuracy demonstrates that we need to think further about the drivers of near-term inequality. To predict inequality in the short-run, we should pay significant attention to policies which impact the income distribution and to past trends in the series, maybe identifying a robust naïve approach. 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. 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 (1980-2015)**

	Tax Units (Fiscal Income)		Household Eq. (Personal Income)		
	Top 1% Share	Top 10% Share	90/10 Ratio	Gini Index	Theil Index
Mean	16.17	40.89	10.01	45.03	37.59
Std. Dev	3.85	4.82	0.513	1.42	2.43
Min	9.32	32.23	8.89	41.65	31.70
Max	22.56	50.47	11.35	47.2	40.75
1980*	9.39	32.23	8.89	41.65	31.70
2015*	22.03	50.47	11.13	47.11	40.51
Structural Breaks (IIS)				1982, 2007	2007

*Source:* Own calculations from 1975-2015 PSZ & CPS (March Supplement).

\* represents levels in these years, rather than differences.

**Table 2: Stationarity of Series, 1980-2015  
P-values for Dickey-Fuller Unit Root Test (1980-2015)**

	Tax Units (Fiscal Income)		Household Eq. (Personal Income)		
	Top 1% Share	Top 10% Share	90/10 Ratio	Gini Index	Theil Index
<b>Series in Levels</b>					
	0.733	0.929	0.739	0.526	0.530
<b>Series First-Differenced</b>					
	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 1975-2015 PSZ & CPS (March Supplement).

**Table 3: Explanatory vars for different Pseudo-Out-of-Sample periods**

Measure	Unit of Observation	2012-2015	2003-2006
Top 1% Share	Tax Units (Fiscal Income)	–	ffpr,ms1_ls,hs_fem
Top 10% Share	Tax Units (Fiscal Income)	–	ffpr,col_fem
90/10 Ratio	Household Eq. (Personal Income)	ffpr, col, ln_gdp	lfpr,lskill,hs_col
Gini Index	Household Eq. (Personal Income)	lfpr, unemp	col_fem
Theil Index	Household Eq. (Personal Income)	ms1_ms2, serv_emp	–

*Source:* Own calculations from 1975-2015 PSZ & CPS (March Supplement).

## 8.2 Figures

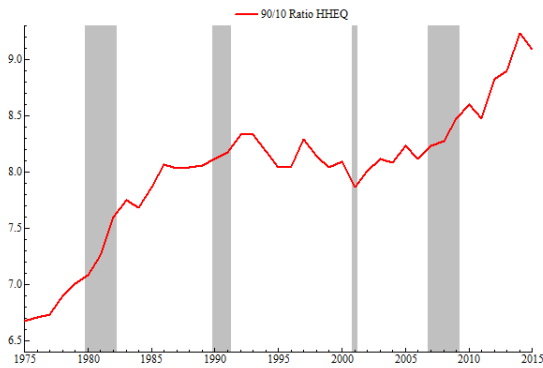
**Figure 1: Plots**



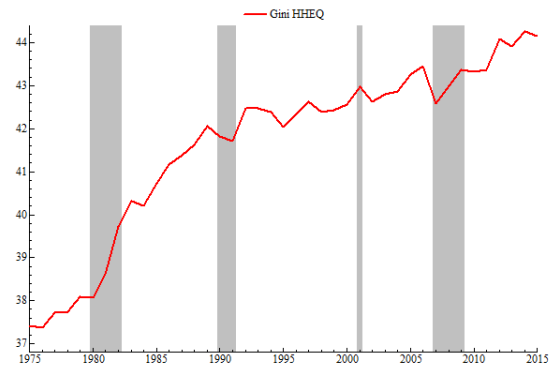
**(a) Top 1 Share (PSZ)**



**(b) Top 10 Share (PSZ)**



**(c) 90/10 Ratio (CPS)**



**(d) Gini Index (CPS)**

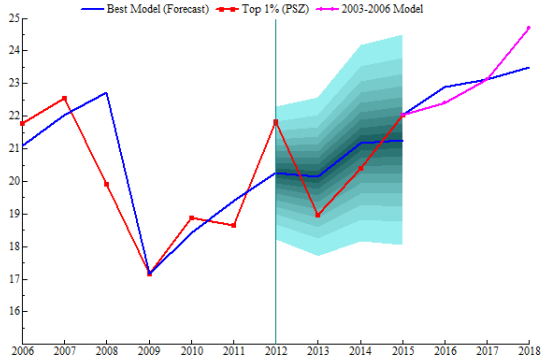


**(e) Theil Index (CPS)**

Source: Own calculations from 1975-2015 PSZ & CPS (March Supplement).

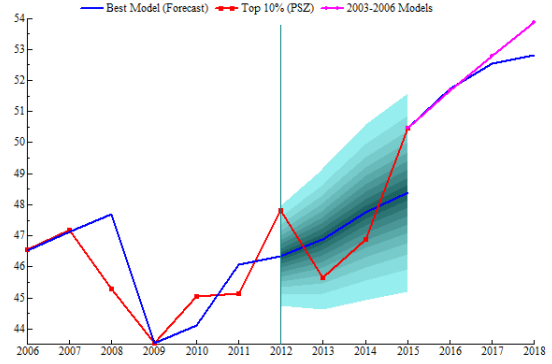


**Figure 2: Forecasts**



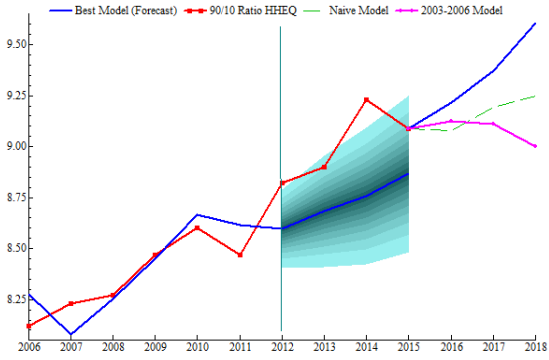
**Best model:**  $\Delta \widehat{Top1}_t = 0.787 - 0.327 \Delta Top1_{t-1} + 0.01 \Delta Top1_{t-2} - 0.21 \Delta Top1_{t-3} - 3.42d2001 - 3.07d2002 - 4.298d2009 + \epsilon_t$   
 RMSE: 1.119, MAPE: 5.1457

**(a) Top 1 Share (PSZ)**



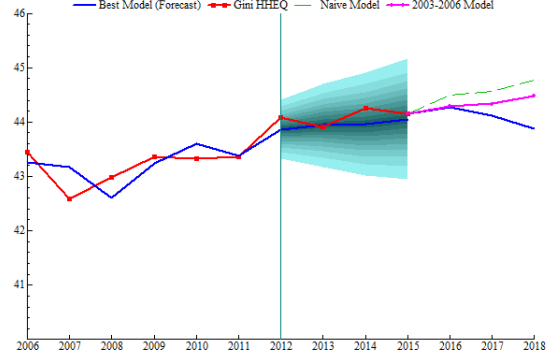
**Best model:**  $\Delta \widehat{Top10}_t = 0.8028 + 0.0645 \Delta Top10_{t-2} - 0.173 \Delta Top10_{t-3} - 3.084d1987 - 3.455d2001 - 1.671d2002 - 2.45d2009 + \epsilon_t$   
 RMSE: 1.486, MAPE: 2.956

**(b) Top 10 Share (PSZ)**



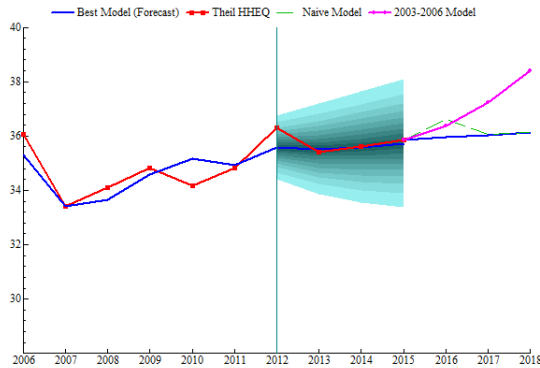
**Best model:**  $\Delta \widehat{9010hheq}_t = 0.0285 - 0.0785 \Delta \Delta lfpr_{t-2} - 0.0717 \Delta \Delta lfpr_{t-3} + 0.0216 \Delta col_{t-1} + 0.159 \Delta col_{t-2} + 2.166 \Delta ln\_gdp_{t-1} - 0.318d2001 + \epsilon_t$   
 RMSE: 0.303, MAPE: 3.123

**(c) 90/10 Ratio (CPS)**



**Best model:**  $\Delta \widehat{Gini}_t = 0.089 + 0.053 \Delta Gini_{t-2} - 0.492 \Delta \Delta lfpr_{t-1} - 1.117 \Delta \Delta lfpr_{t-2} - 0.686 \Delta \Delta lfpr_{t-3} - 0.181 \Delta unemp_{t-2} + \epsilon_t$   
 RMSE: 0.191, MAPE: 0.363

**(d) Gini Index (CPS)**



**Best model:**  $\Delta \widehat{Theil}_t = 0.344 + 118.6 \Delta \frac{mskill1}{mskill2}_{t-2} - 20.88 \Delta serv\_emp_{t-3} - 2.702d2007 - 1.088d1998 + \epsilon_t$   
 RMSE: 0.373, MAPE: 0.675

**(e) Theil Index (CPS)**

Source: Own calculations from 1975-2015 PSZ & CPS (March Supplement).

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## Appendix

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, Piketty, and Saez (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**

	90/10	Gini	Theil
1992	21.54	47.66	40.47
1993	24.05	49.91	49.23
<b>Percent Change</b>	11.7%	4.7%	21.7%

*Source:* Own calculations from 1975-2015 PSZ & CPS (March Supplement).

**Table A2: Tax Units - Fiscal Income**

dTop 1% Share		dTop 10% Share	
Constant	0.787 (0.787)	Constant	0.8028 (0.199)
d_top1_PSZ(1)	-0.327 (0.175)	d_top10_PSZ(2)	0.0645 (0.138)
d_top1_PSZ(2)	0.010 (0.148)	d_top10_PSZ(3)	-0.173 (0.144)
d_top1_PSZ(3)	-0.210 (0.158)	d1987	-3.084 (0.994)
d2001	-3.420 (1.271)	d2001	-3.455 (1.001)
d2002	-3.070 (1.429)	d2002	-1.671 (1.005)
d2009	-4.298 (1.375)	d2009	-2.450 (0.995)
Adj-R2	0.357	Adj-R2	0.438

*Source:* Own calculations from 1975-2015 PSZ.

**Table A3: CPS - Personal Income**

90/10 HHEQ		Gini HHEQ		Theil HHEQ	
Constant	0.029 (0.058)	Constant	0.089 (0.074)	Constant	0.344 (0.316)
d2_ffpr(2)	-0.079 (0.067)	d_gini_hheq(2)	0.053 (0.195)	d_ms1_ms2(2)	118.6 (65.63)
d2_ffpr(3)	-0.072 (0.070)	d2_lfpr(1)	-0.492 (0.492)	d_serv_emp(3)	-20.88 (63.10)
d_col(1)	0.022 (0.081)	d2_lfpr(2)	-1.117 (0.333)	d2007	-2.702 (0.745)
d_col(2)	0.159 (0.084)	d2_lfpr(3)	-0.686 (0.268)	d1998	-1.088 (0.728)
d_ln_gdp(1)	2.166 (1.063)	d_unemp(2)	-0.181 (0.085)		
d2001	-0.318 (0.127)				
Adj-R2	0.239	Adj-R2	0.244	Adj-R2	0.373

Source: Own calculations from 1975-2015 CPS (March Supplement).

**Table A4: Top 1% (PSZ) Out-of-Sample Forecast Comparison**

Year	2013-2016		2003-2006	
	Best Model	Naïve Model	Best Model	Naïve Model
2015 (actual)	22.03	22.03	22.03	22.03
2016 (forecast)	22.90	–	22.40	22.62
2017 (forecast)	23.12	–	23.13	23.21
2018 (forecast)	23.50	–	24.70	23.80
RMSE	1.119	–	1.002	2.516
MAPE	5.146	–	4.600	10.16

Source: Own calculations from 1975-2015 PSZ.

**Table A5: Top 10% (PSZ) Out-of-Sample Forecast Comparison**

Year	2013-2016		2003-2006	
	Best Model	Naïve Model	Best Model	Naïve Model
2015 (actual)	50.47	50.47	50.47	50.47
2016 (forecast)	51.73	–	51.66	51.16
2017 (forecast)	52.55	–	52.79	51.85
2018 (forecast)	52.81	–	53.86	52.54
RMSE	1.49	–	1.27	1.89
MAPE	2.96	–	2.36	3.45

Source: Own calculations from 1975-2015 PSZ.

**Table A6: 90/10 Ratio HHEQ**

Year	2013-2016		2003-2006	
	Best Model	Naïve Model	Best Model	Naïve Model
2015 (actual)	9.09	9.09	9.09	9.09
2016 (forecast)	9.22	9.08	9.13	9.11
2017 (forecast)	9.37	9.19	9.11	9.15
2018 (forecast)	9.61	9.25	9.00	9.19
RMSE	0.303	0.409	0.049	0.063
MAPE	3.123	4.345	0.522	0.734

Source: Own calculations from 1975-2015 CPS (March Supplement).

**Table A7: Gini HHEQ**

Year	2013-2016		2003-2006	
	Best Model	Naïve Model	Best Model	Naïve Model
2015 (actual)	44.15	44.15	44.15	44.15
2016 (forecast)	44.27	44.50	44.29	44.28
2017 (forecast)	44.12	44.56	44.33	44.54
2018 (forecast)	43.88	44.77	44.41	44.76
RMSE	0.191	0.266	0.074	0.090
MAPE	0.363	0.475	0.161	0.150

Source: Own calculations from 1975-2015 CPS (March Supplement).

**Table A8: Theil HHEQ**

Year	2013-2016		2003-2006	
	Best Model	Naïve Model	Best Model	Naïve Model
2015 (actual)	35.85	35.85	35.85	35.85
2016 (forecast)	35.96	36.60	36.39	–
2017 (forecast)	36.02	36.05	37.23	–
2018 (forecast)	36.12	36.14	38.39	–
RMSE	0.373	0.462	0.393	–
MAPE	0.675	0.947	0.998	–

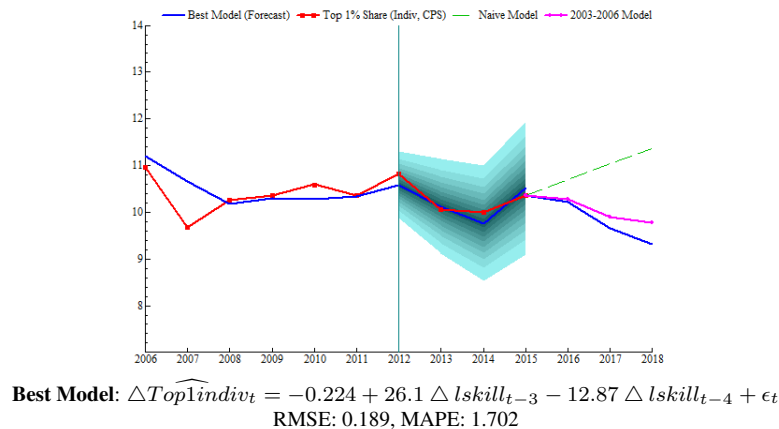
Source: Own calculations from 1975-2015 CPS (March Supplement).

**Table A9: Top 1 indiv**

Year	2013-2016		2003-2006	
	Best Model	Naïve Model	Best Model	Naïve Model
2015 (actual)	10.36	10.36	10.36	10.36
2016 (forecast)	10.22	10.35	10.27	10.47
2017 (forecast)	9.66	10.34	9.89	10.35
2018 (forecast)	9.32	10.32	9.78	10.32
RMSE	0.189	0.324	0.190	0.305
MAPE	1.702	2.747	1.456	2.627

Source: Own calculations from 1975-2015 CPS (March Supplement).

**Figure A1: Top 1 Share (Individuals-CPS)**



### 8.3 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+)

#### 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. 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.

#### Macroeconomic Variables

**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.