GEORGETOWN UNIVERSITY
Center on Education and the Workforce

Help Wanted:
Projections of Jobs and Education Requirements Through 2018

Technical summary

by

Anthony P. Carnevale

Nicole Smith

Jeff Strohl*

* With design and methodological contributions by Avinash Bhati.

cew.georgetown.edu | 3300 Whitehaven Street, NW | Suite 5000 | Washington, DC 20057 | t 202.687.4922 | f 202.687.3110

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I. INTRODUCTION

This paper documents the methodology used by the Georgetown University Center on Education and the Workforce (the Center) to project educational demand for the US economy. The Center has undertaken this project to enrich current and future estimates of educational demand provided by the government.

Appendix 4 of the report Help Wanted: Projections of Jobs and Education Requirements Through 2018 provides a detailed comparison of the core differences in outcome from employing the Center's methodology and the BLS' methodology to estimating education demand. The report can be found at http://cew.georgetown.edu

WHY UNDERTAKE THIS RESEARCH? DOES BLS NOT PROJECT EDUCATION DEMAND?[1]

The official employment projections most often used by policy makers and educators are created by the BLS biennially. BLS projections data on educational and occupational demand are both useful and highly regarded. They provide the statistical bedrock for our labor market information systems; without which, the labor market community and labor economists would be left lacking. The BLS methodology, however, **systematically under-predicts** the demand for postsecondary education and training.

To illustrate:

- BLS 1996-2006 projections data state that 25 percent of jobs would require postsecondary degrees and awards by 2006; however, 34.3 percent of the labor force actually had postsecondary degrees and awards, according to Census data. This 9.3 percentage point differential represents 12.3 million workers with postsecondary education above BLS forecasts (see Table 1).[2]
- BLS data imply that requirements for postsecondary education are actually declining, not increasing. For example, the 1996-2006 education and training data projected that jobs requiring Bachelor's degrees in 2006 would be 13.1 percent of the total (excluding BA plus work experience), and yet the Bureau's 2008-2018 projections dropped the BA requirement for its 2008 baseline to 12.3 percent (see Table 1).

[1] Since we've written this report, two very substantial changes in the Bureau of Labor Statistics (BLS) methodology have taken place:
(1) the abandonment of the cluster method and
(2) the use of the full distribution on educational requirements in the base year.
These changes represent steps in the right direction but are still not enough to correct the biases in national education projections that their methodology produces.

[2] The fact that the BLS reports that 12.3 million workers had postsecondary education that was not required to work in their jobs disagrees in concept with the general research finding that the U.S. has been under-producing postsecondary talent since the mid-80s, resulting in a substantial wage premium for postsecondary educated workers over those with high school or less (Goldin and Katz, 2008). It also leads to a steady drumbeat of reports that argue the opposing view that a great many Americans are overqualified for their jobs because we are overproducing postsecondary talent.

- The difference between BLS projections and *actual* levels of postsecondary education keep growing.[3] BLS 1998-2008 projections data list 25.1 percent of jobs, or 37.8 million workers, as requiring postsecondary degrees and awards. By 2008, 40.1 percent of the labor market, or 60.5 million people, actually had postsecondary degrees and awards. This 15 percentage point differential represents an undercount of 22.6 million workers with postsecondary credentials in the base year of our analysis (see Table 1).[4]

Table 1: Comparison of BLS education and training requirements and education among employed workers in 1996 and 2008.

	BLS 1996[1]		Labor Market[2] 1996		BLS 2008		Labor[2] Market 2008	
	%	**,000s**	**%**	**,000s**	**%**	**,000s**	**%**	**,000s**
Total PSE ne PSE voc awards	**25%**	**33,008**	**34.3%**	**45,397**	**25.1%**	**37,884**	**40.1%**	**60,524**
1st professional degree	1.3	1,707	1.6	2,118	1.3	2,001	1.7	2,566
Doctoral degree	0.8	1,016	1.1	1,456	1.4	2,085	1.4	2,113
Master's degree	1	1,371	5.9	7,809	1.7	2,531	7.3	11,018
BA+, with work experience	6.8	8,971	NA	NA	4.3	6,516		
Bachelor's degree	12	15,821	17.6	23,294	12.3	18,584	20.4	30,790
Associate's degree	3.1	4,122	8.1	10,721	4.1	6,129	9.3	14,037
Post 2nd Vocational training	6.1	8,091	NA		5.8	8,787		
Work experience in a related occupation	7.5	9,966	NA		9.6	14,517		
Long term on-the-job-training	9.3	12,373	NA		7.2	10,815		
Moderate-term on-the-job-training	12.7	16,792	NA		16.3	24,569		
Short-term on-the-job-training	39.4	52,125	NA		36	54,396		

Sources: [1]Silvestri,G (1997), "*Occupational employment projections to 2006",* Monthly Labor Review, Table 6, p.82, Nov. 1997. BLS. [2]CPS March Supplement, various years. [3] Lacey, A and B. Wright (2009),"*Occupational employment projections to 2018"*, Monthly Labor Review, Table 3, p.88, Nov. 2009.

Note: BLS has 132.4 million jobs listed in 1996. A 9.3 percentage point difference between the BLS estimate and the actual labor force equates to 12.3 million workers. In 2008, employment is given as 150,932 and the 15 percentage point difference between the BLS estimate and the actual labor force equates to a 22.6 million difference. All calculations have used BLS employment numbers multiplied by shares calculated in the labor market.

We believe that in an economy where the detailed relationships between education and occupations are fast becoming the arbiter of economic opportunity, we need to begin experimenting with more robust methods for matching future job demands with education requirements.

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[3] Our projections show 43 million more postsecondary workers in 2018 than the BLS assignment method projects.

[4] The BLS assignment method understates the actual number of workers with higher education by 47 percent in its 1998-2008 data. In a robustness test of our method applied retrospectively to the 1998-2008 projections, our method came much closer. It overstates the actual number of postsecondary workers in the census data (ACS) by just 4 percent.

Building Capacity for Projecting Educational Demand

Our method combines dynamic forecasts of education within occupations with occupational forecasts provided by Economic Modeling Specialist Incorporated (EMSI) that are calibrated to total employment forecasts from Macroeconomic Advisors (MA). That is, we use updated GDP and employment projections from MA. These data become feedstock for an Input-Output (I/O) model developed by EMSI. The EMSI model produces detailed industry and occupational employment data adjusted for the most current and detailed labor market information from the ongoing recession (see Figure 1).

Robustness of the modeling procedure is tested using several methods:

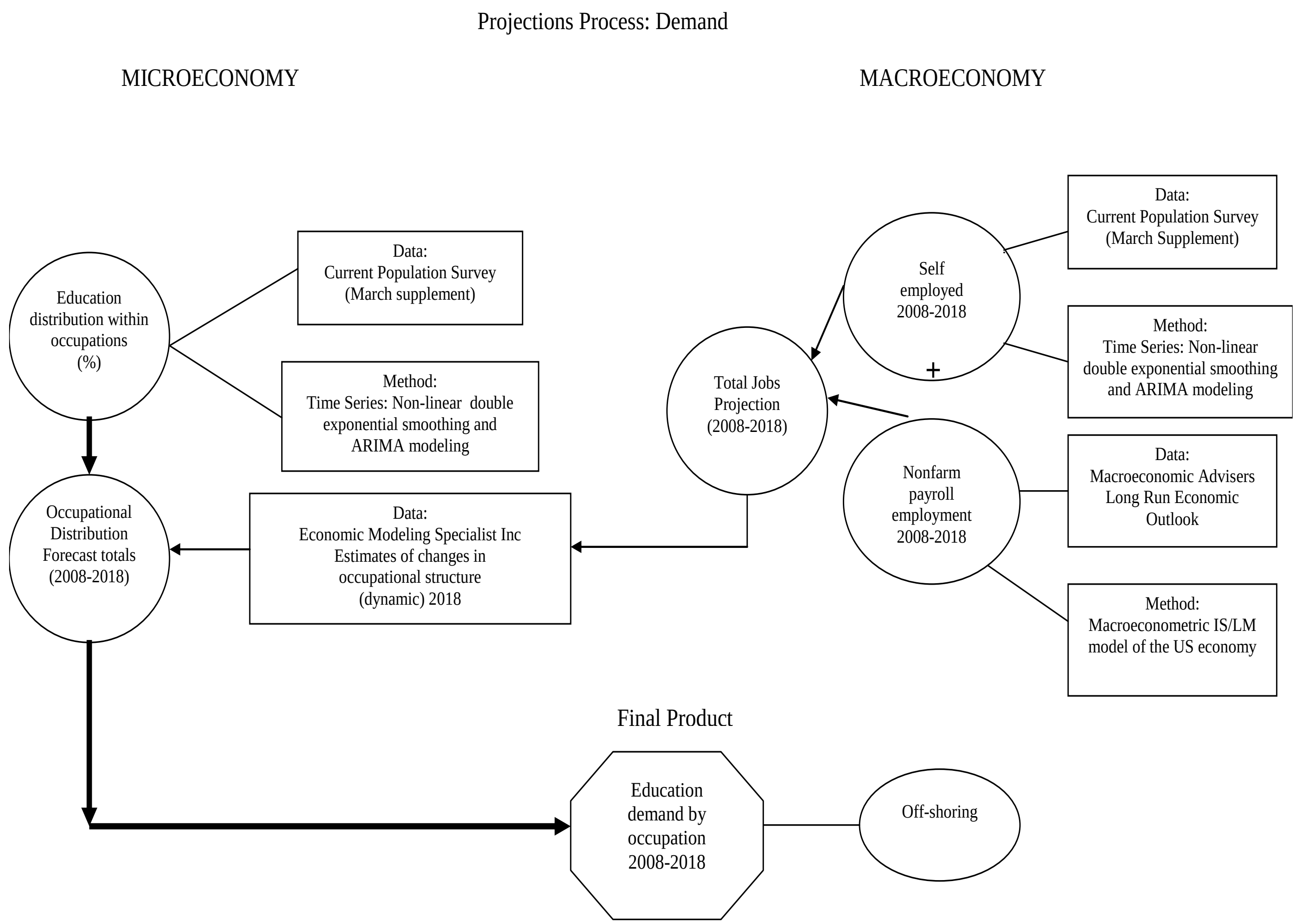
- Evaluation of model fit: Comparisons of the root mean squared errors (RMSE) and the coefficient of variation between models to monitor the scope of outliers.
- In-sample forecasting: The model is estimated on a portion of the sample and is then used to predict outcomes on the remainder of the sample to test the extent to which the model accurately predicts known events. In addition, we judge the extent of the variation between observed and predicted over varying lag lengths in the forecast horizon.
- Comparison with alternative approaches: Educational demand is forecast using a Markov transition probabilities process and compared to the Center's time-series approach.

We believe that our methods have advantages over traditional BLS cluster and category methods for the following reasons:

- Allows for possible change in the occupational distribution;
- Absence of non-separable education cluster assumptions;
- Allows for possible change in the educational distribution across occupation;
- Incorporates macroeconomic shocks, business cycles and the stimulus into estimates of national job creation;
- Creates annual forecasts.

We hope that our methods will provoke discussion and add to a much-needed conversation about educational demand and labor market linkages among labor market economists.

Figure 1: Projections Process for Demand



II. PROBLEMS WITH CURRENT OFFICIAL PROJECTIONS

Single entry education level or assignment method is subjective and introduces bias

The BLS assignment attempts to measure educational demand by assigning the "…most significant source of education or training…" to each occupation level, then aggregating for the national economy across those education and training levels. Requirements, however, vary for each job. As a result, the assignment method does not accurately measure the educational requirement for any job, but instead represents a subjective categorization that is often not reflective of market conditions. A closer look at the very background data BLS uses in the assignment method to create one education and training level per job, demonstrates a wide variety of educational credentials in each occupation, regardless of what designation the BLS assigns. For example:[5]

- The assignment method resulted in 22 out of 42 occupations designated by the BLS as "AA" occupations having more workers with Bachelor's than Associate's degrees currently working in these fields.
- The assignment method is more consistent for Bachelor's degrees, where only 12 occupations actually have higher graduate level concentrations. [6]
- Doctoral degree assignments are off six out of 11 times, and Master's degrees are accurate roughly half of the time.
- Jobs listed as requiring a Doctoral degree actually have a workforce of 28.4 percent Bachelor's degrees; 29.3 percent Master's degrees; and 32.6 percent doctoral or first professional degrees.
- Jobs listed as requiring Master's degrees actually consist of 30.8 percent Bachelor's degrees; 39.6 percent Master's degrees; and 14.9 percent Doctoral or first professional degrees.
- Jobs listed as requiring Bachelor's degrees (no work experience) actually consist of 7.8 percent Associate's degrees; 42.9 percent Bachelor's degrees; 20.9 percent Master's degrees; and 5.3 percent Doctoral or 1st professional degrees.

A comparison of these results against a known distribution of education among prime age workers, for instance, clearly demonstrates large differences between expert "assignment" and actual distributions of education in occupations. For example, in their employment and total job openings by education and training report, BLS estimates 21% of the working population as having a Bachelor's degree and above. CPS calculations, however, reveal that this figure is closer to 30%. BLS assigns 3.9% of workers with an Associate's degree, while CPS estimates Associate's degree holders at approximately 10% of workers in 2006.

Now the BLS asserts that they use entry-level education and training requirements for each job, which they propose is lower than the education level of incumbents who may require additional education for advancement in their careers. While this is true at any point in time, it is a very static view of the relationship between education, training and employment. For example, this static understanding of the relationship will deduce that entry level research analysts require a

[5] Authors' calculations based on BLS Table 1.11, data not shown. Spreadsheet available upon request.
[6] Authors' calculations based on BLS Table 1.11

Bachelor's degree today, while more seasoned senior analysts have Master's degrees or better. However, a dynamic understanding will deduce that research analysts in the 1980s or 1990s traditionally would have required less education and training than they do today.[7]

BLS projects occupational growth, but holds education within occupational groups constant in its projections.

Consequently, growth in postsecondary requirements using official data reflects only occupational shifts and ignores increases in postsecondary requirements that occur within occupational categories. Thus, if used without proper adjustments, the BLS methodology leads to underestimates of both current and future postsecondary education requirements in the labor market.

For example, as can be observed in Table 2 (below), holding the educational distribution within occupations constant from 1983 (column A) to 2001 (column B) leads to 10 percentage points fewer workers with some college and three percentage points fewer workers with Bachelor's degrees and above than actually occurred in 2001 (column C).[8]

Table 2: Holding Education Constant within Occupations
Understates Education Growth over Time

	(A) Education In 1983	(B) Education in 2001 given 1983 educational distribution	(C) Real 2001 Educational demand given both upskilling and redistribution of occupations.
High school dropouts	15%	14%	9%
High school graduates	40%	38%	31%
Some college/Associate's degrees	19%	19%	29%
Bachelor's degree and higher	25%	29%	31%

Source: Authors' calculations using CPS data; multiple years.

BLS groups education requirements into clusters, which are used to determine future demand, *if and only if 20% or more of employment fall into one of these groups* [Recently discontinued].[9]

[7] In its 2008/2018 projections, and most likely in response to criticism of the previous methodology, BLS now uses the distribution of education and training requirements for occupations in its projections data, apparently abandoning their old misgivings about the diminished utility of the latter raised in previous methodological discussions.
[8] Attainment is not measured in the CPS before 1992 so we converted degrees attained to years of schooling and grouped 13-15 years of schooling for some college in this example. Accepted techniques exist (Jaeger, etc.) to bridge the code change in 1992 to convert years of schooling to AA's, but for purposes of illustration, this was not necessary. In the main report, we will show the difference in forecast demand by degree type between trending and fixed coefficients.
[9] Apparently due to immense criticism of its shortcomings, BLS removed the cluster method entirely from its 2008/2018 projections data released in November 2009.

The vast majority of occupations include incumbents with a wide range of educational attainment. In order to assign a dominant attainment level for an occupation, BLS assigns current educational requirements to occupations by choosing the predominant educational credential among the incumbent workers in the occupation. The rule in deciding the predominant educational qualification is to set aside groups of incumbents in the occupation that represent less than 20 percent of the total. For example, suppose Occupation X includes 19 percent with bachelor's degrees or higher, 19 percent with a high school degree or less and 62 percent with some college. That occupation would be counted as not requiring a Bachelor's degree, even though 19 percent of the incumbents have one. BLS does not take into account whether the highest earnings and entry-level growth in the occupation accrues to those with baccalaureate or graduate education.

BLS defines education requirements as categories, which are clustered and non-separable. Up to its most recent 2006/2016 employment and educational demand projections, BLS categorizes educational requirements, using ACS data, as high school (HS), some college (SC) and college (C) (or any combination of the three). Using these categories, there is no explicit way to determine education requirements beneath a high school degree, nor a way to separate these clusters into independent categories.[10] At least 19 percent of workers in that occupation must have achieved a particular educational attainment level for that level to be considered one of the "education clusters" for that occupation. This methodology essentially results in a reversion to the mean as low and high levels of education are excluded if they do not pass this 19 percent litmus test referenced earlier. While simplifying, we believe that too much information is lost in this clustering process. Further, users of these data can benefit from a larger number of categories that are available in the ACS data.

BLS has proposed modifications to their truncation or "cluster" method which will be discarded in favor of one which uses the entire educational distribution available in the ACS data. As a result, the attainment cluster system will be replaced by one that uses the distribution of education (seven categories if we combine professional and Doctoral degrees) available in the ACS. These changes will remove the bias towards the middle that results from truncation. However, BLS will continue to use only one year's observation of the attainment distribution to forecast the distribution 10 years out. This move towards using the entire educational distribution to define educational demand goes a long way towards removing serious biases in educational demand, but we believe it does not go far enough.

III. OUR APPROACH TO FORECASTING EDUCATIONAL DEMAND

We have a four-step approach to forecasting educational demand:

Step One: Forecasting Educational Distributions within Occupations
Step Two: Estimating Long-Term Employment Projections (the Macro Economy)
Step Three: Estimating Change in the Occupational Structure

[10] One could revert to the assignment of 11 workforce training and formal education categories that the BLS develops, but there is not consistency between these methods.

Step Four: Projecting Educational demand to 2018

A. Step One: Forecasting Educational Distributions within Occupations

Because BLS holds education change within occupational categories constant, its estimates do not explicitly incorporate “skill-biased technical change”[11] – a dynamic that is prominent in other trend data. In order to more fully capture this dynamic, we use a more information-rich approach of trending the full distribution of educational attainment to generate projections of educational demand within occupations.

The Center forecasts changes in the educational distribution by eight levels of education attainment using a time-series method as the first step in the projections process. We use data from the March Current Population Survey (CPS) to estimate the proportion of persons within occupations by eight educational attainment levels:

1. High school dropouts
2. High school graduates
3. Some college, but no degree
4. Associate’s degrees
5. Bachelor’s degrees
6. Master’s degrees
7. Professional degrees
8. PhDs

We then develop projections based on trend data since 1992 for each of these education attainment levels within twenty two occupational categories drawn from the BLS’ Standard Occupational Classification (SOC) occupations.[12] These include the following occupational groupings:[13]

1. Management
2. Business and Financial Operations
3. Computer and Mathematical Science
4. Architecture and Engineering
5. Life, Physical and Social Science
6. Community and Social Services
7. Legal
8. Education, Training and Library
9. Arts, Design, Entertainment, Sports and Media
10. Healthcare Practitioner and Technical
11. Healthcare Support
12. Protective Services
13. Food Preparation and Serving
14. Buildings and Grounds Cleaning and Maintenance
15. Personal Care and Service
16. Sales and Related
17. Office Administrative Support
18. Farming, Fishing and Forestry, and Hunting
19. Construction and Extraction
20. Installation, Maintenance and Repair
21. Production
22. Transportation and Material Moving

[11] Skill-biased technical change is a shift in the production technology that results in increased demand for workers with relatively higher human capital due to their increased relative productivity levels.
[12] Changes in the occupational code during the time period were bridged using a crosswalk developed at Westat, Inc.
[13] Later, we separated Business and Finance, Architecture and Engineering and Life, Physical and Social Sciences to create 25 occupational categories.

As stated above, we draw our data on the relationships between the eight educational attainment levels in the twenty two occupational categories from the Current Population Survey conducted in March of every year.[14]

The March CPS is a nationally representative, cross-sectional data set which provides information on the socioeconomic characteristics of the American population. There are about 50,000 households with detailed information on resident demographic and labor market behavior. Our decision to use the CPS over the much larger American Community Survey (ACS) rests solely with the longevity of the former. [15] That is to say, since our methodological framework is time-series in nature, we sought to obtain the longest possible dataset available with information pertaining to educational and occupational characteristics of the population.[16] The relatively longer series also makes it easier to demonstrate skill-biased technical change within occupations in the data as the proportion of more highly skilled workers within an occupation increases with time.

The March CPS details *inter alia* the highest education level attained and occupation of respondents to the survey. We use data on the weighted percentage of workers employed in a particular occupation and with a particular level of education as an estimate of 'realized demand' for education within that occupation. Because of changes in the education code in 1992, we have two time-frames based on the same methodological approaches. [17]

Changes in the occupational code in 2002 were bridged using a crosswalk developed at Westat, Inc. The occupational recode in 2002 was extensive and was non-unique, which required a probabilistic crosswalk made possible because the survey double-coded occupations for three years to provide empirical comparison between the two systems.[18]

We assume that each of the time series variables in the model is one observation of an underlying data-generating process. We assume that this process consists of the summation of both a stochastic and deterministic component.[19] As such, each data point in the stochastic series may be considered as the sample first moment of a probability distribution of an underlying population for each point in time of the time-series variable (with associated moments of each of the distributions). There are initially 27 observations (1983-2009) and the lag of the prediction is 19.[20] Small sample size considerations in this case limits our ability to assume asymptotic

[14] 3-digit occupational detail is provided in the main report for occupations that are large enough to provide a representative sample.
[15] The CPS has been conducted for over 50 years (although a smaller segment is available to us due to definitional changes). The ACS was first conducted in 1996 in a subsample of US counties. In addition, the transition to the ACS as the standard from which to derive educational clusters has been a recent change for the BLS.
[16] The CPS fulfils this requirement although the authors recognize that sample size bias might require pooling of some years for state and other smaller scale comparisons.
[17] 1983-2009 and 1992-2009.
[18] These data can be found in the US Census Bureau's Technical Document 65, "The Relationship Between the 1990 Census and Census 2000 Industry and Occupational Classification Systems." The program for this crosswalk is available upon request.
[19] The stochastic random process must be modeled.
[20] Indeed, due to a change in the definition of educational attainment by the CPS in 1992, our sample size is reduced to allow for the greater degree of specificity in the definitions of education.

properties of the sample realizations as they pertain to approximating population moments of the data generating process in the limit.

We use two methods to estimate the percentage change in the educational distribution within occupation through time. Our objective is to find an economic model that is "parsimonious, plausible and informative" and best represents past information to generate conceivable forecasts of educational demand within occupations.

- Method One: a non-linear exponential smoothing method with the added restriction that the estimated proportions for each education level sum to one for each of the years in the forecast horizon. Exponential smoothing is a time series method which uses past observations of a series to forecast the future. It is a variant of a moving average process which places relatively greater emphasis on the most recent past and includes information on the time trend in the data.

- Method Two: assuming that the educational distribution for each occupation is a probability density function, we create transition matrices that are advanced from 2008 to 2018.

Method One

We first use a non-linear exponential smoothing technique to estimate the educational distributions across time. We chose a non-linear smoothing technique because of its simplicity in design and application, its desirable small sample properties and the exponentially declining emphasis placed on more distant observations. That is, the model explicitly incorporates knowledge on the low probability of change in the educational distribution for recent observations, and relatively higher probability of change over time as evidenced by skill-biased technical change in human capital requirements.

$$S_t = f(S_{t-l}) \qquad (1)$$

S_t = observed education proportion within an occupation in time period t

l= lag length

$$S_t = \alpha\, y_t + (1-\alpha)(S_{t-l}), \qquad 0 \le \alpha \le 1 \qquad (2)$$

In general, when applying exponential smoothing, each smoothed term is a weighted average of the current observation and the smoothed value of the previous observation. This is a very easy and functional method from a forecasting perspective. This framework has the advantage of producing dynamic out-of-sample forecasts, where smoothing parameters are chosen to minimize in-sample sum-of-squared prediction errors. Another advantage of exponential smoothing is it requires little data to forecast. The dataset contains 27 observations from 1983 to 2009 inclusive for a more restrictive set of education categories and 18 observations from 1992 to 2009 inclusive. Exponential smoothing attaches a greater significance to the most recent observations with an exponential decline in the contribution of older observations in determining forecasts; an assumption that is quite plausible, incorporating more information than a random walk assertion.[21] The rate at which the weights of older observations decline is determined by the size of the smoothing constant selected. The closer this value is to 1, the less significant are older observations. In addition, relatively noisy data should be matched with smaller values for the smoothing constant.

Where the data exhibit trend or cyclical characteristics, a double exponential smoothing method is more appropriate.[22] This time, the exponential smoothing model contains two weighing factors, α and γ and an additional equation (4) which accounts for changing trend. Specifically,

$$S_t = \alpha\, y_t + (1-\alpha)(S_{t-l} + b_{t-1}), \qquad 0 \le \alpha \le 1 \qquad (3)$$

$$b_t = \gamma(S_t - S_{t-l}) + (1-\gamma)\, b_{t-1} \qquad 0 \le \gamma \le 1 \qquad (4)$$

The dampening parameters determine the extent to which we want to emphasize the contributing role of the most recent and oldest observations. The closer the size of α and γ to 1, the greater the relative role of more recent observations in determining the future forecast values.

<u>Method Two</u>

The second approach used for predicting long-term demand uses transition matrices. Unlike the double exponential smoothing—which relies exclusively on the past shares of a particular education attainment category for projecting demand—the transition matrix approach relies exclusively on the transitions of the shares among education categories to model the demand dynamics within an occupation. The transition matrix approach can be used to model dynamics across several time periods (by controlling the order of the matrix). In the current analysis, given data limitations, we have used a first order matrix.

A transition probability matrix (P) is a square matrix with eight educational categories as the rows and the columns. The elements of the matrix (p_{kj}) represent the proportion of share of the j^{th} education category that moves to the k^{th} category between two time periods. Since the categories are exhaustive, any education category that experiences a loss in its share must be offset by a gain in some other category.

[21] Decomposing the series into a trend, seasonal and irregular component is the usual econometric procedure. ARMA, Box-Jenkins framework and (G)ARCH modeling are also generally accepted univariate methods.
[22] We can use a Holt-Winter's smoothing technique where the data display seasonality but this method is more appropriate for monthly or quarterly data.

Let the share of education category j ($\forall j = 1, ..., 8$) within occupation i ($\forall i = 1, ..., 22$) at time t ($\forall t = 1992, ..., 2009$) be denoted as ($y_{itj}$). Then the basic demand dynamics within an occupation are represented by the following equation:

$$y_{tj} = \sum_{k=1}^{K} p_{kj} \, y_{t-1,k} + e_{tj} \tag{5}$$

where the p_{kj} are stationary transition probabilities over the relevant period, and

$$\sum_{j=1}^{J} p_{kj} = 1 \qquad \forall k = 1, \ldots, K \tag{6}$$

imposes the condition that the p_{kj} represent proper probabilities.

In order to proceed, we can make the simple assumption that $\sum_{t}^{T} e_{tj} = 0$, or the more general assumption that $\sum_{t}^{T} e_{tj} \, x_{ti} = 0$ where x_{ti} may be a set of fixed macro-economic or trend predictors. In the current analysis, we include an intercept and a time trend to allow the within-occupation demand dynamics to evolve with time.

Given our small sample size (18 years), rather than make strong assumptions about the error terms e_{tj}, following Golan, Judge, and Miller (1996) we re-parameterize them into proper probabilities as well. Let $e_{tj} = \sum_{m=1}^{M} \upsilon_m \, w_{mtj} = 1 \quad (\forall t, j)$ where $\sum_{m=1}^{M} w_{mtj} = 1 \quad (\forall t, j)$. This augmented version of the demand dynamics, along with moment conditions utilizing the time trend, can be represented as

$$\sum_{t=2}^{T} y_{tj} \, x_{ti} = \sum_{t=2}^{T} x_{ti} \sum_{k=1}^{K} p_{kj} \, y_{t-1,k} + \sum_{t=2}^{T} x_{ti} \sum_{m=1}^{M} \upsilon_m \, w_{mtj} \tag{7}$$

with the adding up constraints $1 = \sum_{m=1}^{M} \upsilon_m \, w_{mtj}$ and $1 = \sum_{j=1}^{J} p_{kj}$.

The model results in an ill-posed inversion problem. There are $K + J + TJ$ constraints linking $KJ + MTJ$ unknowns. Since the number of unknowns is larger than the number of constraints linking them, an infinite number of solutions can satisfy the constraints.

To solve this problem, we use the Generalized Cross Entropy approach (Golan, Judge, and Miller 1996). Assuming a set of prior probabilities p_{kj}^{0} and w_{mtj}^{0}, we minimize the Kullback-Leibler (KL) directed divergence measure while ensuring that all moment and adding up constraints are satisfied. This ensures that we will derive the most conservative inferences possible while maintaining that the model is consistent with the evidence. The KL measure is defined as:

$$KL = \sum_{k,j}^{K} p_{kj} \log\left(\frac{p_{kj}}{p_{kj}^{0}}\right) + \sum_{m,t,j}^{M,T,K} \log\left(\frac{w_{mtj}}{w_{mtj}^{0}}\right) \tag{8}$$

The inferential problem is thus converted into a constrained optimization problem whereby the objective function (the KL directed divergence function) is minimized, subject to all moment and adding up constraints. The optimization problem can be solved using the Lagrange method. The resulting solutions take the form:

$$\hat{p}_{kj} = \frac{p_{kj}^0 \exp(\sum_{t=2}^T \sum_{l=1}^L y_{t-1,k}\, x_{tl}\, \beta_{jl})}{\sum_{j=1}^K p_{kj}^0 \exp(\sum_{t=2}^T \sum_{l=1}^L y_{t-1,k}\, x_{tl}\, \beta_{jl})} \equiv \frac{p_{kj}^0 \exp(\sum_{t=2}^T \sum_{l=1}^L y_{t-1,k}\, x_{tl}\, \beta_{jl})}{\Omega_k} \tag{9}$$

and

$$\hat{w}_{mtj} = \frac{w_{mtj}^0 \exp(\sum_{l=1}^L v_m\, x_{tl}\, \beta_{jl})}{\sum_{m=1}^M w_{mtj}^0 \exp(\sum_{l=1}^L v_m\, x_{tl}\, \beta_{jl})} \equiv \frac{w_{mtj}^0 \exp(\sum_{l=1}^L v_m\, x_{tl}\, \beta_{jl})}{\psi_{tj}} \tag{10}$$

where β_{jl} are the Lagrange multipliers associated with the moment constraints. Here Ω_k and ψ_{tj} are termed partition functions that ensure that the probabilities sum to one. The optimal values can be inserted back into the primal objective function and a dual unconstrained optimization problem can be derived. The dual is typically no more difficult to estimate than a standard maximum-likelihood problem.

Once the Lagrange multipliers are estimated, the transition probabilities matrix can be recovered and used to project future demand. In matrix notation, we may compute recursive demand projections as $\hat{y}_{t+f} = y_t \hat{P}^f$ where $\hat{P}^f$ represents the transition probability matrix multiplied by itself f times.

The above model was estimated for each of the i ($\forall i = 1,\ldots, 22$) occupations and educational demand was projected out nine years (from 2010 through 2018, inclusive). We used this approach to augment our analysis of the double exponential smoothing model to assess the robustness of our projections. Indeed, the two approaches rely on very different information sets. The double exponential smoothing approach makes heavy use of historic data for a particular share with minimal concern for within occupation dynamics. The transition probability matrix approach makes heavy use of within occupation dynamics with minimal concern for the historic trends (beyond the first lag). To the extent that estimates from these approaches provide consistent predictions, our confidence in the projections are bolstered.

Using both methods, we complete the first step in the projections process of estimating the growth rate of the distribution of education within occupation.

B. Step Two: Estimating Long-Term Employment Projections (the Macro-economy)

The Center generates projections of the demand for education in the US economy, adjusted for the unforeseen recession by incorporating assumptions of the behavior of job growth and job creation within the larger macro-economy. Since the beginning of the Great Recession of 2007,

7.8 million jobs have been lost, with 40% of the job loss occurring since January of 2009.[23] With this in mind, the Center has partnered with MA and EMSI to produce forecasts of job creation to 2018.[24] At the macro level, MA forecasts project non-farm payroll employment totals that incorporate estimates of jobs created by the American Recovery and Reinvestment Act, 2009 (ARRA), more popularly known as the stimulus package. Projections of self-employment (unincorporated) are appended to non-farm payroll employment to obtain forecasts of total job creation in the economy. Unpaid family workers, agricultural employees and paid private household workers have been excluded from our definition of the total employment.[25]

Proprietor ownership and the educational demand associated with this subset of workers are estimated separately using the Bureau of Economic Analysis (BEA) estimates of non-farm and farm proprietors as the source for these data. These values include both incorporated and unincorporated self-employed workers and are "based on IRS tax data that reflect the address from which the proprietor's individual tax return is filed, which is usually the proprietor's residence."[26]

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[23] January is also the peak of the job losses at 741,000. Job losses have declined consistently since that month and were estimated at 467,000 in June 2009 with substantial declines in the rate of losses in manufacturing and professional and business services.

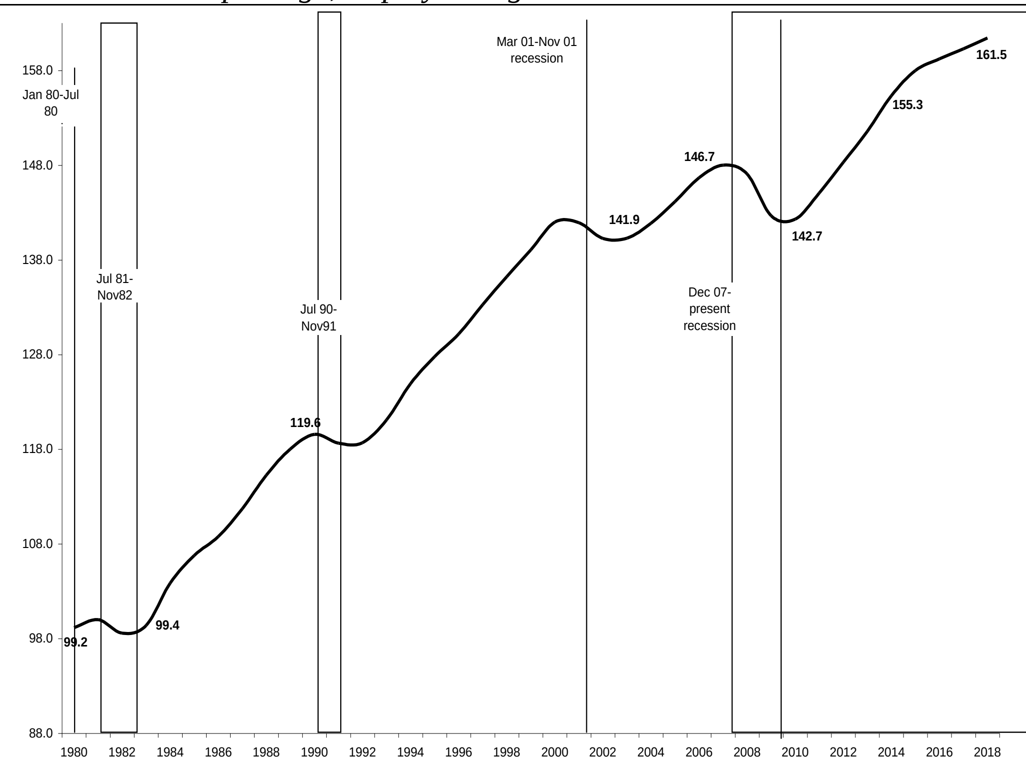
[24] Current government projections are to 2016.

[25] They accounted for 2.9 million workers in April 2009.

[26] It is necessary to distinguish between the BLS' definition of self-employed and the BEA's definition of proprietors due to the vast differences in methodology and outcome of the two datasets. On average, for example, BLS estimates the self-employed (unincorporated) at 10.08 million workers in 2008, while the self-employed (incorporated) account for about 5.78 million for a total of 15.86 million self-employed workers in 2008. On the other hand, the BEA proprietors are a little over twice BLS' self employed at 36.13 million in 2007.

Figure 2: Projections of job growth in the US economy through 2018*

With the stimulus package, employment growth set to resume in 2011



Source: Georgetown University Center on Education and the Workforce's Analysis of Macroeconomic Advisers (MA) Long-term Economic Outlook, March 2009.

*Non-farm payroll employment is combined with estimates of self-employed to estimate total employment. Unpaid family workers, agricultural employees and paid private household workers have been excluded from our definition of total employment.

The current economic recession started in December 2007 and is proving to be the most significant economic downturn in the post-war era on a variety of counts, far surpassing the 1981-82 record in unemployment levels, job loss and decline in personal wealth. In response to this current crisis, the Obama administration signed the $787 billion dollar ARRA bill into law in February of 2009. The bill aims to create or save at least 3.5 million jobs by the 4th quarter of 2010, while 2.7 million workers are expected to move from part-time to full-time employment.[27] Through the initiatives of the proposed fiscal stimulus package, "90 percent of the jobs produced would be in the private sector, including hundreds of thousands in construction and manufacturing."[28]

[27] The 3.5 million jobs figure was provided by Romer and Bernstein (2009). Mark Zandi of Moody's Economy.com estimates the number of jobs created or saved to be closer to 2.2 million. Macroeconomic Advisers (2009) estimate the stimulus package will boost employment by "roughly 2.6 million jobs."

[28] Bacon, Perry. "Obama Stresses Plan's Job Potential." *The Washington Post*. 11 January 2009.

In the context of job creation, a stimulus package should be considered as a catalyst that will speed the economy's return to full employment.[29] Because of changing trends and the mixing of new and replacement jobs versus the stimulus' aim to 'create or maintain' jobs, it is difficult to answer what exactly the impact of stimulus job creation will be as a percentage of total jobs created in the economy. We can, however, use existing evidence to provide compelling estimates. According to BEA, between 1990 and 2008 there were an average of 2.4 million jobs created annually, with a peak of 4 million in 1998 and a trough of -0.75 million between 1990-1991. Framed by these trend data, if the predicted 3.65 million jobs are new and created over two years, the stimulus would contribute at least 75% of normal job creation per year.[30]

Historic trends demonstrate an active business cycle underlying the dynamics of the US economy. Downturns have occurred roughly every 10 years, but each downturn has been followed by recovery (see Figure 2). Reinhart and Rogoff (2008) use historical data on past financial crises to show that unemployment continues to rise for four years, on average, over the down phase of the cycle, but recover after that. In fact, the evidence points to a lag between the official end of economic recessions in 1990/1991 and 2001and the eventual increase in overall employment numbers. This phenomenon has been characterized as a "jobless recovery." At the micro level, jobless recoveries could be indicative of structural change as defined by permanent differential job recovery by industry. Two separate papers suggest a changing structure to economic recoveries since the 1990/1991 recession. Groshen and Potter (2003) use aggregate payroll information and payroll by industry to show that job growth no longer recovers in tandem with GDP growth. Daly et. al. (2009) use worker flows into and out of unemployment involuntary part-time employment and temporary layoffs to forecast a weak labor market recovery for this current recession.

In Figure 2, we also observe evidence of an ever increasing lag-length between the end of recessions (as defined by positive changes in the growth rate of Gross Domestic Product [GDP]) and the growth rate of jobs in the economy. Figure 2 also shows a continued decline in overall employment throughout 2010 with a slow and continuous increase by 2011. Given historical trends, we should therefore expect dampened job creation and job growth for some time after the official end of this recession (marked by consecutive increases in the rate of growth of GDP).

Estimates of non-farm payroll employment numbers are derived in the context of a larger macroeconomic model of the US economy which makes standard neoclassical assumptions within a general equilibrium framework. The macroeconomic model used by MA—the Washington University Macro Model (WUMMSIM)—is a quarterly econometric system consisting of 745 equations, 134 estimated behavioral equations and 201 exogenous variables of

[29] Other analyses focus on counterfactual measures of the extent job growth in the absence of such a package. Zandi (2008) estimated a loss of 6.5 million jobs from the peak in employment at the start of 2008 to the bottom in employment by late 2010 if the government had not implemented a stimulus package and instead stuck to the automatic stabilizers of the taxes and transfers. Macroeconomic Advisers believes that the stimulus package will boost "employment by roughly 2.6 million." Fiscal Stimulus to the Rescue – Final Answer! Macro Focus. Volume 4, Number 4. February 2009.

[30] The time frame for stimulus spending is February 17, 2009 through September 30, 2011.

the US economy.[31] It assumes a long-run vertical Phillips curve, a long-run neoclassical model of fixed investment, labor demand, pricing and distribution of income, a life-cycle model of consumption, a transactions model of money demand and an expectations model of the term structure of interest rates. Exogenous variables are observed or hypothesized and incorporated to obtain a solution to identities and behavioral equations in the model.[32]

Goods Market Equilibrium

$$Q \cong C(Q) + I(Q,r) + G_0 + X(Q_f) - IM(Q) \qquad (11)$$

Q - output C- consumption

I - investment G- government expenditure

r – real interest rates X – exports

IM - imports

Money/Credit Equilibrium

$$M_0/P = L(Q,r) \qquad (12)$$

M_0/P – real money supply

Aggregate Supply

$$Q=Q(K(r), E, t) \qquad (13)$$

K - productive capital stock E -employment, or hours,

t - the state of technology, or total factor productivity

Non-farm payroll employment is combined with estimates of self-employed.[33] Total employment in 2018 is the second step in this projections process used to forecast educational demand. In Step Three of our projections process we deal with changes in industry and occupational structure.

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[31] Other notable clients that use the WUMMSIM econometric model to create estimates of the macro economy in its employment projections are the Bureau of Labor statistics and the White House (in forecasting the macroeconomic impact of the stimulus package).

[32] These assumptions are equivalent to the belief of the absence of a long-run trade-off between inflation and employment with a consistent and stable, non-accelerating rate of unemployment NAIRU (currently estimated at 5.2%); that wages equate to the value of their marginal product; labor and product markets clear; money demand is determined by interest rates (speculative activity) and income levels (transactions activity); a trade-off exists between current and future consumption; and that interest rates reflect inflation-risk premia in their construction.

[33] Unpaid family workers, agricultural employees and paid private household workers have been excluded from our definition of total employment.

C. Step Three: Estimating Change in the Occupational Structure

The Center adjusts for one of the most significant critiques of the BLS methodology used to forecast occupational demand (offered by Bishop 1991, 1992). Although fairly old, this critique is still surprisingly relevant. Bishop argues that the BLS has “consistently under-predicted the growth of skilled occupations”; specifically, he demonstrates the extent to which BLS underestimated the growth of managerial and professional jobs in the 1990s in favor of the growth of laborers and service jobs. He also cites several possible reasons for this outcome that range from an outdated input-output matrix, incorrect estimates of productivity growth and the inability of BLS to incorporate changes in the occupational composition of industries across time. We attempt to address this set of concerns, initially raised by Bishop, by enlisting the assistance of EMSI to provide forecasts of employment by occupation adjusted for current and projected industry job losses and calibrated to national forecasts of job decline and job growth to 2018.

Structural change in the US economy, including recent substantial reductions in manufacturing and retail employment, can have a substantial impact on the occupational mix. The Quarterly Census of Employment and Wages (QCEW) census and the Current Employment Statistics (CES) conducted from an industry perspective. As such, seasonal reports produced by the BLS on changes in the employment situation are nested solely in an industrial context.

We use EMSI to obtain estimates of changes in occupational distribution through time. EMSI combines data, updated on a quarterly basis, from over 80 government and private-sector sources. In so doing, we capture occupational growth trends and information on skill-biased technological change in the data. Forecasting changes in the occupational staffing mix is the third step in this projections process. Total employment is subdivided into non-farm payroll employment and self-employed workers. The former are derived from the QCEW censuses and reflect the occupational distribution of the Occupational Employment Statistics (OES) surveys. The latter are derived from the CPS and reflect the occupational distribution of the CPS and ACS surveys.

D. Step Four: Projecting Educational demand through 2018

Estimates of educational distribution within each 2-digit SOC occupation (Step One) are combined with forecasts of structural change in the occupational distribution through time obtained in Step Two. Forecasts of changes in the occupational distribution are based on neoclassical assumptions set forth in the WUMMSIM macro-econometric model (Step Three) of the US economy that incorporate information on the recession, stimulus package, and business cycles into final estimates of national and state levels of occupational demand.

This process provides an estimate of the number of jobs within each occupation that require an education level equivalent to each of the eight levels of education that are observed in CPS data. We later sum each educational level across occupations to get an estimate of national educational demand.

As noted above, BLS projects educational demand using an assumption of time-invariant fixed education coefficients within occupations which are then arbitrarily truncated if a particular education type concentrates less than 20 % (cluster method). Our estimates of educational demand are an advance compared to the cluster method used by BLS for the following reasons:

- **Allows for possible change in the educational distribution across occupation**. The assumption of a fixed distribution of education within occupations is flawed in that it consistently underestimates the demand for higher-education. At the Center, we assume that the distribution of education changes overtime within occupations. *Information exists on these trends and should be used to improve projected educational demand*. Forecasting the full educational distribution is in keeping with the up-skilling of the American worker through time. We use the actual education characteristics of the American worker and make no assumptions regarding entry-level requirements. In fact, entry-level requirements for jobs today are almost universally higher than entry-level requirements in the past. Had BLS truly used entry level requirements for the occupations reflected in employer surveys and survey data as stated, their educational forecasts would reflect higher proportions of postsecondary education and training.
- **Absence of non-separable education cluster assumptions.** The entire educational distribution available in the CPS data is used to generate forecasts; thus removing the bias towards the middle jobs that results from BLS truncation.
- **Allows for possible change in the occupational distribution.** We assume structural changes in the macro-economy impact the occupational distribution of jobs in the US economy. For example, long-term reductions in manufacturing ought to be reflected in reductions in occupations that are unique or dominant to that industry. By incorporating changes in the occupational distribution, we change the occupational staffing rations in such a way that allows structural changes if the data support them.
- **Incorporates macroeconomic shocks, business cycles and the stimulus into estimates of national job creation.** As a result, while adhering to general, long-run full employment assumed by all government agencies in determining the equilibrium number of occupations, we allow for short-run fluctuations and departure from the steady state that are reflected in booms and recession.
- **Creates annual forecasts.** In a related point, this process allows us to see the progression in educational demand for every year of the 10-year forecast and not only the beginning and end of the forecast horizon.

IV. PRELIMINARY RESULTS OF ROBUSTNESS TESTING

We have defined three procedures to test for the robustness or stability of our model where robustness is defined as the degree to which a model performs in a predictable fashion irrespective of possible violations of the conditions under which the model is optimal.

Procedure One: In-Sample Model Performance

We estimate the model equation for a portion of the available data then test for the predictive success of model estimates by comparing them to the 'true' observed values for that time period. This is first done in a recursive fashion with the assumption that model accuracy is an increasing function of the number of data points used and inversely related to the length of the forecast horizon. We use the root mean squared error (RMSE) to calculate the extent of differences between the actual and fitted values. Since the main purpose of this model is prediction, the RMSE is a good measure of the extent to which the model predicts the response.[34] Lower values of RMSE indicate better fit in a nested context. See Appendix Table A.

As expected, the extent of the accuracy of the model declines (as measured by larger relative RMSE values per model) with stepwise single period ahead forecasts. These results are presented in detail in Appendix Table B. By the time, we get to the 9th period ahead (chosen since our model estimates forecast data up to 2009 out to 2018) model accuracy is reduced, but only marginally. Specifically, the average coefficient of variation ranges from 1.46 to 1.60 for 1-period ahead and 9-period head forecasts respectively, and declines in a non-linear fashion.

Appendix figures A1-A22 graphically show the actual and predicted proportion distribution of workers by education level within each of the 22 SOC 2-digit occupations. In general, the in-sample model estimates predict trend fairly well. On average, there is a one-period lag on turning points, but these are also in the appropriate direction. In occupations with significant concentrations by education type, the tail education levels tend to be relatively more erratic and therefore present a challenge to model predictability. That is to say, where small proportions of an occupation might contain workers who identify relatively low or high levels of highest education level attained, the high degree of variability in the actual cross-sectional data on an annual basis is reflected in the reduced ability of the prediction to model all fluctuations smoothly. Even in these cases, however, general trend is predicted fairly well.

Procedure Two: Standard Coefficient Testing

Statistical significance of the smoothing parameters and transition probabilities are also a standard part of the robustness tests in this paper. We also test for coefficient stability in a model framework.

Preliminary results of the forecasting exercise are presented in the appendix, table B. To facilitate comparison among equations in the system, we calculate the coefficient of variation (CV) within each model. The model RMSE and mean of the predicted variable are both expressed in the same unit so that taking their ratio makes the resultant statistic unit-neutral. The model with the smaller CV has predicted values that are closer to the actual values. The CV values are presented in Appendix Figure B. Coefficient values greater than two standard deviations from the mean of the predicted values are highlighted as outliers in this graph with

[34] The RMSE is the square root of the variance of the residuals. It is therefore a comparison of observed data points are to the model's predicted values. The mean absolute percentage error (MAPE) is also popular to evaluate forecasts from simple models such as these.

relatively lower predictive power.[35] In general, we find very predictable outcomes in these outliers. For example, the proportion of PhDs employed in farming, fishing and forestry occupations in the economy is generally small and very noisy on an annual basis, thus increasing the likelihood of low predictability in a model which relies heavily on the most recent past to predict the future.

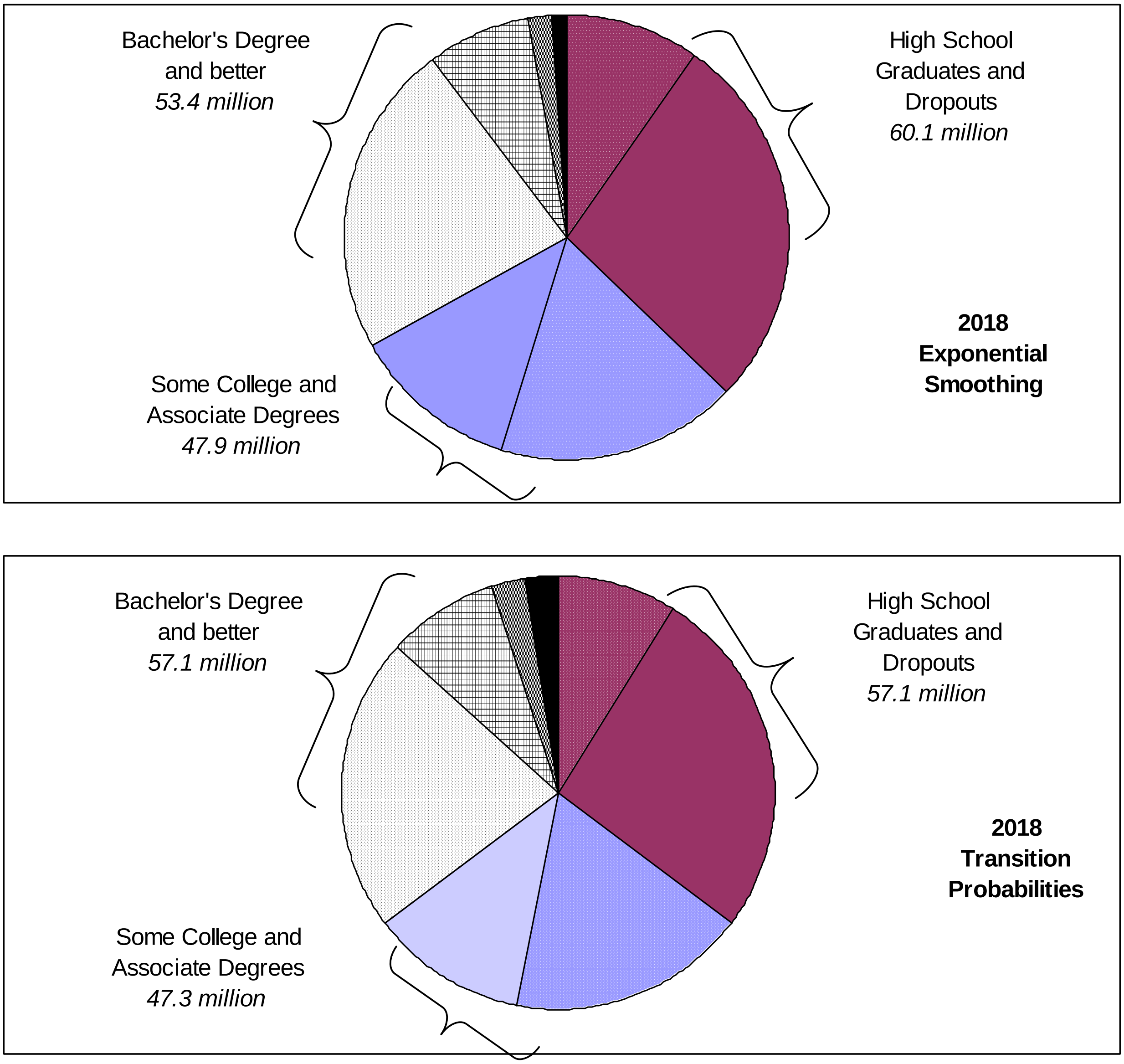
Procedure Three: Stability of Estimates Derived from Alternative Model Assumptions and Processes

We approach Step One of the estimation procedure from two alternative perspectives. Both the simplified time series exponential smoothing approach and Markov transition probability matrices model produce estimates of the proportion of education level within occupations that are highly plausible and similar in outcomes. We provide a brief summary of the results here with greater detail in the paper for which this is a technical appendix.

There is overall consistency from using both methods in the 2018 forecast of occupations requiring some college and Associate's degrees. The major source of disparity in the results therefore lies in the comparison between high school graduates and less and Bachelor's degrees and better. There is a four million difference in both estimates on either side of the tail of the distribution of education level requirements. The transition probabilities model is biased upwards in forecasting a greater demand for Bachelor's degrees and better and biased downwards in forecasting a lower demand for high school graduates and dropouts – relative to the exponential smoothing model.

[35] Confidence intervals are used in the construction of an upper and lower bound for alternative levels of educational demand.

Figure 3: Summary estimates of the demand for education to 2018
using two alternative forecasting strategies



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VI. APPENDICES

Appendix Table A: Root Mean Squared Error of Equations in Smoothing Model

Occ_ED	**RMSE**	**Occ_ED**	**RMSE**	**Occ_ED**	**RMSE**	**Occ_ED**	**RMSE**
pocc11	0.306	*pocc21*	0.235	*pocc31*	0.201	*pocc41*	0.332
pocc12	0.559	*pocc22*	0.951	*pocc32*	1.094	*pocc42*	1.146
pocc13	0.829	*pocc23*	1.269	*pocc33*	1.270	*pocc43*	1.674
pocc14	0.459	*pocc24*	1.104	*pocc34*	0.837	*pocc44*	1.627
pocc15	1.100	*pocc25*	1.233	*pocc35*	1.612	*pocc45*	2.080
pocc16	0.740	*pocc26*	1.126	*pocc36*	1.662	*pocc46*	1.408
pocc17	0.155	*pocc27*	0.270	*pocc37*	0.174	*pocc47*	0.304
pocc18	0.187	*pocc28*	0.171	*pocc38*	0.512	*pocc48*	0.213
pocc51	3.302	*pocc61*	0.466	*pocc71*	3.255	*pocc81*	0.242
pocc52	2.219	*pocc62*	1.532	*pocc72*	1.360	*pocc82*	0.788
pocc53	2.254	*pocc63*	1.690	*pocc73*	1.446	*pocc83*	0.741
pocc54	10.029	*pocc64*	1.140	*pocc74*	2.310	*pocc84*	0.428
pocc55	5.537	*pocc65*	2.430	*pocc75*	4.240	*pocc85*	0.803
pocc56	7.290	*pocc66*	2.351	*pocc76*	17.006	*pocc86*	0.847
pocc57	5.930	*pocc67*	0.697	*pocc77*	14.703	*pocc87*	0.310
pocc58	6.813	*pocc68*	0.630	*pocc78*	4.121	*pocc88*	0.291
pocc91	0.609	*pocc101*	0.292	*pocc111*	1.484	*pocc121*	0.725
pocc92	1.627	*pocc102*	0.680	*pocc112*	2.339	*pocc122*	1.971
pocc93	1.561	*pocc103*	0.919	*pocc113*	2.400	*pocc123*	2.061
pocc94	1.229	*pocc104*	1.514	*pocc114*	1.493	*pocc124*	1.459
pocc95	2.772	*pocc105*	1.026	*pocc115*	0.965	*pocc125*	1.723
pocc96	1.259	*pocc106*	0.868	*pocc116*	0.463	*pocc126*	0.423
pocc97	0.322	*pocc107*	0.751	*pocc117*	0.296	*pocc127*	0.206
pocc98	0.322	*pocc108*	0.774	*pocc118*	0.088	*pocc128*	0.104
pocc131	1.015	*pocc141*	1.495	*pocc151*	1.511	*pocc161*	0.481
pocc132	1.328	*pocc142*	1.852	*pocc152*	1.623	*pocc162*	1.061
	1.277	*pocc143*	1.102	*pocc153*	1.150	*pocc163*	0.688
pocc133							
pocc134	0.588	*pocc144*	0.671	*pocc154*	0.947	*pocc164*	0.431
pocc135	0.676	*pocc145*	0.739	*pocc155*	1.407	*pocc165*	0.934
pocc136	0.258	*pocc146*	0.295	*pocc156*	0.579	*pocc166*	0.366
pocc137	0.132	*pocc147*	0.075	*pocc157*	0.128	*pocc167*	0.106
pocc138	0.073	*pocc148*	0.065	*pocc158*	0.169	*pocc168*	0.068
pocc171	0.312	*pocc181*	2.787	*pocc191*	1.294	*pocc201*	0.791
pocc172	0.893	*pocc182*	2.420	*pocc192*	1.299	*pocc202*	1.549
pocc173	0.657	*pocc183*	2.184	*pocc193*	0.848	*pocc203*	1.486
pocc174	0.490	*pocc184*	0.980	*pocc194*	0.486	*pocc204*	1.204
pocc175	0.355	*pocc185*	1.476	*pocc195*	0.434	*pocc205*	0.962
pocc176	0.137	*pocc186*	0.309	*pocc196*	0.181	*pocc206*	0.334
pocc177	0.075	*pocc187*	0.394	*pocc197*	0.081	*pocc207*	0.068
pocc178	0.040	*pocc188*	0.248	*pocc198*	0.060	*pocc208*	0.090
pocc211	0.912	*pocc221*	0.980	*pocc215*	0.434	*pocc225*	0.907

Appendix Table A: Root Mean Squared Error of Equations in Smoothing Model (continued)

pocc212	0.849	*pocc222*	1.339	*pocc216*	0.151	*pocc226*	0.210
pocc213	0.510	*pocc223*	1.219	*pocc217*	0.057	*pocc227*	0.052
pocc214	0.539	*pocc224*	0.458	*pocc218*	0.038	*pocc228*	0.058

Appendix Table B: Stepwise Comparisons of Root Mean Squared Error of Equations in Smoothing Model up to 9 Periods Ahead

	Number of periods ahead								
	1	2	3	4	5	6	7	8	9
pocc11new	0.222	0.286	0.358	0.371	0.367	0.324	0.319	0.284	0.296
pocc12new	0.756	0.842	0.805	0.697	0.700	0.613	0.613	0.552	0.545
pocc13new	0.789	0.955	0.970	0.958	0.933	0.703	0.724	0.861	0.836
pocc14new	0.231	0.258	0.254	0.483	0.499	0.494	0.495	0.477	0.473
pocc15new	1.370	1.366	1.320	1.427	1.388	1.020	0.989	1.144	1.121
pocc16new	0.842	0.712	0.706	0.822	0.822	0.801	0.803	0.792	0.772
pocc17new	0.261	0.169	0.162	0.182	0.189	0.185	0.179	0.170	0.174
pocc18new	0.145	0.092	0.091	0.150	0.169	0.176	0.171	0.169	0.168
pocc21new	0.284	0.260	0.259	0.261	0.251	0.234	0.243	0.246	0.243
pocc22new	1.595	1.512	1.443	1.256	1.251	0.994	0.991	0.939	0.911
pocc23new	1.085	1.100	1.094	1.256	1.319	1.274	1.317	1.276	1.272
pocc24new	1.468	1.159	1.206	1.108	1.148	0.938	0.936	1.111	1.083
pocc25new	1.158	1.310	1.310	1.073	1.039	1.140	1.102	1.209	1.181
pocc26new	0.926	0.813	0.789	1.223	1.175	1.135	1.100	1.070	1.092
pocc27new	0.217	0.215	0.206	0.222	0.215	0.249	0.240	0.251	10.266
pocc28new	0.143	0.164	0.157	0.130	0.134	0.137	0.144	0.177	0.181
pocc31new	0.177	0.186	0.183	0.178	0.231	0.228	0.225	0.215	0.208
pocc32new	1.301	1.358	1.397	1.328	1.278	1.213	1.195	1.146	1.115
pocc33new	0.655	0.838	1.134	1.143	1.098	1.066	1.043	1.131	1.195
pocc34new	1.381	1.174	1.148	0.919	0.928	0.886	0.942	1.048	1.026
pocc35new	1.353	1.196	1.771	1.718	1.718	1.669	1.616	1.600	1.653
pocc36new	2.462	1.788	1.705	2.160	2.078	1.920	1.873	1.584	1.559
pocc37new	0.198	0.166	0.167	0.145	0.147	0.165	0.173	0.160	0.170
pocc38new	0.462	0.584	0.557	0.547	0.532	0.555	0.550	0.536	0.521
pocc41new	0.422	0.384	0.379	0.377	0.363	0.346	0.334	0.264	0.367
pocc42new	1.672	1.278	1.258	1.368	1.323	1.020	1.018	1.092	1.216
pocc43new	2.319	2.091	2.034	2.143	2.098	1.822	1.784	1.827	1.781
pocc44new	1.494	1.723	1.663	1.882	1.838	1.767	1.783	1.662	1.642
pocc45new	1.582	1.511	1.441	2.187	2.210	2.174	2.145	2.172	2.115
pocc46new	1.218	1.366	1.424	1.216	1.170	1.532	1.486	1.428	1.475
pocc47new	0.187	0.179	0.176	0.215	0.207	0.220	0.212	0.298	0.327
pocc48new	0.309	0.262	0.259	0.280	0.269	0.228	0.224	0.231	0.228
pocc51new	0.369	0.353	0.341	2.804	2.629	2.607	2.969	3.316	3.350
pocc52new	2.137	2.483	2.500	2.522	2.424	2.398	2.328	2.321	2.269
pocc53new	1.789	1.885	2.162	2.377	2.295	2.262	2.188	2.136	2.087
pocc54new	1.071	1.272	1.215	6.896	7.243	6.804	9.150	9.481	10.090
pocc55new	2.708	2.598	2.477	3.181	3.538	3.816	4.922	4.923	5.756
pocc56new	0.827	0.826	0.804	4.404	5.557	5.367	6.615	6.901	7.331
pocc57new	0.749	0.926	0.906	3.401	3.385	3.357	4.887	5.524	5.845
pocc58new	2.211	2.415	2.413	5.388	5.685	5.254	6.502	6.731	6.951
pocc61new	0.681	0.722	0.709	0.591	0.569	0.477	0.462	0.451	0.476
pocc62new	1.666	1.755	1.673	1.960	1.919	1.811	1.753	1.620	1.572

Appendix Table B: Stepwise Comparisons of Root Mean Squared Error of Equations in Smoothing Model up to 9 Periods Ahead (continued)

	Number of periods ahead								
	1	2	3	4	5	6	7	8	9
pocc63new	2.200	2.153	2.087	2.054	1.975	1.894	1.841	1.795	1.748
pocc64new	1.106	1.024	0.977	1.016	1.053	1.105	1.072	1.089	1.153
pocc65new	2.438	1.855	2.408	2.409	2.320	2.735	2.735	2.610	2.533
pocc66new	2.885	2.690	2.791	2.787	2.798	2.666	2.628	2.513	2.446
pocc67new	0.837	0.790	0.780	0.734	0.706	0.742	0.720	0.676	0.719
pocc68new	0.707	0.739	0.708	0.669	0.643	0.632	0.612	0.619	0.616
pocc71new	2.905	3.639	3.534	3.462	3.333	3.215	3.111	3.347	3.249
pocc72new	1.414	1.230	1.221	1.123	1.269	1.316	1.277	1.310	1.299
pocc73new	1.704	1.242	1.220	1.337	1.293	1.143	1.155	1.336	1.323
pocc74new	1.666	2.121	2.263	2.489	2.628	2.521	2.438	2.403	2.364
pocc75new	4.053	4.514	4.382	3.999	4.130	4.184	4.061	4.379	4.249
pocc76new	14.888	19.669	19.547	18.487	17.866	17.126	16.568	17.439	16.943
pocc77new	13.715	15.600	15.053	15.681	15.278	14.633	14.271	15.163	14.813
pocc78new	4.390	5.252	5.073	4.616	4.436	4.318	4.201	3.893	3.861
pocc81new	0.200	0.188	0.181	0.201	0.246	0.234	0.248	0.232	0.228
pocc82new	0.906	0.775	0.879	0.722	0.728	0.648	0.690	0.671	0.713
pocc83new	0.901	0.907	0.902	0.870	0.853	0.798	0.771	0.737	0.735
pocc84new	0.319	0.311	0.323	0.395	0.384	0.395	0.409	0.402	0.420
pocc85new	0.800	0.891	0.853	0.875	0.849	0.838	0.831	0.817	0.794
pocc86new	1.013	0.994	0.954	0.925	0.897	0.843	0.820	0.784	0.856
pocc87new	0.269	0.301	0.339	0.366	0.366	0.339	0.328	0.336	0.335
pocc88new	0.401	0.363	0.349	0.341	0.327	0.300	0.304	0.303	0.304
pocc91new	0.846	0.771	0.735	0.522	0.547	0.566	0.609	0.656	0.642
pocc92new	1.650	1.659	1.585	1.579	1.640	1.617	1.579	1.582	1.575
pocc93new	1.951	1.941	1.916	1.878	1.807	1.807	1.850	1.582	1.552
pocc94new	1.583	1.394	1.421	1.305	1.332	1.299	1.255	1.121	1.093
pocc95new	2.651	2.145	2.406	2.585	2.537	2.513	2.749	2.768	2.718
pocc96new	1.231	0.873	0.884	1.100	1.070	1.291	1.288	1.208	1.224
pocc97new	0.410	0.423	0.409	0.326	0.335	0.358	0.353	0.375	0.364
pocc98new	0.315	0.288	0.294	0.302	0.311	0.311	0.321	0.313	0.334
pocc101new	0.263	0.252	0.240	0.351	0.357	0.336	0.324	0.307	0.299
pocc102new	0.738	0.725	0.692	0.679	0.723	0.719	0.738	0.782	0.760
pocc103new	0.952	0.974	0.936	0.926	0.890	0.922	0.900	0.867	0.855
pocc104new	1.462	1.568	1.727	1.657	1.688	1.630	1.575	1.578	1.549
pocc105new	0.971	0.972	1.146	1.179	1.273	1.223	1.188	1.085	1.068
pocc106new	0.838	0.627	0.844	0.836	0.804	0.838	0.866	0.828	0.869
pocc107new	0.699	0.779	0.751	0.714	0.776	0.704	0.763	0.758	0.753
pocc108new	0.571	0.739	0.749	0.838	0.805	0.782	0.757	0.740	0.763
pocc111new	1.584	1.645	1.596	1.673	1.611	1.565	1.545	1.424	1.384
pocc112new	3.131	3.193	3.048	2.554	2.454	2.406	2.364	2.123	2.203
pocc113new	3.364	3.016	2.889	2.736	2.711	2.619	2.573	2.509	2.447
pocc114new	0.712	1.192	1.199	1.438	1.631	1.527	1.595	1.542	1.521
pocc115new	0.688	0.560	0.658	0.783	0.855	0.727	0.931	1.020	0.993
pocc116new	0.510	0.521	0.540	0.440	0.436	0.412	0.451	0.492	0.479

Appendix Table B: Stepwise Comparisons of Root Mean Squared Error of Equations in Smoothing Model up to 9 periods ahead (continued)

	Number of periods ahead								
	1	2	3	4	5	6	7	8	9
pocc117new	0.381	0.401	0.398	0.277	0.269	0.263	0.265	0.305	0.303
pocc118new	0.063	0.081	0.077	0.058	0.060	0.066	0.075	0.062	0.061
pocc121new	1.007	0.931	1.206	1.042	1.011	0.777	0.753	0.769	0.808
pocc122new	2.502	2.132	2.067	1.925	2.035	1.939	1.876	2.071	2.089
pocc123new	1.911	2.070	2.221	1.969	1.896	2.083	1.980	2.170	2.106
pocc124new	1.593	1.606	1.557	1.244	1.200	1.233	1.220	1.150	1.209
pocc125new	1.895	1.944	2.127	1.845	1.802	1.593	1.568	1.812	1.785
pocc126new	0.444	0.419	0.400	0.437	0.460	0.510	0.500	0.484	0.472
pocc127new	0.128	0.154	0.152	0.187	0.205	0.207	0.206	0.195	0.210
pocc128new	0.069	0.065	0.079	0.076	0.089	0.087	0.084	0.107	0.110
pocc131new	0.883	0.955	0.980	0.880	0.924	0.909	0.995	0.999	1.005
pocc132new	1.404	1.371	1.342	1.317	1.267	1.255	1.214	1.313	1.310
pocc133new	1.699	1.475	1.447	1.243	1.367	1.373	1.327	1.256	1.235
pocc134new	0.760	0.846	0.818	0.699	0.693	0.695	0.672	0.638	0.666
pocc135new	0.530	0.615	0.595	0.768	0.742	0.665	0.655	0.632	0.618
pocc136new	0.363	0.336	0.320	0.372	0.358	0.281	0.279	0.271	0.263
pocc137new	0.177	0.133	0.127	0.160	0.162	0.148	0.145	0.157	0.152
pocc138new	0.044	0.040	0.039	0.066	0.066	0.075	0.073	0.075	0.073
pocc141new	1.471	1.355	1.477	1.199	1.218	1.289	1.282	1.236	1.532
pocc142new	1.222	1.164	1.980	2.028	1.965	2.006	1.998	1.954	1.912
pocc143new	0.782	0.759	1.068	1.003	1.006	1.005	0.998	1.028	0.998
pocc144new	0.845	0.832	0.809	0.749	0.755	0.620	0.626	0.656	0.642
pocc145new	0.528	0.635	0.708	0.634	0.610	0.725	0.701	0.728	0.708
pocc146new	0.267	0.281	0.268	0.325	0.347	0.271	0.268	0.259	0.267
pocc147new	0.099	0.110	0.105	0.106	0.105	0.097	0.095	0.090	0.087
pocc148new	0.061	0.071	0.075	0.066	0.064	0.069	0.069	0.060	0.060
pocc151new	2.323	1.638	1.718	1.688	1.685	1.630	1.578	1.551	1.505
pocc152new	1.326	1.821	1.904	1.780	1.740	1.843	1.832	1.668	1.618
pocc153new	1.196	1.181	1.135	1.223	1.286	1.230	1.195	1.163	1.145
pocc154new	1.339	0.939	1.001	0.973	0.946	0.893	0.865	1.079	1.099
pocc155new	1.236	1.328	1.295	1.248	1.286	1.537	1.553	1.416	1.397
pocc156new	0.909	0.891	0.851	0.663	0.640	0.638	0.631	0.614	0.601
pocc157new	0.188	0.188	0.179	0.138	0.133	0.160	0.162	0.151	0.149
pocc158new	0.231	0.231	0.224	0.175	0.178	0.203	0.197	0.196	0.191
pocc161new	0.497	0.567	0.552	0.497	0.478	0.383	0.413	0.410	0.400
pocc162new	1.065	1.037	1.009	1.157	1.213	1.109	1.156	1.116	1.084
pocc163new	0.780	0.935	0.981	1.020	0.982	0.825	0.803	0.720	0.701
pocc164new	0.480	0.426	0.411	0.390	0.412	0.399	0.388	0.438	0.445
pocc165new	1.067	1.018	0.987	0.815	0.821	0.960	0.963	0.944	0.921
pocc166new	0.512	0.493	0.471	0.355	0.345	0.340	0.369	0.389	0.380
pocc167new	0.162	0.131	0.125	0.136	0.132	0.125	0.121	0.115	0.113
pocc168new	0.062	0.056	0.054	0.040	0.042	0.041	0.041	0.049	0.066
pocc171new	0.218	0.270	0.312	0.279	0.269	0.269	0.261	0.259	0.252
pocc172new	0.906	0.916	0.874	0.871	0.893	0.858	0.872	0.922	0.895

Appendix Table B: Stepwise Comparisons of Root Mean Squared Error of Equations in Smoothing Model up to 9 Periods Ahead (continued)

	Number of periods ahead								
	1	2	3	4	5	6	7	8	9
pocc173new	0.926	0.896	0.877	0.787	0.756	0.632	0.648	0.656	0.647
pocc174new	0.400	0.427	0.433	0.447	0.502	0.408	0.406	0.507	0.502
pocc175new	0.348	0.303	0.289	0.272	0.280	0.284	0.334	0.356	0.391
pocc176new	0.095	0.122	0.153	0.147	0.147	0.142	0.137	0.127	0.136
pocc177new	0.096	0.092	0.095	0.080	0.079	0.080	0.079	0.082	0.082
pocc178new	0.050	0.052	0.051	0.051	0.050	0.051	0.050	0.046	0.047
pocc181new	2.508	3.442	3.283	3.163	3.054	2.915	2.848	2.906	2.851
pocc182new	2.839	3.373	3.226	2.966	2.851	2.938	2.878	2.815	2.731
pocc183new	1.793	1.949	1.896	2.445	2.360	2.202	2.158	2.171	2.222
pocc184new	1.136	0.913	0.978	0.946	0.916	0.817	0.885	0.755	0.817
pocc185new	1.048	1.080	1.044	1.255	1.522	1.391	1.360	1.429	1.486
pocc186new	0.362	0.356	0.342	0.341	0.353	0.348	0.336	0.328	0.323
pocc187new	0.327	0.223	0.225	0.213	0.205	0.215	0.212	0.207	0.407
pocc188new	0.246	0.242	0.252	0.256	0.256	0.292	0.282	0.277	0.268
pocc191new	0.859	0.741	0.798	0.900	0.920	0.919	0.993	1.096	1.229
pocc192new	1.402	1.311	1.317	1.018	1.048	1.105	1.074	0.964	1.167
pocc193new	0.824	0.860	0.903	0.829	0.890	0.783	0.862	0.848	0.822
pocc194new	0.455	0.438	0.425	0.475	0.459	0.455	0.495	0.493	0.501
pocc195new	0.696	0.572	0.576	0.577	0.561	0.575	0.557	0.436	0.444
pocc196new	0.169	0.176	0.187	0.232	0.246	0.212	0.228	0.189	0.185
pocc197new	0.066	0.067	0.064	0.073	0.073	0.083	0.082	0.084	0.083
pocc198new	0.035	0.048	0.046	0.044	0.048	0.051	0.049	0.049	0.060
pocc201new	0.644	0.563	0.659	0.705	0.799	0.752	0.777	0.751	0.746
pocc202new	1.401	1.399	1.335	1.571	1.509	1.563	1.542	1.630	1.583
pocc203new	1.456	1.372	1.569	1.488	1.667	1.566	1.547	1.489	1.448
pocc204new	1.398	1.398	1.498	1.179	1.142	1.054	1.085	1.100	1.089
pocc205new	0.703	0.727	0.702	0.930	0.954	1.084	1.048	0.993	0.969
pocc206new	0.290	0.252	0.248	0.269	0.268	0.267	0.258	0.260	0.261
pocc207new	0.061	0.056	0.054	0.075	0.073	0.069	0.067	0.066	0.064
pocc208new	0.129	0.095	0.091	0.088	0.085	0.081	0.080	0.089	0.092
pocc211new	0.737	0.750	0.728	1.094	0.856	0.872	0.850	0.820	0.907
pocc212new	0.812	0.865	0.971	1.096	1.061	0.997	1.013	0.973	0.955
pocc213new	0.586	0.411	0.485	0.524	0.511	0.498	0.520	0.527	0.561
pocc214new	0.449	0.467	0.448	0.455	0.452	0.481	0.467	0.460	0.448
pocc215new	0.369	0.365	0.376	0.392	0.382	0.405	0.461	0.466	0.463
pocc216new	0.166	0.169	0.168	0.144	0.139	0.131	0.128	0.127	0.124
pocc217new	0.079	0.058	0.062	0.063	0.060	0.062	0.061	0.064	0.062
pocc218new	0.047	0.035	0.035	0.038	0.040	0.041	0.040	0.039	0.041
pocc221new	0.845	0.809	0.903	1.109	1.103	1.082	1.053	1.023	0.993
pocc222new	1.834	1.570	1.499	1.486	1.437	1.401	1.408	1.369	1.376
pocc223new	1.633	1.417	1.358	1.279	1.235	1.204	1.197	1.148	1.251
pocc224new	0.471	0.448	0.428	0.481	0.463	0.449	0.436	0.434	0.450
pocc225new	0.609	0.574	0.756	1.033	1.040	1.008	0.975	0.944	0.923

Appendix Table B: Stepwise Comparisons of Root Mean Squared Error of Equations in Smoothing Model up to 9 Periods Ahead (continued)

	Number of periods ahead								
	1	2	3	4	5	6	7	8	9
pocc226new	0.206	0.204	0.208	0.216	0.209	0.203	0.202	0.207	0.203
pocc227new	0.045	0.045	0.055	0.057	0.073	0.064	0.062	0.061	0.063
pocc228new	0.071	0.069	0.068	0.065	0.065	0.060	0.059	0.060	0.059

Appendix Table C: Occupational and Education Codes Used in Model Estimation

SOC Code	Occupation name	Model Code
11-0000	Management occupations	1
13-0000	Business and financial operations occupations	2
15-0000	Computer and mathematical science occupations	3
17-0000	Architecture and engineering occupations	4
19-0000	Life, physical, and social science occupations	5
21-0000	Community and social service occupations	6
23-0000	Legal occupations	7
25-0000	Education, training, and library occupations	8
27-0000	Arts, design, entertainment, sports, & media occupations	9
29-0000	Healthcare practitioner and technical occupations	10
31-0000	Healthcare support occupations	11
33-0000	Protective service occupations	12
35-0000	Food preparation and serving related occupations	13
37-0000	Building & grounds cleaning & maintenance occupations	14
39-0000	Personal care and service occupations	15
41-0000	Sales and related occupations	16
43-0000	Office and administrative support occupations	17
45-0000	Farming, fishing, and forestry occupations	18
47-0000	Construction and extraction occupations	18
49-0000	Installation, maintenance, and repair occupations	20
51-0000	Production occupations	21
53-0000	Transportation and material moving occupations	22

Education Level	Code
High School Dropouts	1
High School Graduates	2
Some College, no degree	3
Associate's Degrees	4
Bachelor's Degrees	5
Master's Degrees	6
Professional Degrees	7
Doctoral Degrees	8

Thus pocc11, is the proportion of persons in occupation 1 and education level 1, while pocc228 is the proportion of persons in occupation 22 and education level 8.

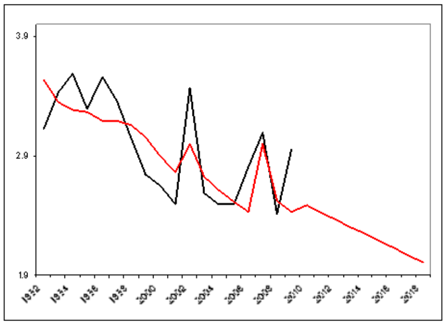
Appendix Figures A1 – A22: Actual and Forecast of Education Proportions

Appendix Fig A1: Actual and Forecast of Education proportions

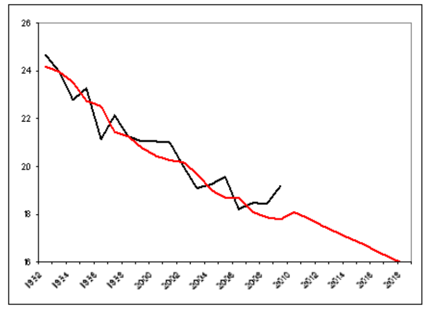
Management Occupations

Actual
Forecast

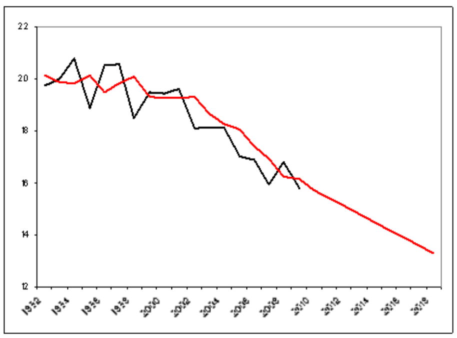
High School Dropouts



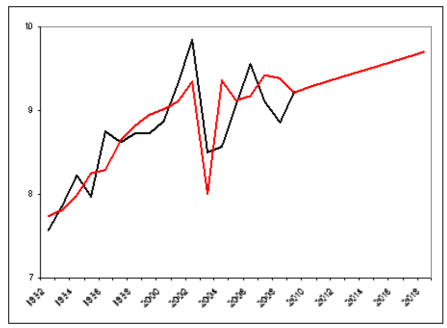
High School Graduates



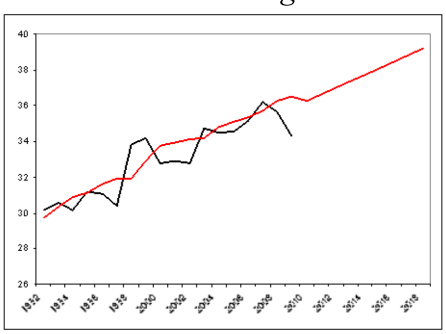
Some College



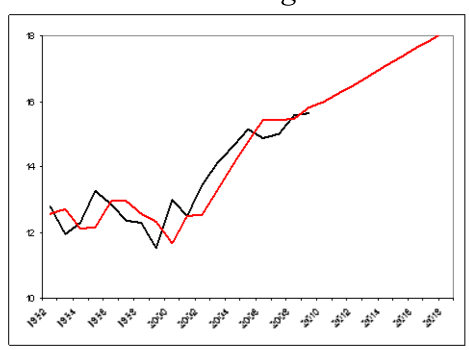
Associate's Degrees



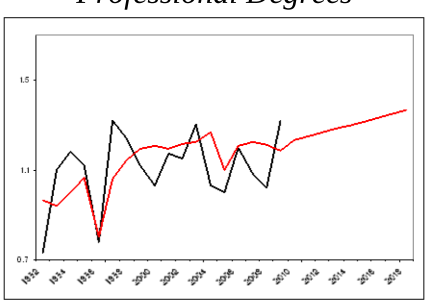
Bachelor's Degrees



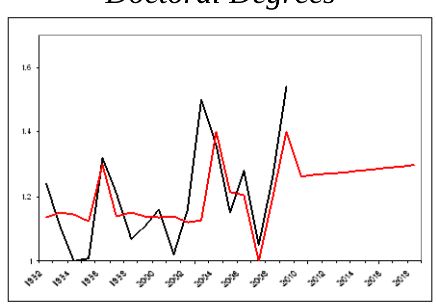
Master's Degrees



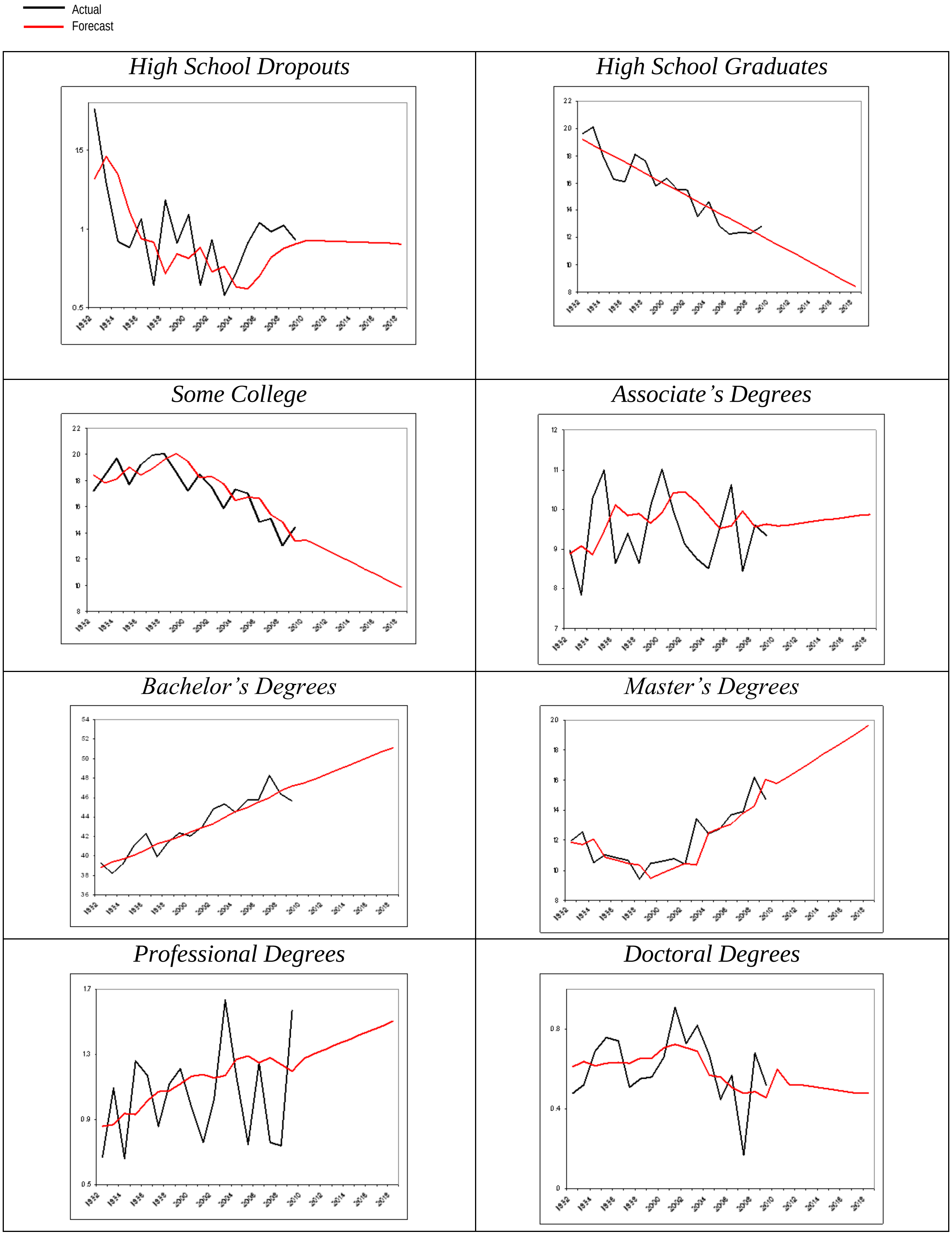
Professional Degrees



Doctoral Degrees



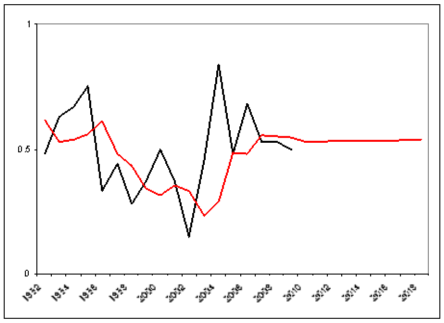
Appendix Fig A2: Actual and Forecast of Education proportions
Business and Financial Operations Occupations



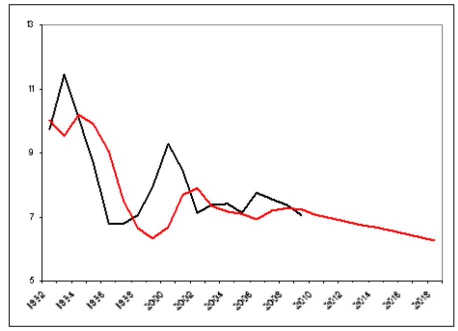
Appendix Fig A3: Actual and Forecast of Education proportions
Computer and Mathematical Science Occupations

Actual
Forecast

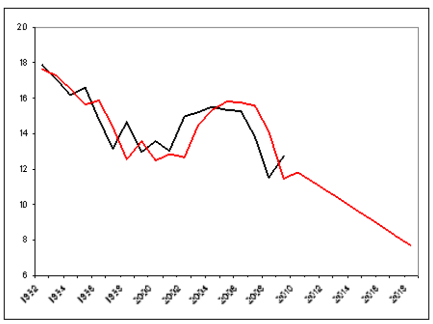
High School Dropouts



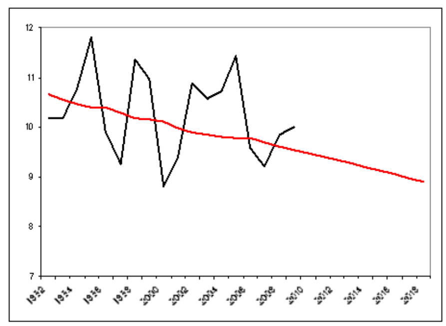
High School Graduates



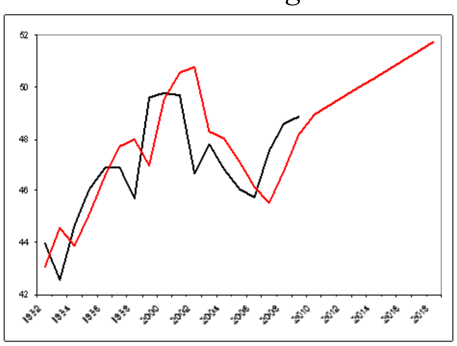
Some College



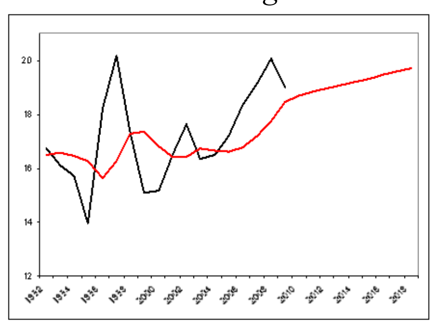
Associate's Degrees



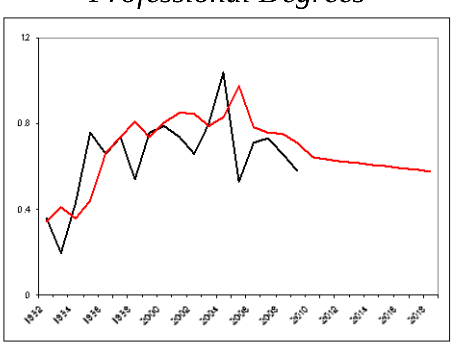
Bachelor's Degrees



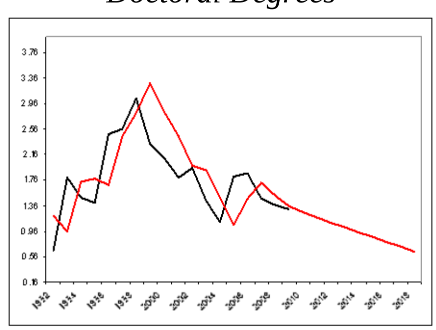
Master's Degrees



Professional Degrees

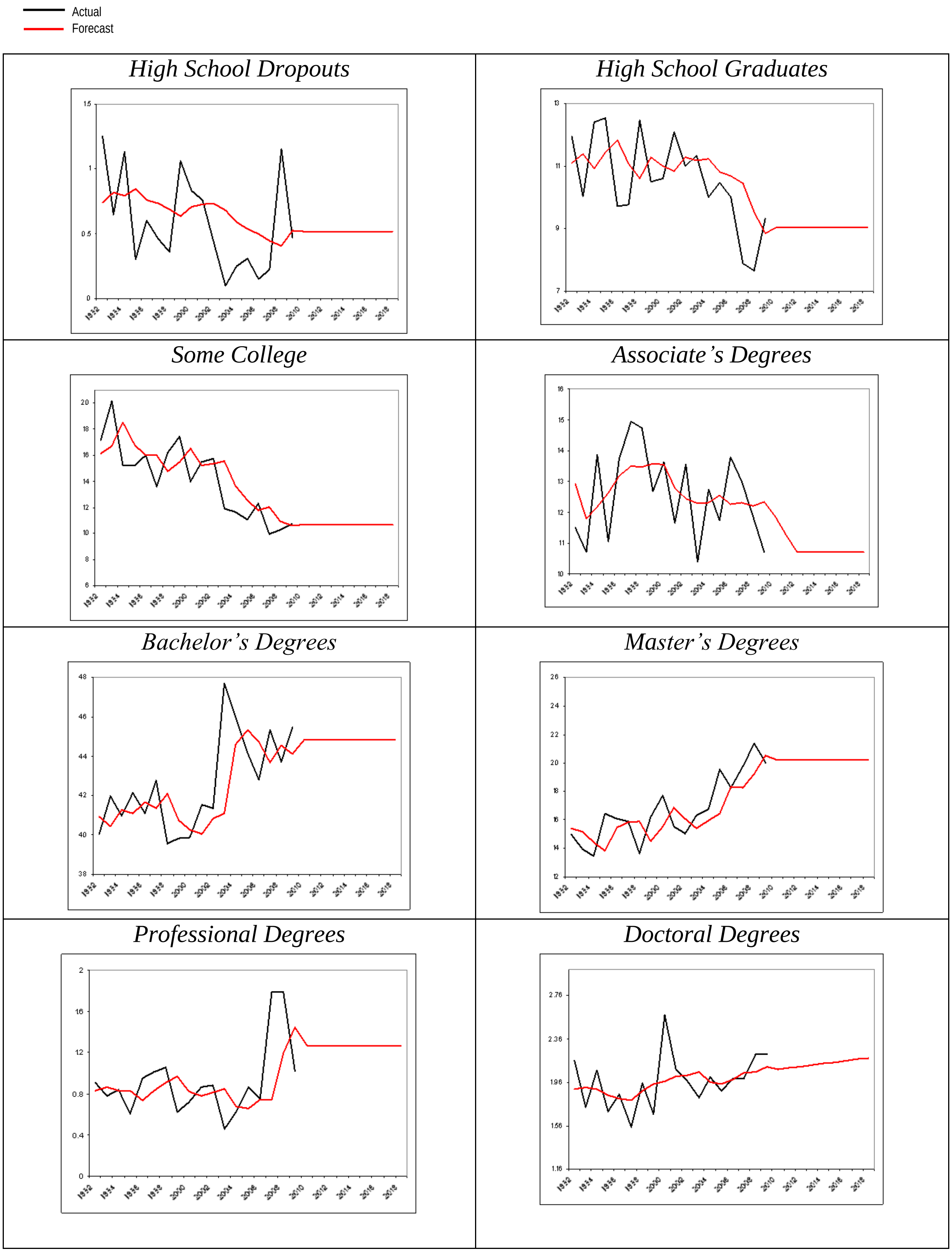


Doctoral Degrees



Appendix Fig A4: Actual and Forecast of Education proportions

Architecture and Engineering occupations

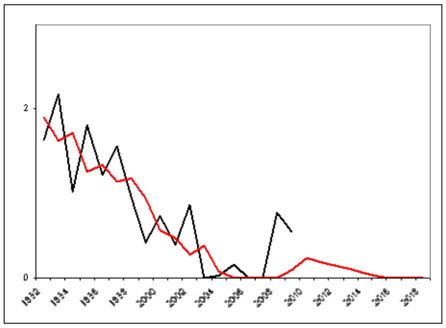


Appendix Fig A5: Actual and Forecast of Education proportions

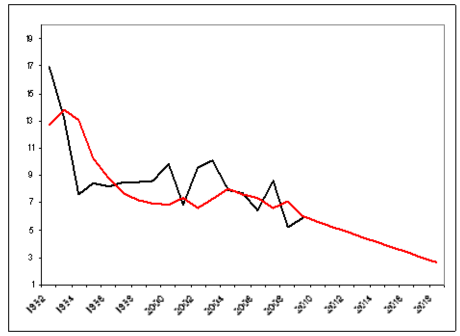
Life, Physical, and Social Science Occupations

Actual
Forecast

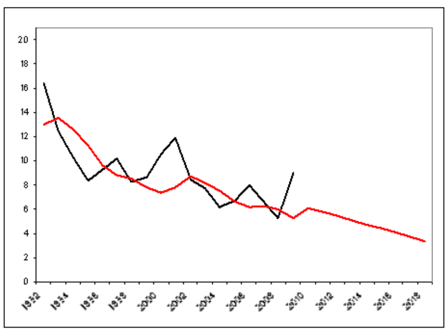
High School Dropouts



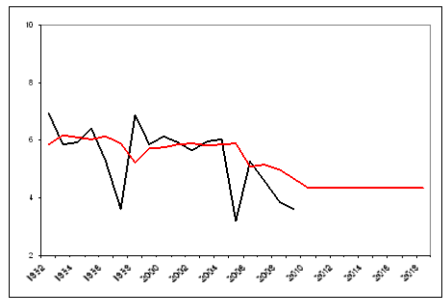
High School Graduates



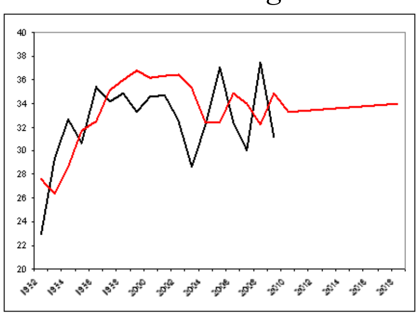
Some College



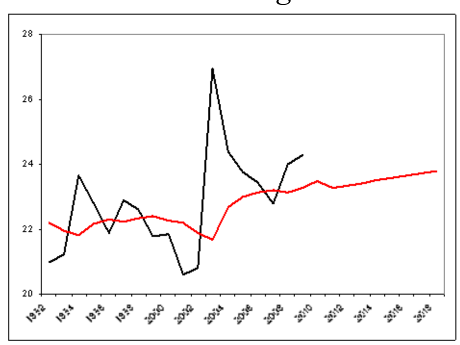
Associate's Degrees



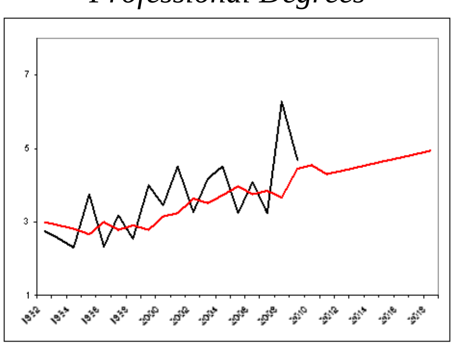
Bachelor's Degrees



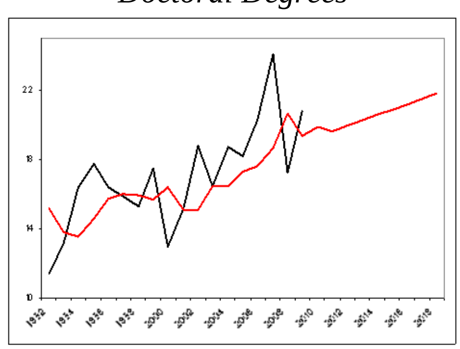
Master's Degrees



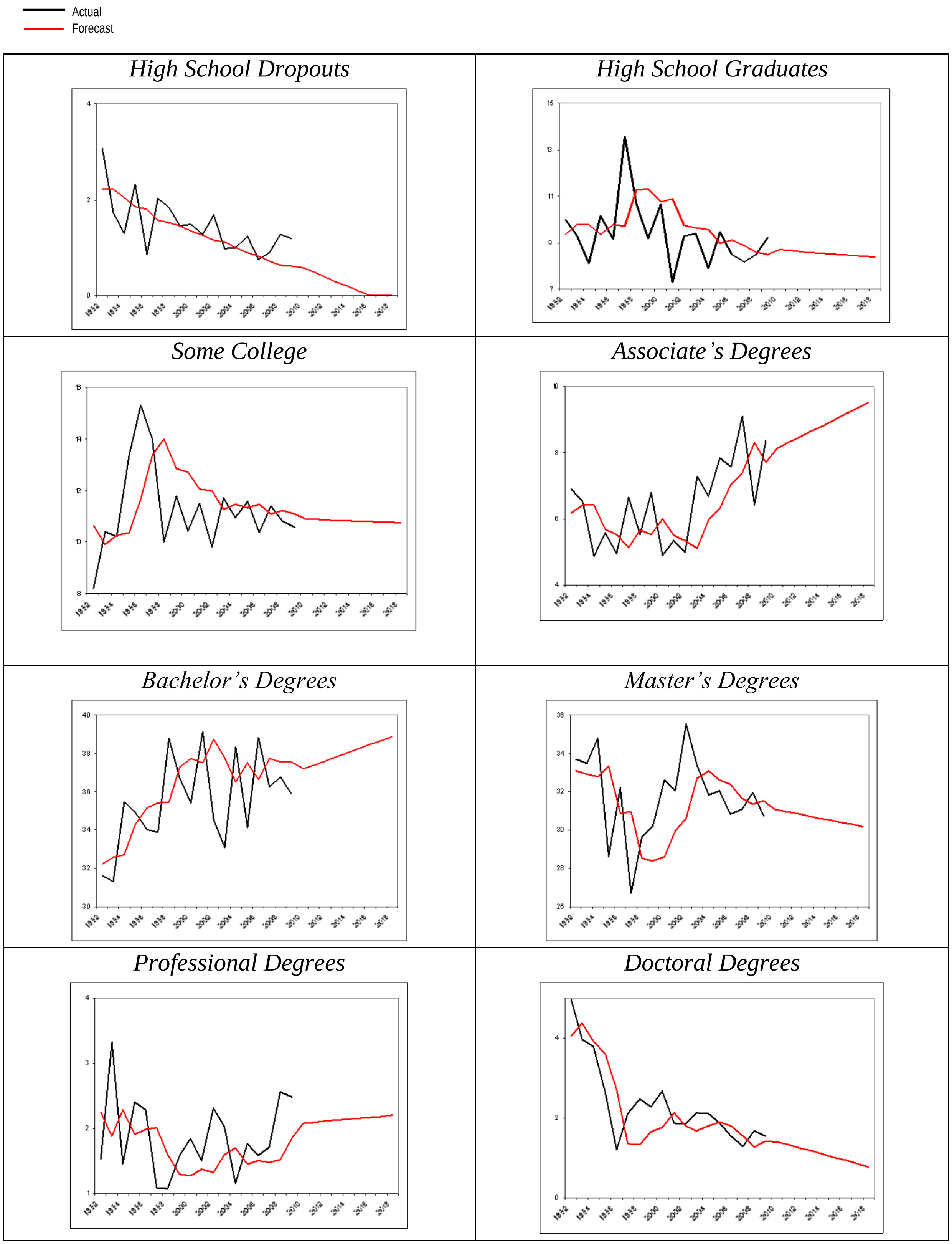
Professional Degrees



Doctoral Degrees



Appendix Fig A6: Actual and Forecast of Education proportions
Community and Social Service Occupations

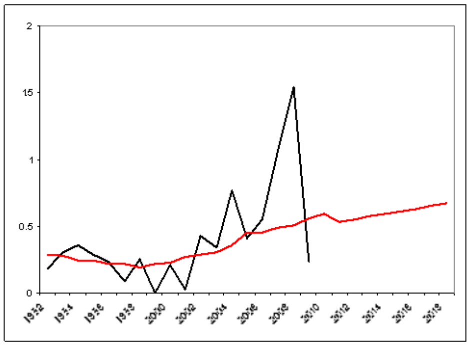


Appendix Fig A7: Actual and Forecast of Education proportions

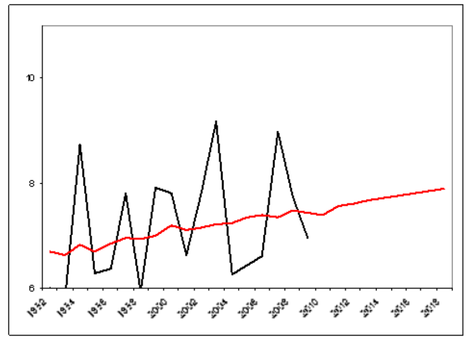
Legal Occupations

Actual
Forecast

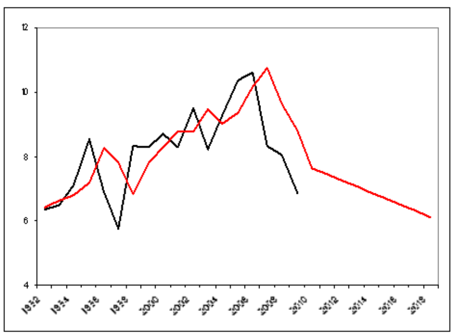
High School Dropouts



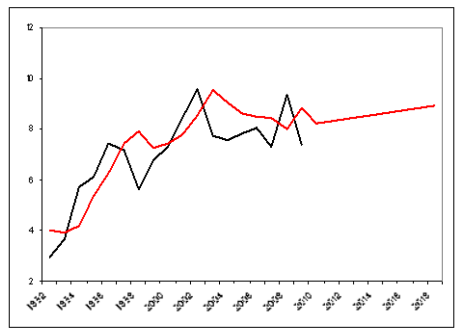
High School Graduates



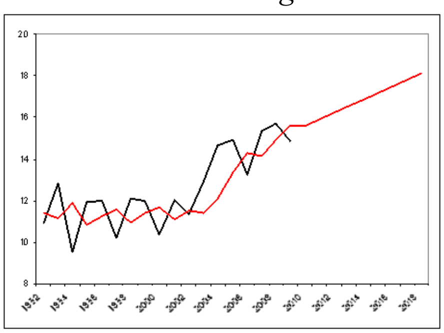
Some College



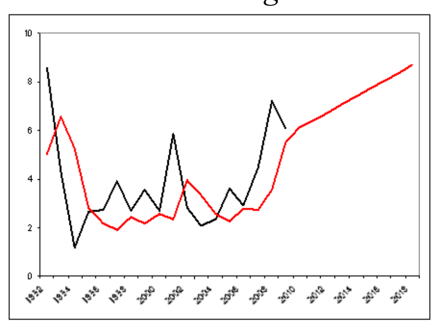
Associate's Degrees



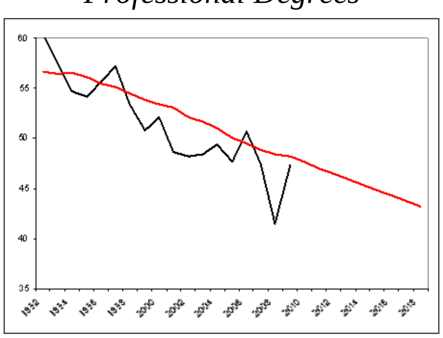
Bachelor's Degrees



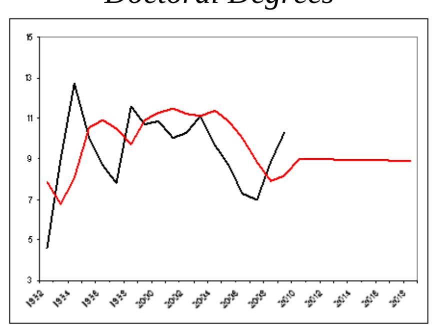
Master's Degrees



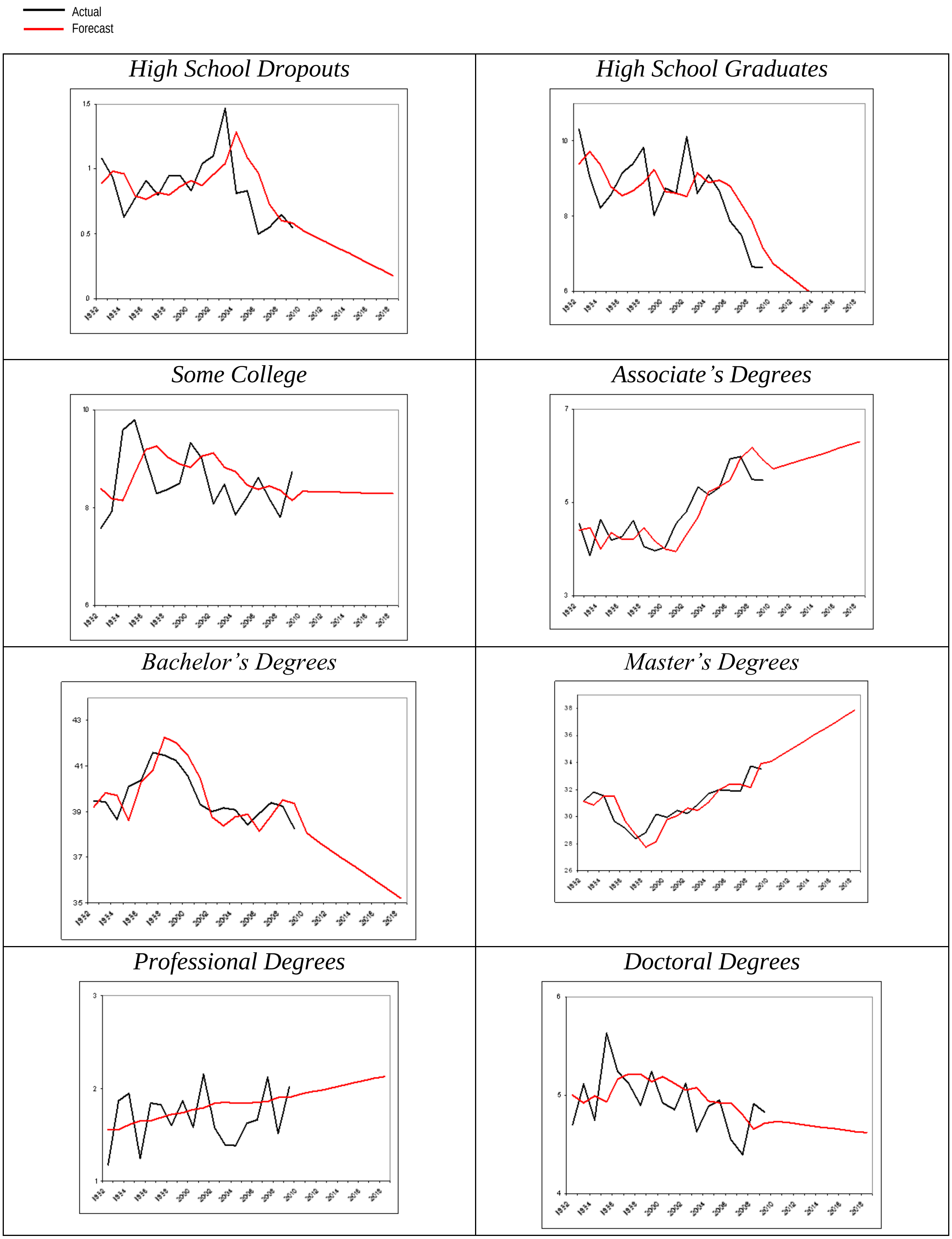
Professional Degrees



Doctoral Degrees



Appendix Fig A8: Actual and Forecast of Education proportions
Education, Training, and Library Occupations

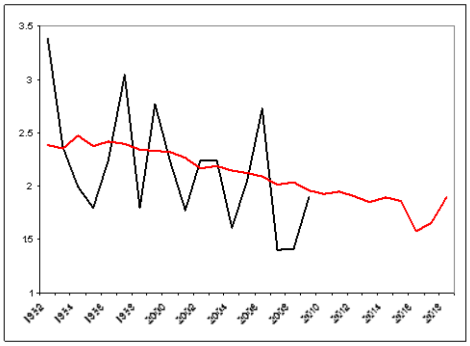


Appendix Fig A9: Actual and Forecast of Education proportions

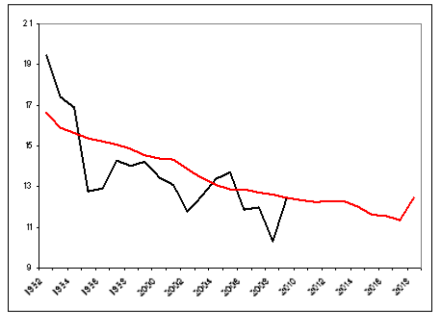
Arts, Design, Entertainment, Sports, & Media Occupations

Actual
Forecast

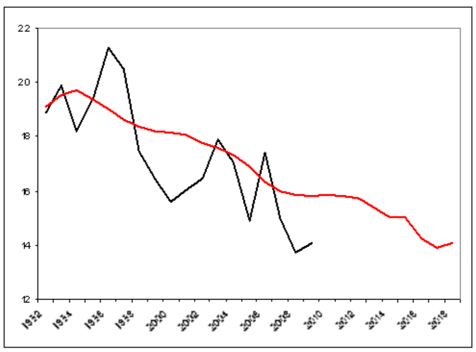
High School Dropouts



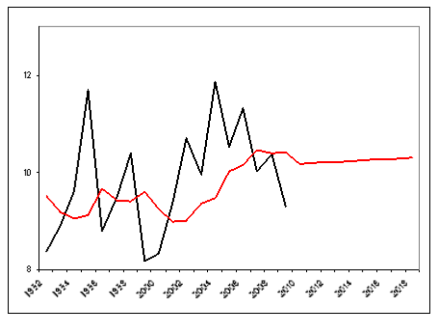
High School Graduates



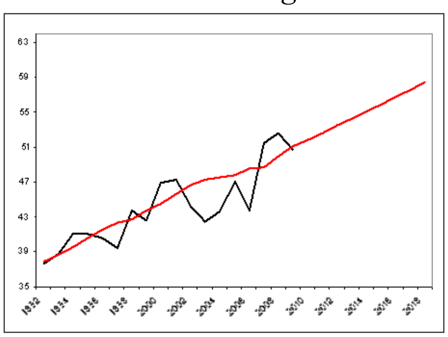
Some College



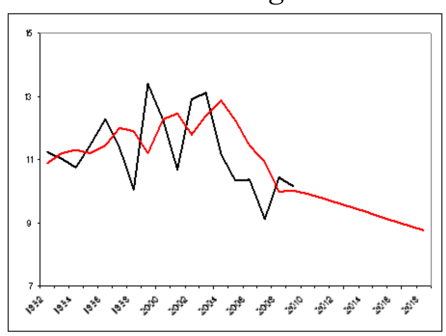
Associate's Degrees



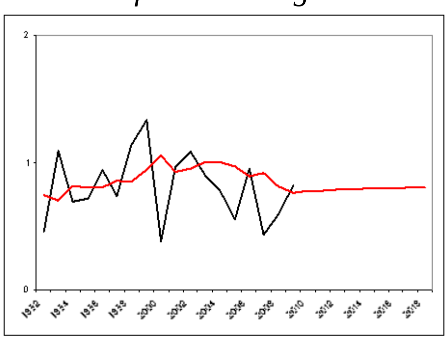
Bachelor's Degrees



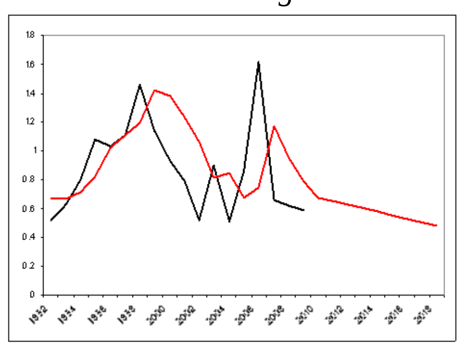
Master's Degrees



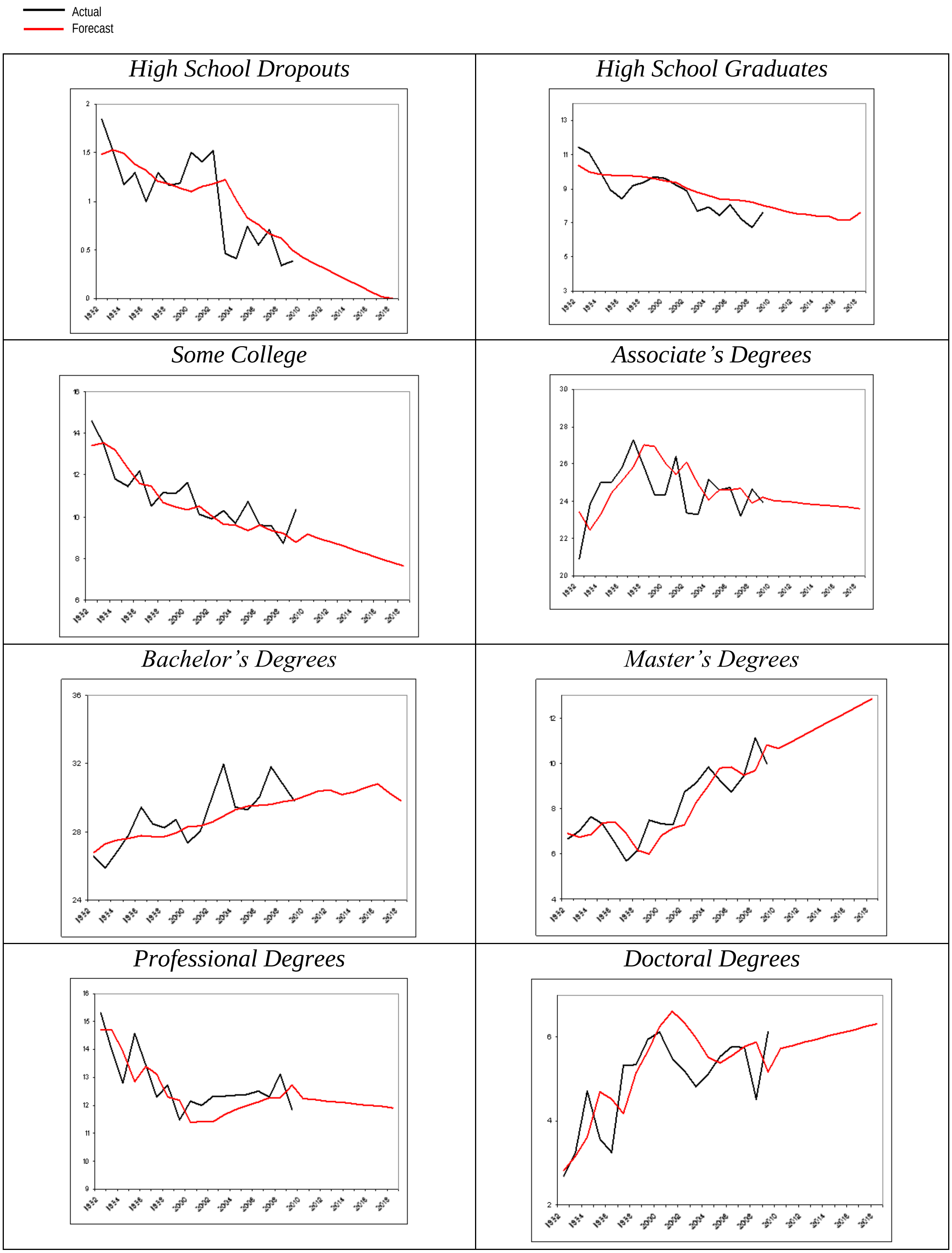
Professional Degrees



Doctoral Degrees



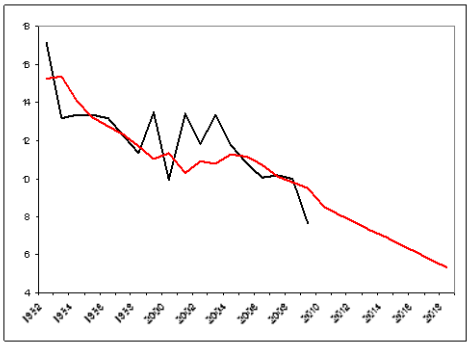
Appendix Fig A10: Actual and Forecast of Education proportions
Healthcare Practitioner and Technical Occupations



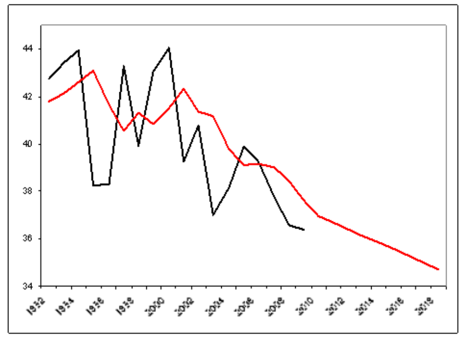
Appendix Fig A11: Actual and Forecast of Education proportions
Health Care Support Occupations

Actual
Forecast

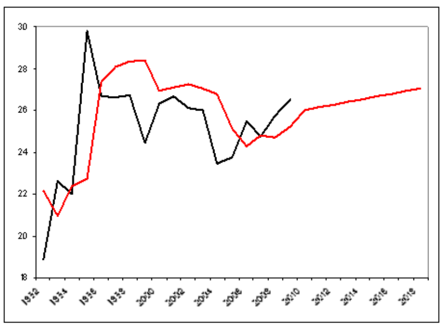
High School Dropouts



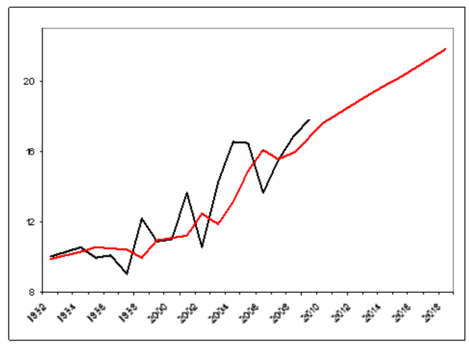
High School Graduates



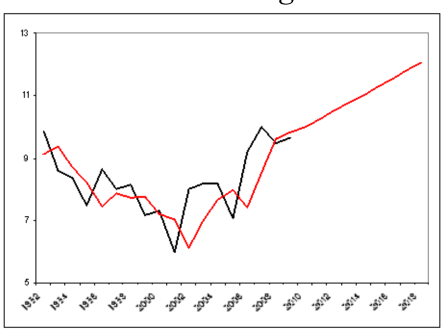
Some College



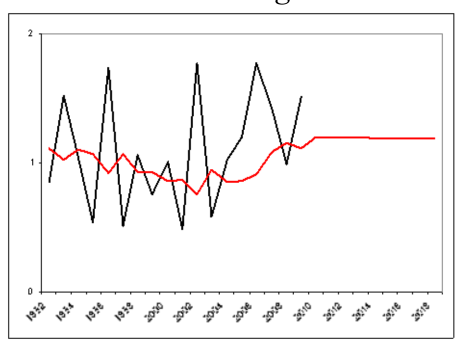
Associate's Degrees



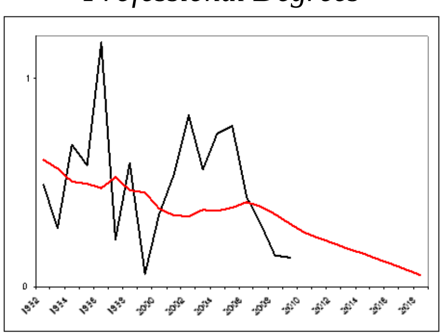
Bachelor's Degrees



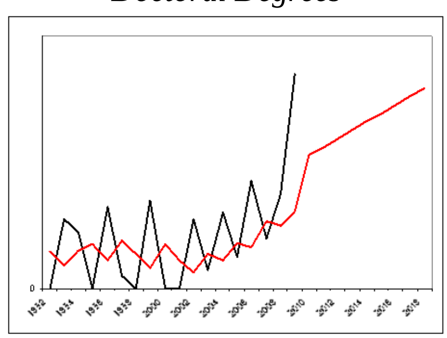
Master's Degrees



Professional Degrees



Doctoral Degrees

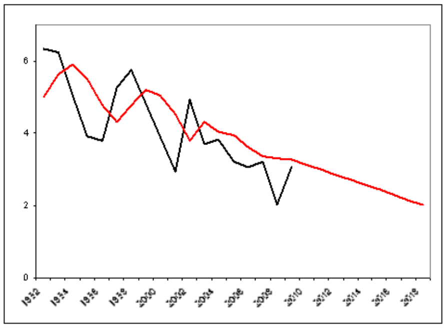


Appendix Fig A12: Actual and Forecast of Education proportions

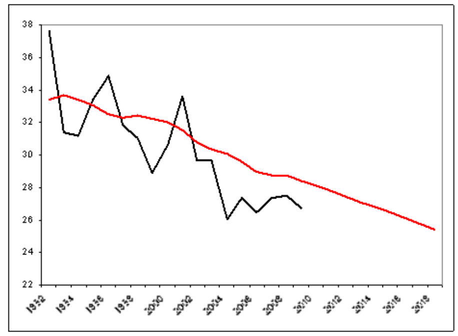
Protective Service Occupations

Actual
Forecast

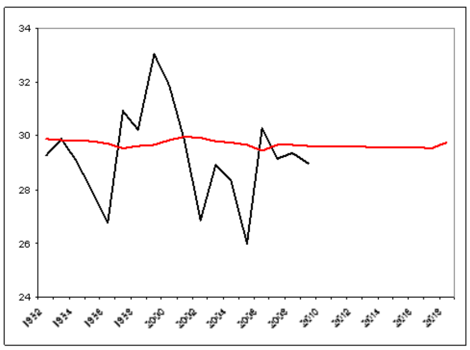
High School Dropouts



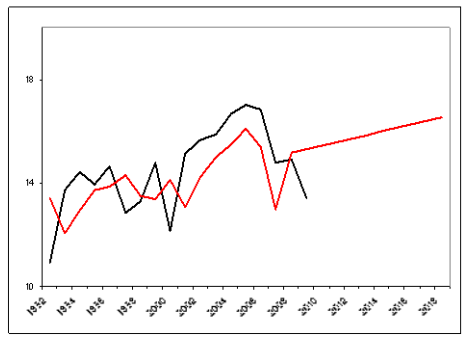
High School Graduates



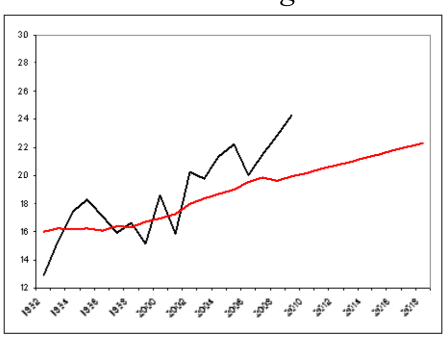
Some College



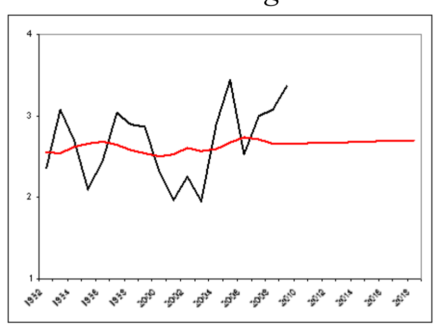
Associate's Degrees



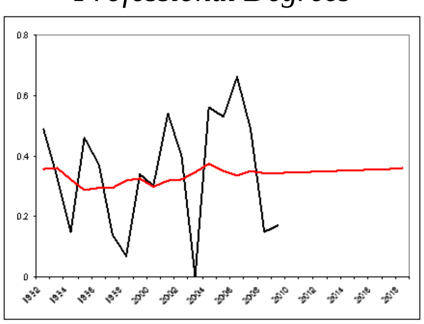
Bachelor's Degrees



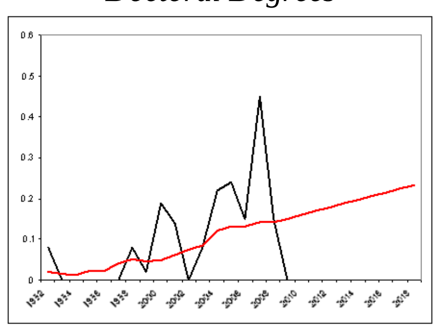
Master's Degrees



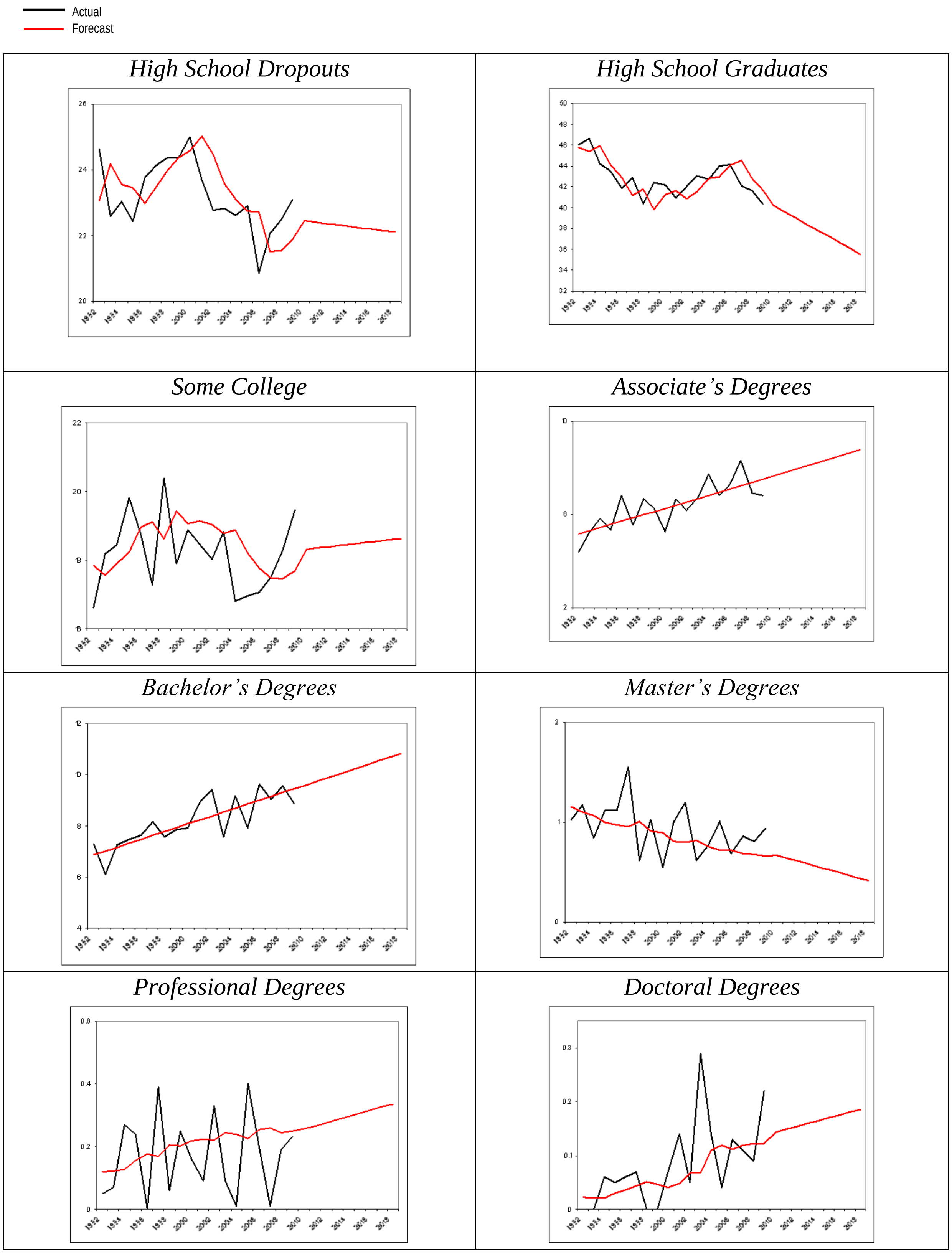
Professional Degrees



Doctoral Degrees



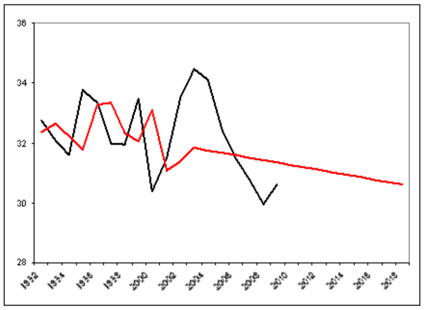
Appendix Fig A13: Actual and Forecast of Education proportions
Food Preparation and Serving Related Occupations



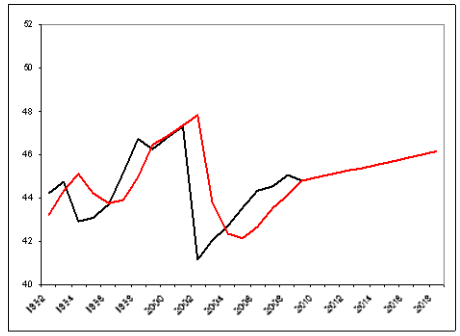
Appendix Fig A14: Actual and Forecast of Education proportions
Building & Grounds Cleaning & Maintenance Occupations

Actual
Forecast

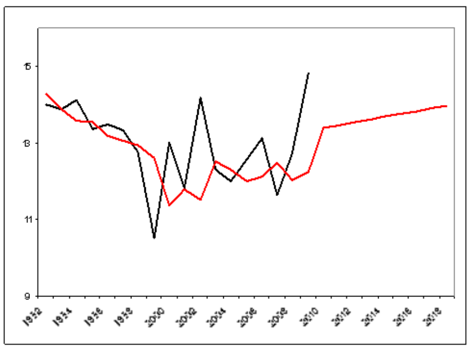
High School Dropouts



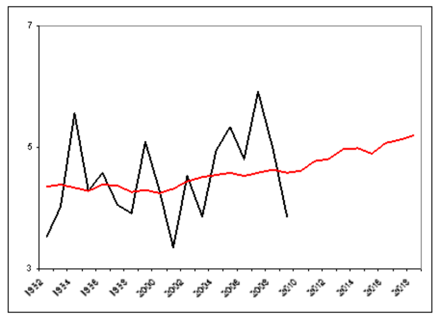
High School Graduates



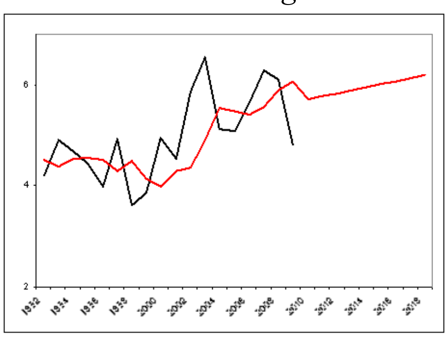
Some College



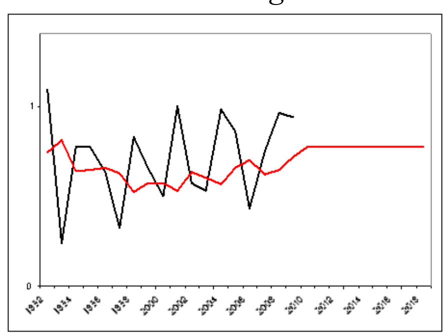
Associate's Degrees



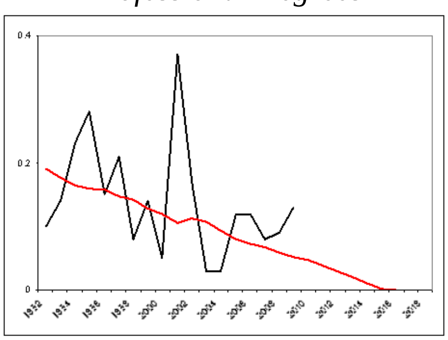
Bachelor's Degrees



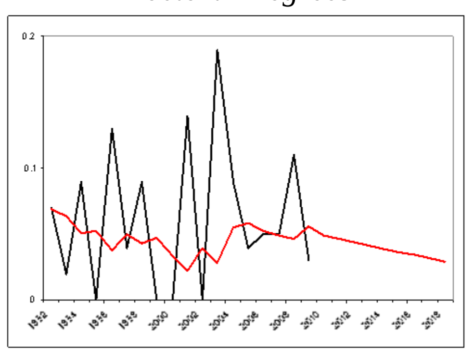
Master's Degrees



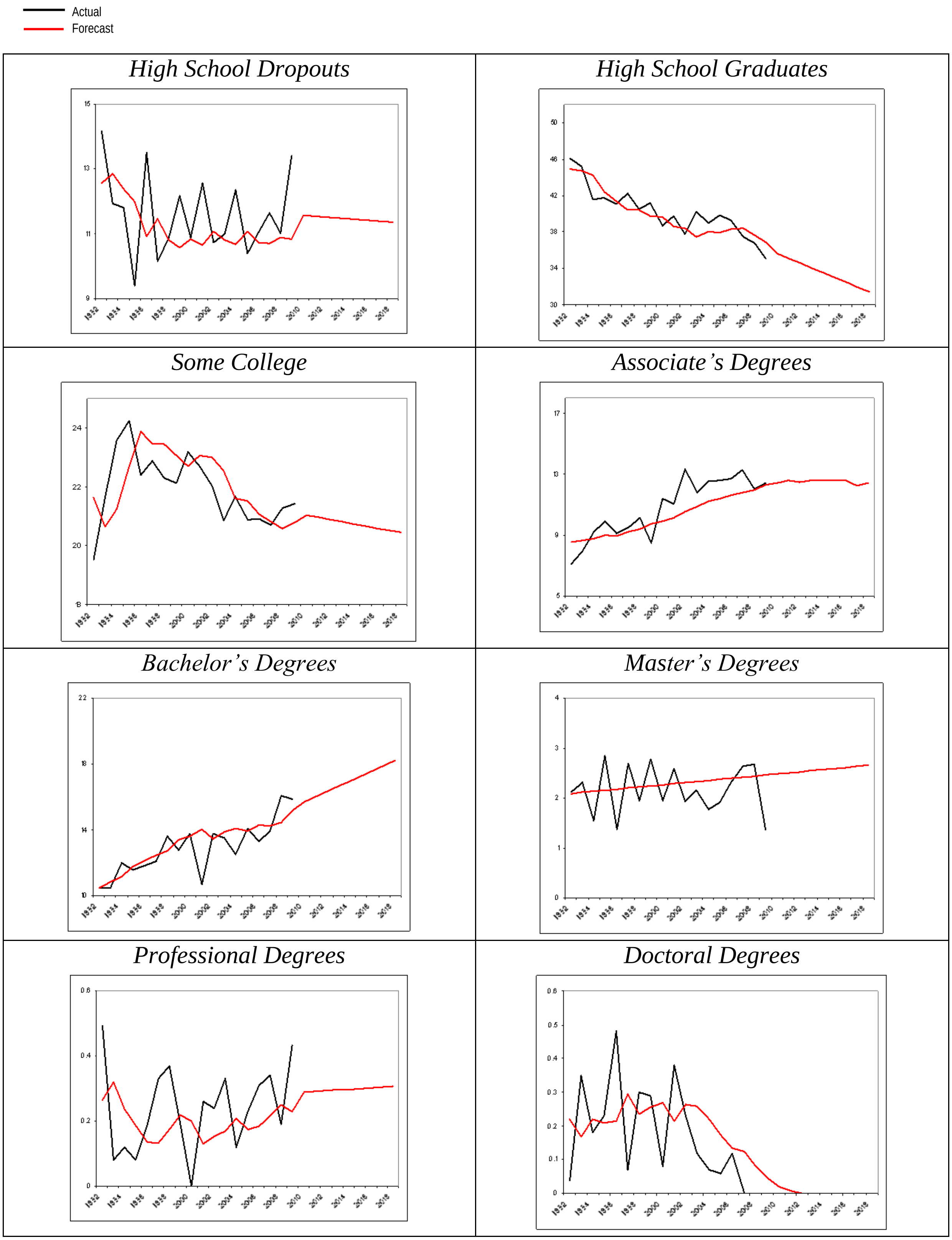
Professional Degrees



Doctoral Degrees

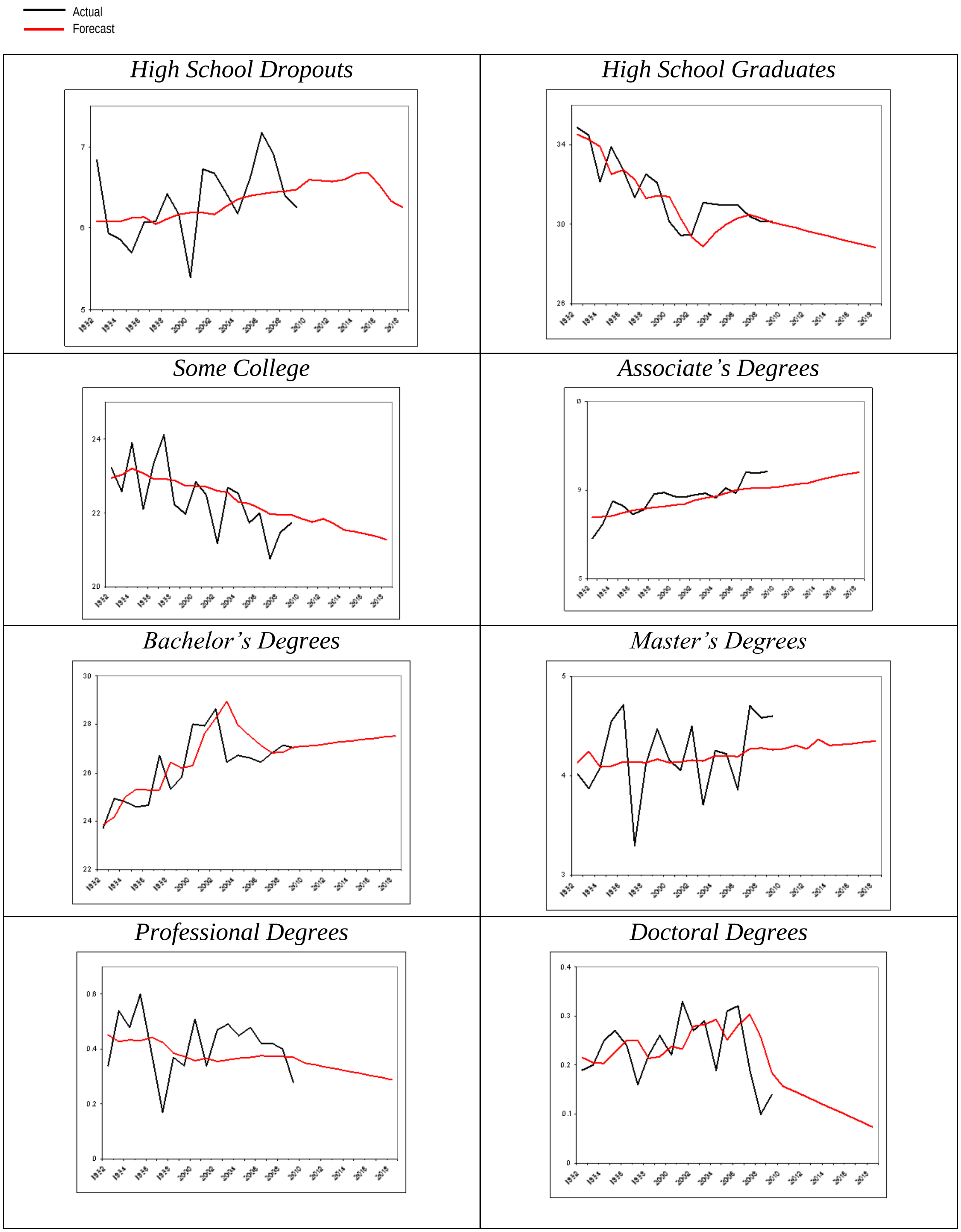


Appendix Fig A15: Actual and Forecast of Education proportions
Personal Care and Service Occupations

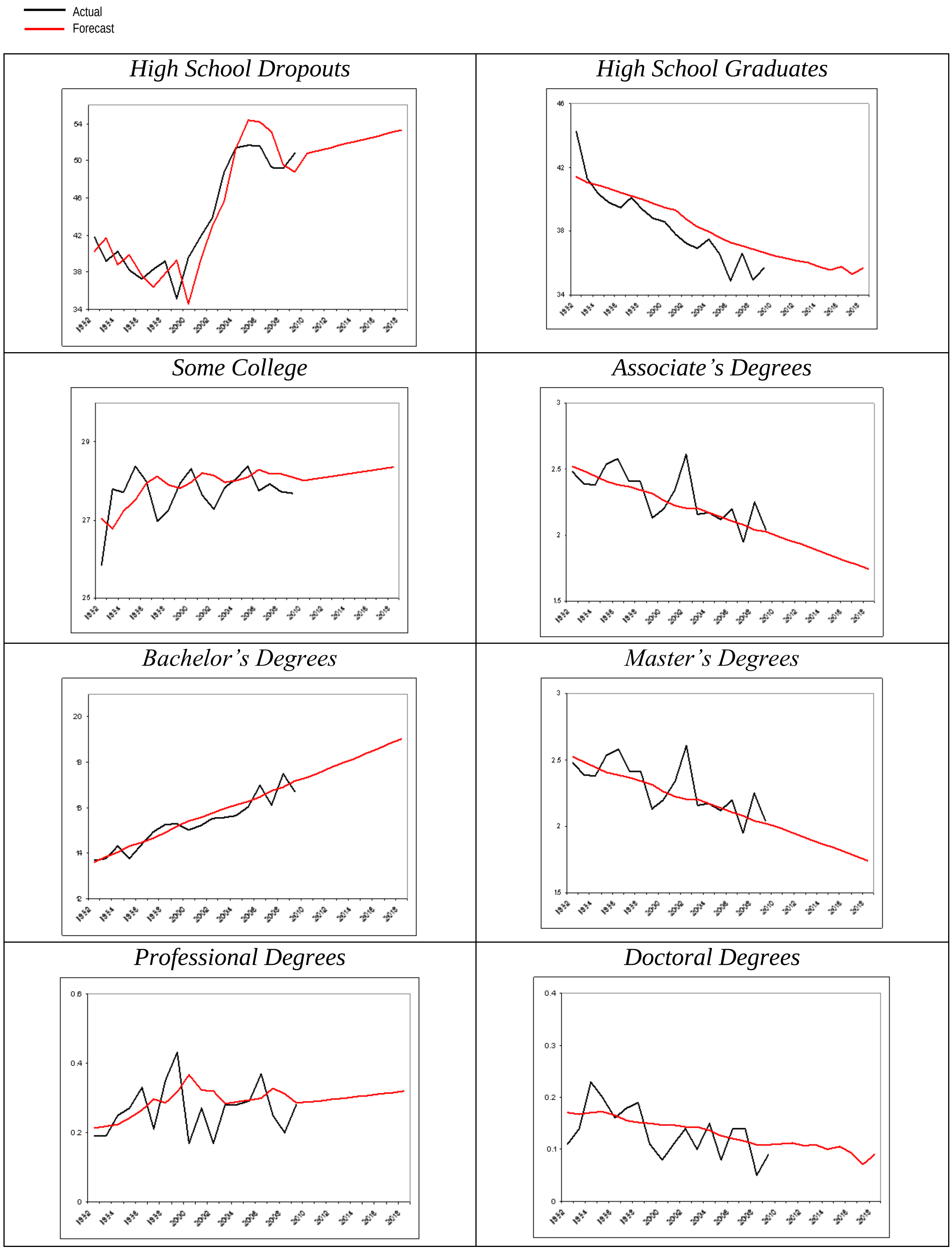


Appendix Fig A16: Actual and Forecast of Education proportions

Sales and Related Occupations

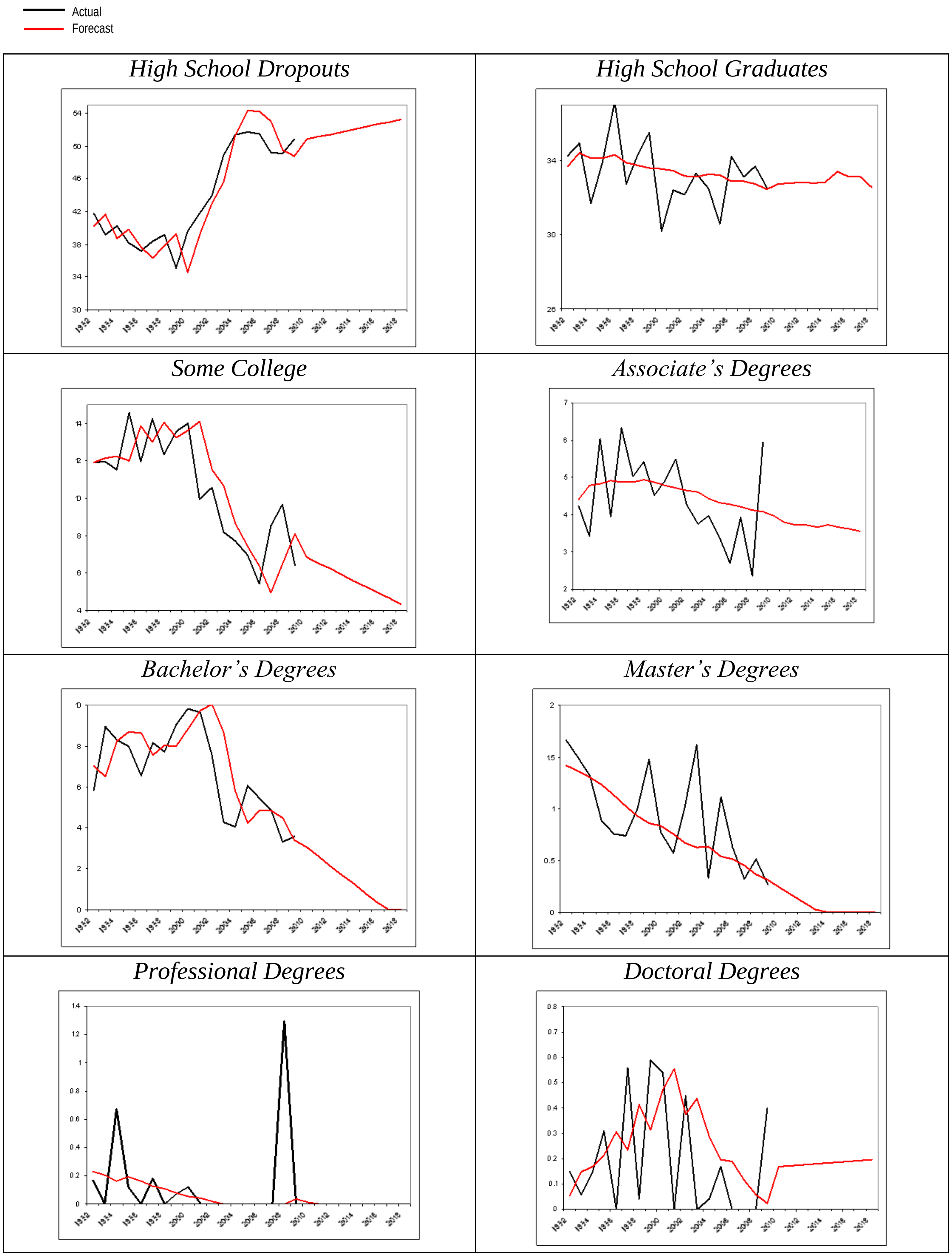


Appendix Fig A17: Actual and Forecast of Education proportions
Office and Administrative Support Occupations

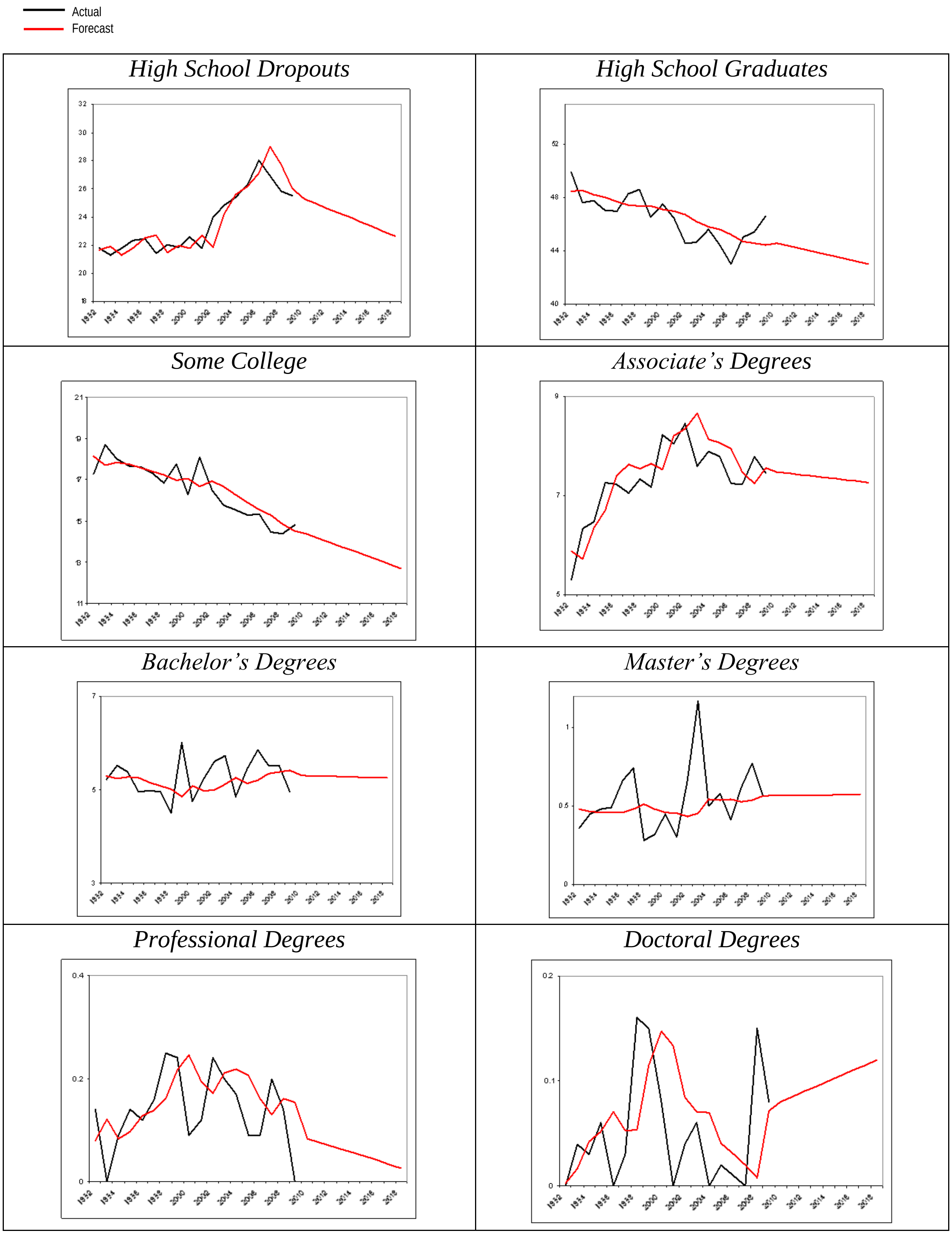


Appendix Fig A18: Actual and Forecast of Education proportions

Farming, Fishing, and Forestry Occupations



Appendix Fig A19: Actual and Forecast of Education proportions
Construction and Extraction Occupations

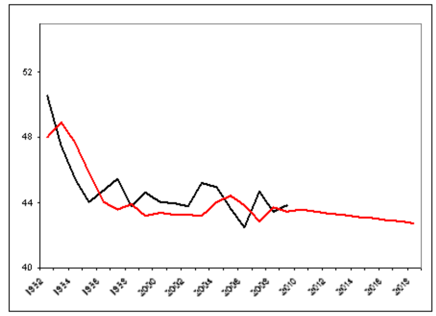


Appendix Fig A20: Actual and Forecast of Education proportions
Installation, Maintenance, and Repair Occupations

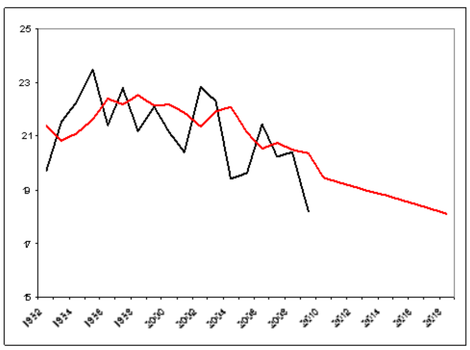
Actual
Forecast

High School Dropouts

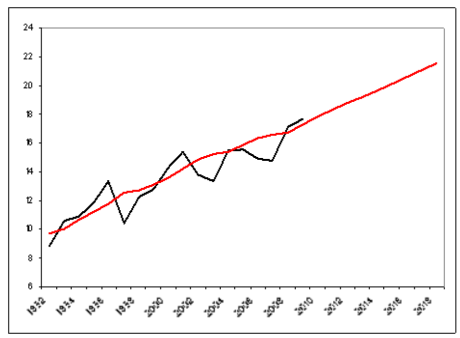
High School Graduates



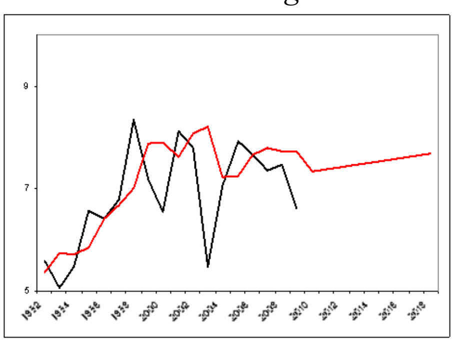
Some College



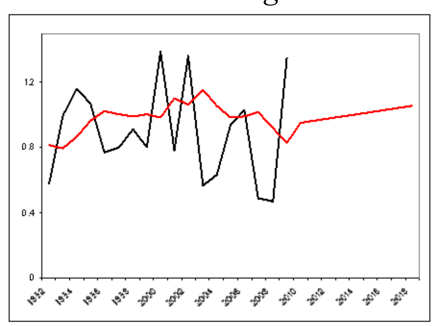
Associate's Degrees



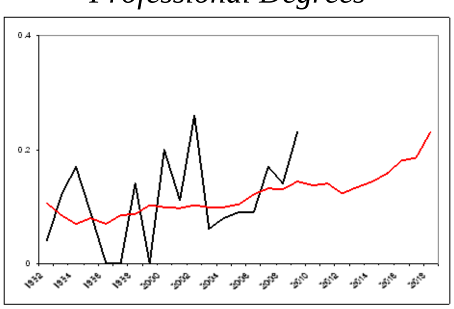
Bachelor's Degrees



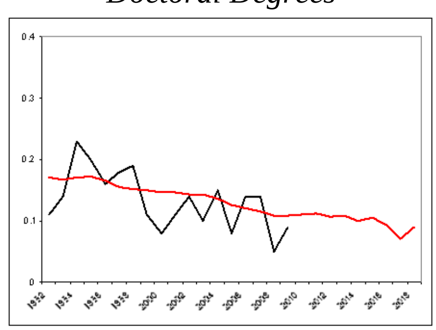
Master's Degrees



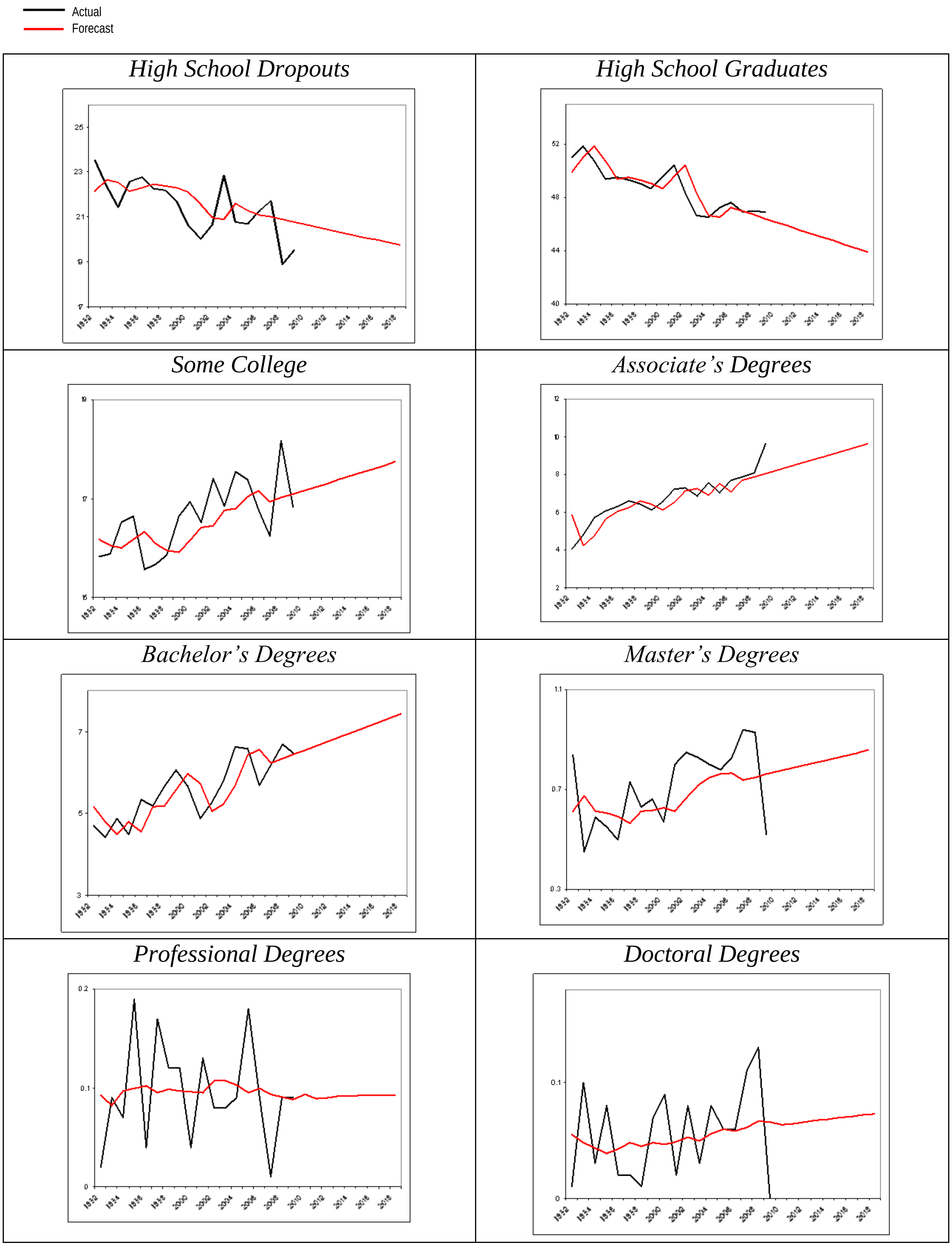
Professional Degrees



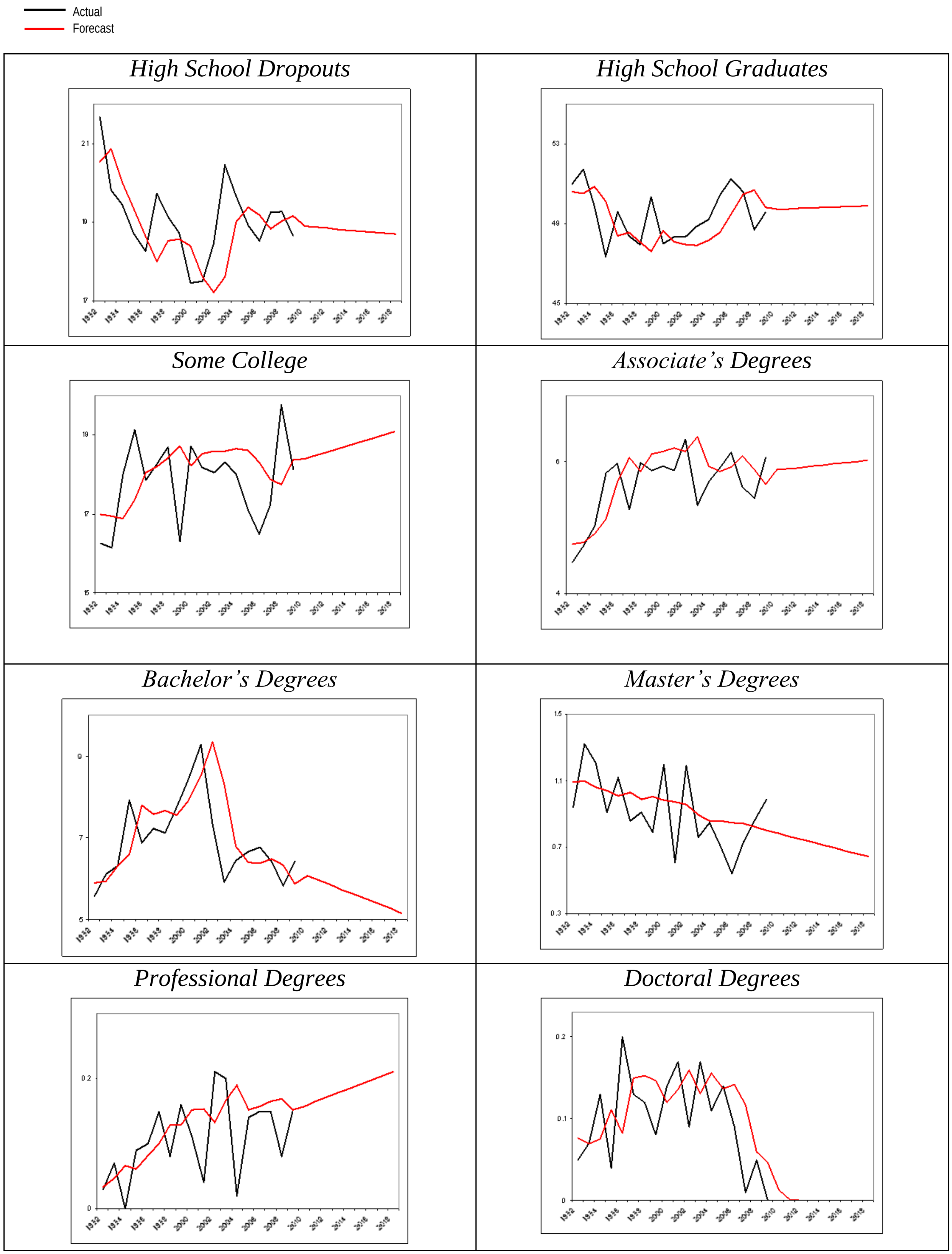
Doctoral Degrees



Appendix Fig A21: Actual and Forecast of Education proportions
Production Occupations

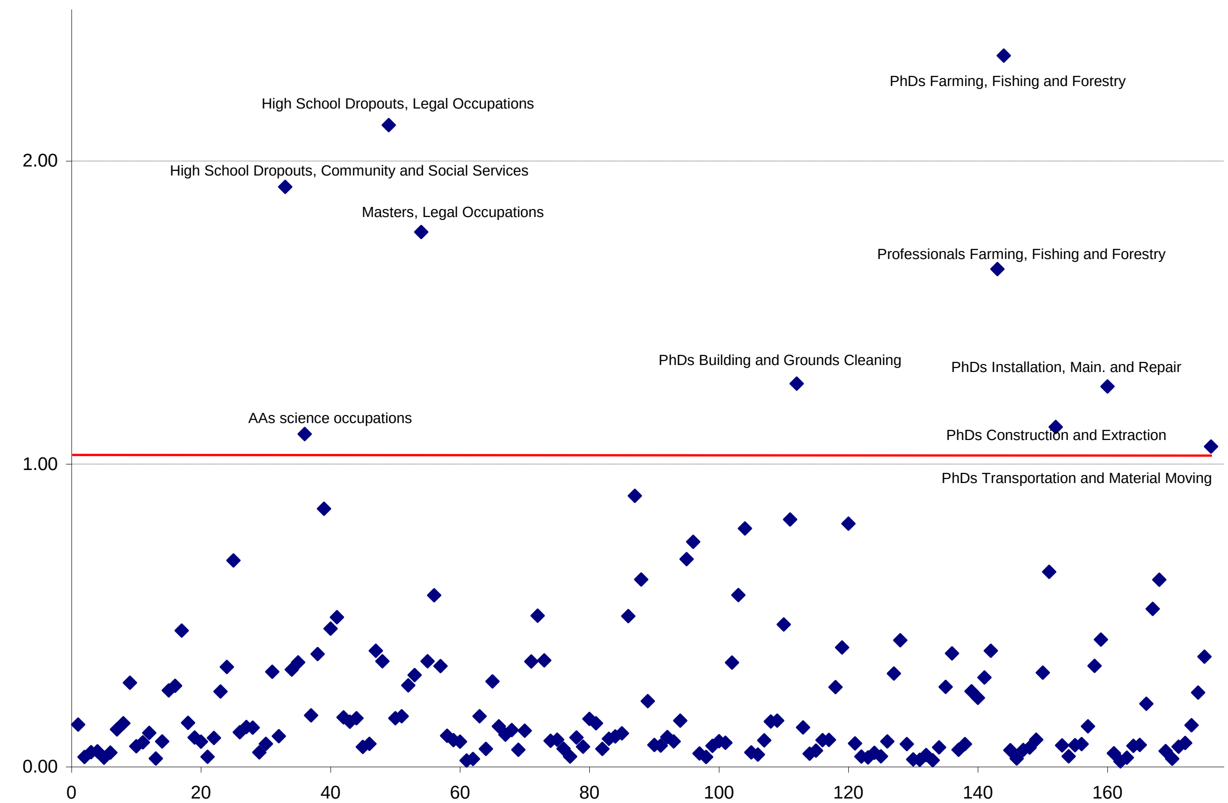


Appendix Fig A22: Actual and Forecast of Education proportions
Transportation and Material Moving Occupations



Appendix Figure B: Coefficient of Variation Comparing Fit Across Models

(Outliers identified)



Source: Author's calculations using RMSE and mean of fitted dependent variable for 176 estimated equations in smoothing model.