The 0.0003 Percent: Short-Run Dynamics of Extreme Wealth in America

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Abstract

This paper analyzes the short-run dynamics and changing sources of wealth among the Forbes 400 list of the wealthiest individuals in the United States, using annual data for 12 years spanning before and after the financial crisis of 2008-9. Over the entire time period the growth of wealth was negatively related to the previous years' wealth, implying a slight degree of wealth convergence within the group. We find that the overall growth of the group's wealth slowed after the crisis but stayed well above the GDP growth rate. Considering the interaction of growth of wealth with personal characteristics, we find that those who can be classified as self-made had a higher average wealth growth rate than their counterparts, although this lead narrowed after the financial crisis, during the Great Recession. Similarly, those with advanced degrees also had higher average growth of wealth in the pre-crisis period. We also examine the mobility of in and out of the Forbes 400, and find that turnover was higher in the period prior to the financial crisis, particularly for self-made individuals and those with advanced degrees. The self-made were also more likely to rise in rank within the Forbes 400 conditional on persisting in the list. By employing an innovative method of dealing with selection bias in a truncated panel, we are able to ascertain that our results are not driven by these biases. We also find some differences in these patterns at the sectoral level, compared to the aggregate group.

JEL Codes: J110, I240.
Key Words: Forbes 400, Financial Crisis, Great Recession, Income Inequality, Wealth Inequality, Higher Education.

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1 Introduction

Recent trends in income and wealth distributions in advanced economies, as well as work by economists (e.g., Piketty (2014)) have refocused attention on increasing economic inequality. An important aspect of this issue is the extreme inequality of wealth in America, evidenced by the status of a few hundred individuals annually listed in the Forbes 400 ranking of the country's wealthiest people.[1] This number makes up about 0.0003 percent of the number of US households, therefore a tiny fraction of the top 1 percent of households by wealth, but their aggregate wealth gives them salience.[2] One important conceptual issue in determining social attitudes to such extreme wealth is the question of how that wealth was generated, and how it has evolved. Recent work has examined the roles played by inheritance, innovation, technology, and education in the process of wealth generation, and has stressed the importance of human capital and technological change. This paper extends such work, to examine further the proposition that technological progress has become a more important driver of new wealth creation over the last decade-and-a-half. The paper also examines the impact of business cycle effects, as captured in differences in the characteristics of this extreme group before and after the financial crisis, to provide a new understanding of the short-run dynamics of extreme wealth in America.

A methodological contribution of this paper is to provide the first econometric analysis of which we are aware of panel data constructed from the Forbes 400 annual lists. Econometric analysis through panel regressions allows us to identify business cycle effects, as well as their interaction with the individual characteristics of those in the list, including age, being "self-made" and educational attainment in the form of advanced university degrees. We also analyze the persistence of individuals in the list, how the list changes over time, and how these changes are related to individual characteristics such as education. We employ a recent econometric innovation to estimate the covariation of wealth with time-invariant characteristics, such as educational attainment, while accounting for the intermittent absence of some individuals from the list due to the rank cutoff. This issue of truncation in the panel is handled with panel data techniques developed to tackle the problem of selection bias, which was made well-known by Heckman (1979).

Several authors have previously used the Forbes 400 data to examine aspects of economic inequality in the United States. For example, Piketty (2014) focuses on increasing global inequality in income and wealth, but for the US specifically, he uses the Forbes 400 list to document increasing wealth concentration over the prior three decades. According to the list, the share of billionaires wealth rose dramatically, from 0.4 percent in 1987 to 1.5 percent in 2012 (Piketty 2014, 432–36). Also for the US, Saez and Zucman (2016) show that wealth inequality has increased considerably at the top of the distribution over the last three decades, but this conclusion is based on wealth estimates constructed from broader administrative income data. A similar conclusion is reached in another study using the Forbes 400 data by

[1] This data source and the data are described in detail in Section 3.

[2] For example, individuals such as Jeff Bezos of Amazon, or families such as the Waltons of Walmart, figure prominently in some political campaigns that seek to highlight economic inequality in the US, and the political influence of other extremely wealthy individuals is sometimes viewed with concern.

Kaplan and Rauh (2013a). That analysis, which is closest to the current paper in scope, use the data at 10 year intervals, from 1982 to 2011, to examine the characteristics of individuals in this set of the extremely wealthy. The authors find that, over this period, the percentage of the Forbes 400 that inherited wealth declined, and that more of those on the list had a college education. Their analysis shows that the Forbes 400 were more likely to be in technology, finance or mass retailing, in 2011 as compared to 1982. Our approach differs from that of Kaplan and Rauh in using annual data, allowing us to examine short run changes and business cycle effects, the latter especially on either side of the financial crisis. The annual data also allows us to explore short-term mobility and persistence of membership in the Forbes 400.[3]

Our analysis of turnover or mobility over recent years, and its relation to the business cycle, is also quite different than the approach of Arnott, Bernstein and Wu (2015). Those authors estimate that the wealth of the individuals in the Forbes 400 rose from 13,800 times US per capita GDP in 1982 to 108,000 times US per capita GDP in 2014, but they mostly emphasize the long run turnover in the list, "Instead, we find huge turnover in the names on the list: only 34 names on the inaugural 1982 list remain on the 2014 list, and only 24 names have appeared on all 33 lists." Of course, some of this turnover is the result of mortality. Therefor, allowing for inheritance, the authors go on to estimate that only 39 percent of the wealth of the original 1982 Forbes 400 list is represented in the 2014 list, so that 61 percent is "new money." However, this neglects the wealth that does not show up on the list, so that it could be that some of that "new money" existed before those individuals made it on to the list[4]. Arnott et al. therefore argue that dynastic wealth is less important than entrepreneurial wealth, both over the period of the three decades of existence of the Forbes 400 list, as well as over longer periods,[5] but, unlike Kaplan and Rauh, they do not provide any quantitative analysis of the sources of new wealth. While our analysis is more short term, and we cannot shed as much light on longer run phenomena in the generation of large fortunes, it is arguable that focusing just on recent years provides a more relevant picture of the current dynamics of extreme wealth.

In the next section, we provide a detailed overview of the Forbes 400 data used in this paper. We first confirm and extend the results of Klass, Biham, Levy, Malcai and Solomon (2006) and Nagayama (2013) that show increasing wealth inequality even among this group of the very richest Americans. Then, we document trends in the number of the Forbes 400 with advanced degrees of any kind (master's, doctorates and professional degrees). This analysis extends the focus of Kaplan and Rauh (2013a), which examines the increased presence of college graduates among the group. We show that the number of those with advanced degrees does not follow a smooth trend in our sample period. In fact, the financial crisis falls roughly in the middle of our sample period, and there appear to be differences in pre- and post-crisis trends of the numbers of those with advanced degrees, those who are self-made (defined in the next section) and in the relative presence of individuals whose fortunes are attributable to

[3]The general literature on wealth inequality is large, and includes, for example, the early analysis of Thurow (1971), as well as more recent contributions such as Alvaredo, Atkinson, Piketty and Saez (2013), Kaplan and Rauh (2013b), Wolff and Gittleman (2014), and DeNardi (2016).

[4]Thus, Donald Trump was wealthy before he made it on to the Forbes 400, so not all of his fortune once he appeared on the list was "new money".

[5]For earlier periods, they use figures constructed by Phillips (2002).

particular sectors. As one example of such sectoral differences, the share of wealth associated with real estate rises rapidly duing the boom period of the first part of the sample, and falls after the financial crisis, while the wealth share of technology and telecom as a sector has the opposite pattern. Several such aspects of the data are discussed in the data overview section, and we believe this kind of analysis has not been conducted previously for the Forbes 400.

After our description and preliminary analysis of the characteristics of the sample, our focus in the subsequent section turns to a consideration of mobility, both in terms of position within the Forbes 400, and in terms of entry and exit. We document changes in entry and exit over the sample period, including differences in these patterns before and after the financial crisis (boom vs. recession). We distinguish differences in patterns for those with and without advanced degrees, and also consider annual patterns of entry, including those who are new entrants, those who are self-made, and those who have both or neither characteristic. This analysis can be seen as complementing that of Arnott et al. (2015), since we examine more recent data, and are able to discuss features of the data that they are not in a position to examine, such as what happens to individuals with advanced university degrees. Broadly, the rates of attrition and persistence in our 12 year period are similar to those documented by Arnott et al. (2015) over their sample of about three decades, although we must repeat the caveat that those dropping out of the list are most unlikely to be moving into poverty![6] In this section, we also provide a regression analysis of persistence in the Forbes 400 list, which is an innovation over previous examinations of persistence.

Our investigation is rounded out by an econometric analysis of our panel data, using the growth rate of wealth as the dependent variable, and allowing for a range of possible specification issues. In particular, we adapt the method of Kripfganz and Schwarz (2013) to deal with non-normality and time-invariant characteristics. Furthermore, we innovate in simultaneously dealing with truncation through an implementation of the Semykina and Wooldridge (2010) correction for selection bias for panel data in the presence of endogeneity. Our results for the overall panel suggest mild wealth convergence among the group, business cycle effects in terms of the GDP growth rate, and also some additional positive boom-year impacts of being self-made and having an advanced degree. However, these results are not always robust to disaggregation by sectors, which suggests that wealth dynamics are quite complex, partly as a result of different sectors having different sensitivity to the business cycle, and to the overlay of longer term trends. In particular, the technology and telecom sector differs in these patterns from the finance sector. We hope our analysis will point the way to further investigation of these complex dynamics at the extreme top of the wealth distribution.

2 Data Overview

As noted in the introduction, we use annual data taken from Forbes magazine, which lists and ranks the magazine's determination of the 400 richest persons in the United States of

[6] The title of their paper is provocative in this respect, beginning with "The Rich get Poorer."

America. This list appears in October every year, and we have compiled data manually for a dozen years, from 2004 to 2015. There are 722 individuals who appear at least once in the Forbes list over these 12 years. Some information, namely wealth and rank, of these persons is only available if they are in the list for the year in question: thus, we have only 4800 observations out of a potential 8664 (722x12) observations. There are other variables that are invariant over time, such as gender, education, and whether the individual was "self-made", in a sense to be made precise later in the paper. In some cases, more than one individual may be listed in one of the 400 positions (e.g., a couple may be listed together), and we treat these cases as one individual or observation, using the characteristics of the member of the couple or family group that we identify as the "main" wealth generator. There is a relatively small number of such cases, and our results are robust to their exclusion.

Data on education, one of our main characteristics of interest, is not consistently available in the Forbes 400 lists, and we have compiled the data on education manually from a variety of sources, including Forbes magazine itself when possible. In some cases, the information was not available or reliable, and so our annual totals do not always equal 400, because we omit such observations. Of course, many individuals appear repeatedly in the list, and, as noted, there are a total of 722 distinct individuals in our 12-year data set. When individuals for whom we were not able to reliably determine their education levels are excluded, our analysis is based on a remaining sample of 696 distinct individuals.

Since data on each individual's wealth in a particular year is only available if they happen to be in the top 400 in that year, observations for some individuals are not available for all 12 years: they may enter or drop out of the list one or more times. This particular kind of truncation in our panel is an important issue that we will deal with in our empirical analysis, since it may lead to selection bias.

In the rest of this section, we describe the data and its properties in some detail, highlighting some of the features and patterns that can be observed. This exploratory data analysis provides some motivation for the subsequent formal analysis. We explore individual characteristics such as age in the first year of our sample, having an advanced degree (anything beyond a bachelor's degree), the sector that is the source of wealth, being "self-made", and being a new entrant.

2.1 Wealth Inequality among the Wealthiest

We begin with a description of the distribution of wealth among the Forbes 400. It is standard to use a Pareto function to model this distribution at the very top end of the wealth spectrum. Using this model, Klass et al. (2006) demonstrated increasing wealth inequality at the very top, for the period 1988 to 2003. Nagayama (2013) extended this type of analysis to 2012, and we provide a similar analysis for our sample period, which extends to 2015.[7]

The model uses a Pareto function connecting wealth to rank, as follows:

[7] For a novel analysis of the economic mechanisms generating the Pareto distribution, see Jones (2015).

$$W_R = AR^{-\frac{1}{\alpha}}.$$

Here, W_R stands for the wealth (in current USD), while R is the rank of that person. Taking a log transformation on both sides, we get:

$$\log W_R = \log A - \frac{1}{\alpha} \log R.$$

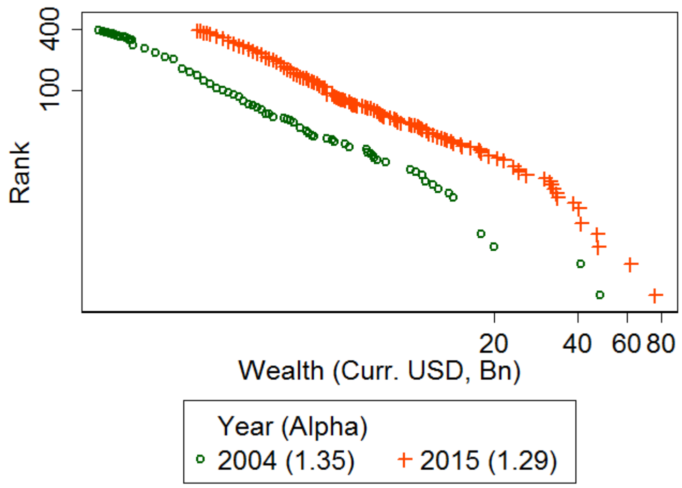
$$\implies \log R = \alpha \log A - \alpha \log W_R.$$

We plot the log transformation of rank vs. wealth for the first and last years of our sample in the top part of Figure 1. The α is estimated as the slope of the fitted least-squares line, and reported below the scatter plots. A lower (higher) α indicates more (less) inequality in the distribution.

In Figure 1, the scatter plot shifts to the right over the period, which reflects increasing nominal wealth. The relative slopes are not apparent from the plots, but the estimated α, as reported in the lower box, did decrease, implying increased inequality over the sample period, consistent with the earlier results of Klass et al. and Nagayama. The lower part of Figure 1 repeats the exercise for the years 2007 and 2013. The estimated α in these two years demonstrates that the increase in wealth inequality within the Forbes 400 was higher in this sub-period than for the entire sample period: indeed, the change was in the opposite direction at the beginning and end of the sample period.

This effect can also be seen in Figure 2, which plots the estimated α for each year of the sample. From 2004-2007 there was a slight reduction in the inequality of wealth among this rarefied set of the extremely wealthy, but post-crisis the inequality measure increased every year till 2013. In the last two years of the sample the trend did reverse. Later in the paper we explore some of the underlying characteristics of those who make up these distributions, how their wealth changed over the sample period, and what kind of turnover there was in the composition of the sample over the years. We will find that, controlling for individual characteristics and economic environment, there was slight convergence in the wealth levels of the Forbes 400.

Figure 1: Forbes 400 Rank vs. Curr. Wealth in Log-Log Scale



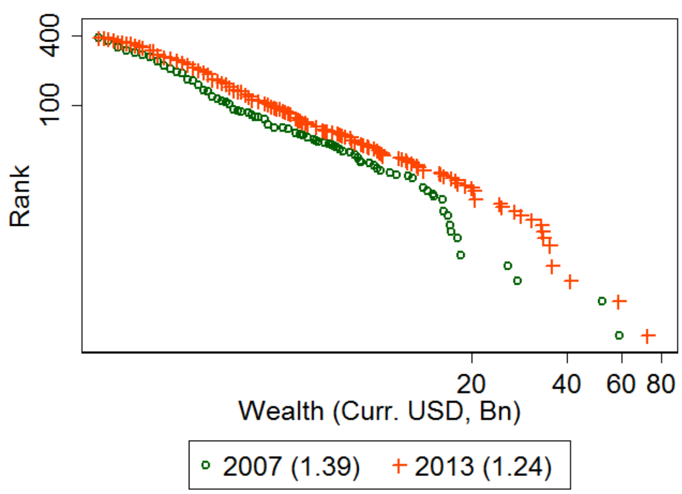


Figure 2: Time Series of α, 2004-2015

2.2 Advanced Degrees

As discussed in the introduction, one of the characteristics we examine is the importance of education in this sample of the extremely wealthy. Kaplan and Rauh (2013a) had documented the increased number of the Forbes 400 with college degrees over a period of three decades. We examine our more recent data for the possible importance of education beyond the bachelor's level, i.e., advanced degrees of any type. US data (Table 1) shows that the earlier US trend of increasing proportions of college graduates has recently been reinforced by acquisition of graduate or advanced degrees (i.e., masters, professional, and doctoral degrees of any kind) at a higher rate as well.

Whereas the national data displays a relatively steady increase in the total numbers (about 700,000 per year) and percent (about 0.22 percentage points per year) of the US population with advanced degrees from 2000 to 2015, the pattern of change in the Forbes 400 is different. The left panel of Figure 3 shows a sizable increase in the number of listed individuals with advanced degrees from 2004 to 2007, but the number levels off and even declines slightly thereafter. The percentage of such individuals in the Forbes 400 goes from about 35 percent in 2004 to 42 percent in 2007, or almost a 20 percent increase in the proportion. This is much more rapid than the national trend in acquisition of advanced degrees. The right panel in Figure 3 illustrates a similar pattern over time, but in terms of the fraction of wealth among the Forbes 400 held by those with advanced degrees, rather than number of individuals. The fraction of wealth levels off, but does not decline from the 2007 peak in the way that the number of individuals does. This suggests that the individuals with advanced degrees who remainin in the Forbes 400 are doing relatively better after 2007.

Next, Figure 4 plots the mean and median wealth for individuals in the Forbes 400, with and without an advanced degree, by year. Since the distribution of wealth among the Forbes 400 is itself very skewed (a small number of exceptionally wealthy individuals among the mere billionaires), the mean is greater than the median for both groups. For those with an advanced degree, after 2008, the mean becomes higher than that for their less educated counterparts. On the other hand, the median for the more educated stays slightly lower than the median for the less educated group. This implies that the wealthier individuals with advanced degrees are driving the comparative effects. This is consistent with the earlier comparison in Figure 3.

Table 1: Number and Percent of US Population 25 and Over with Advanced Degrees

Year	Number ('000s)	Percent
2000	15,006	8.6
2001	15,728	8.7
2002	16,414	9.0
2003	17,169	9.3
2004	17,983	9.7
2005	18,121	9.6
2006	18,567	9.7
2007	19,184	9.9
2008	20,228	10.3
2009	20,938	10.6
2010	21,056	10.5
2011	22,057	10.9
2012	22,730	11.1
2013	23,931	11.6
2014	24,623	11.9
2015	25,445	12.0

Figure 3: Forbes 400 Individuals with Advanced Degrees

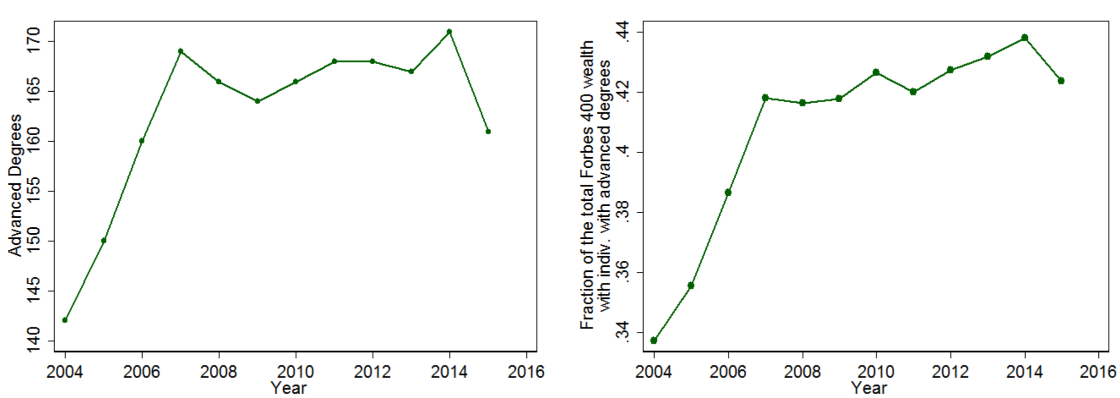
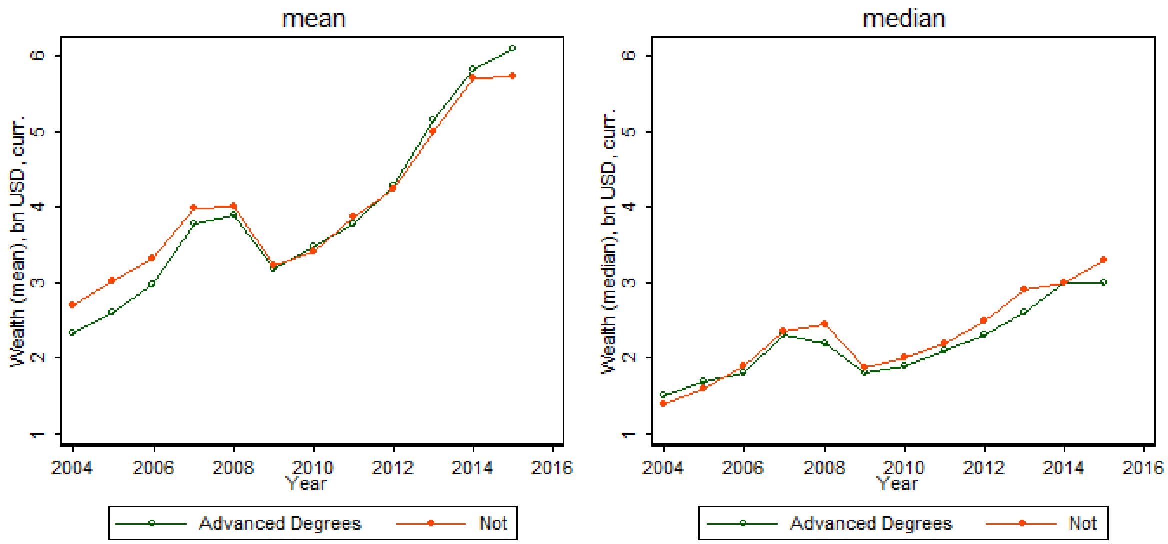


Figure 4: Forbes 400 Wealth by Advanced Degrees



2.3 Sectors

We now describe the industries or sectors with which members of the Forbes 400 can be associated, in terms of where their wealth was generated or resides. We use the classification of sectors in the Forbes lists themselves, with some small modifications, and largely are able to assign individuals to their respective sectors based on the information in the lists. Recall that Kaplan and Rauh (2013a) found, going from 1982 to 2011, that there were increased numbers in three sectors Finance, Technology and Retailing.

Table 2 lists the classification of sectors we are using in this analysis, ranked by the number of unique individuals in each sector. It also reports the percentage with advanced degrees for each sector. It is indeed the case that Finance and Technology (including Telecoms) have the highest representation in the sample of individuals. Retail comes further down the list in terms of numbers. Interestingly, manufacturing is slightly more common as the sector of these extremely wealthy individuals, compared to several service sectors, though not when compared to services as a whole. Note that in our classification, which follows that of Forbes magazine, Diversified Investments and Inheritance are not sectors in the sense of type of economic activity, but represent how the wealth was acquired, or where it is invested. There are some clear, and mostly obvious patterns with respect to the sectors in which individuals with advanced degrees are more likely to be found. Compared to the sample average, these sectors are Finance, Technology and Telecom, Healthcare and Medicine, and Diversified Investments.

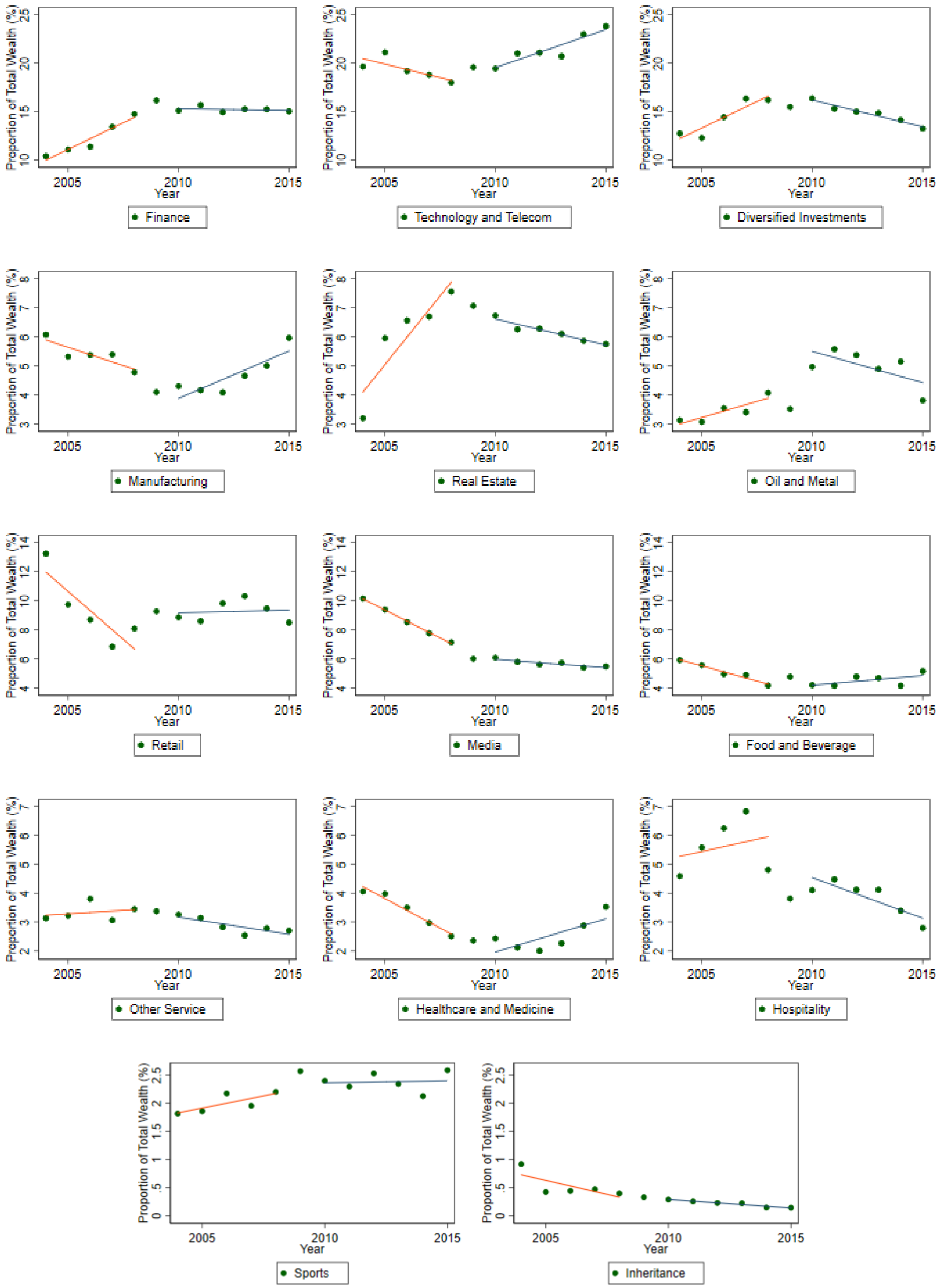
While Table 2 provides counts of individuals who are in the sample at least once over the whole 12 year period, Figure 5 shows how the proportion of wealth of the 400 held within each sector or sector changes over the sample period. Correspondingly, Figure 6 shows how the number of individuals in each sector changes over the sample period. In order to highlight the impact of the financial crisis on trends in the concentration of wealth, these figures include linear fits for 2004-08 and 2010-15, with 2009 not included in either sub-period. This choice is also based on the direct observation from the plots that the most marked changes are around 2009. While the differences in trends before and after 2009 and across sectors may not be fully reflective of what was happening in each sector, they are still useful in suggesting further investigations about the structure of the economy and how it responds to business cycles. Perhaps the most obvious feature of these plots is the real estate boom that occurred prior to the financial crisis and recession. Finance, Diversified Investments, and Hospitality also share some of this feature. Unlike the longer term trends noted by Kaplan and Rauh, considering annual data on either side of a major turning point in the economy provides insight into cyclical factors rather than longer run trends.

Table 2: Unique Individuals and Education by Sector

		Adv. Deg. (%)		Self-Made (%)		
Source of wealth	No.	Yes	No	Yes	No	Total
Finance	109	49.5	50.5	88.1	11.9	100.0
Technology Telecom	107	49.5	50.5	89.7	10.3	100.0
Diversified Investments	70	67.1	32.9	72.9	27.1	100.0
Manufacturing	55	29.1	70.9	54.5	45.5	100.0
Real Estate and Construction	54	33.3	66.7	79.6	20.4	100.0
Oil and Metals	44	29.5	70.5	59.1	40.9	100.0
Retail	42	16.7	83.3	64.3	35.7	100.0
Media	41	26.8	73.2	61.0	39.0	100.0
Food and Beverage	36	13.9	86.1	55.6	44.4	100.0
Other Services	32	21.9	78.1	68.8	31.3	100.0
Healthcare and Medicine	30	53.3	46.7	86.7	13.3	100.0
Hospitality	27	25.9	74.1	37.0	63.0	100.0
Sports	25	36	64	72.0	28.0	100.0
Agriculture	16	18.8	81.3	43.8	56.3	100.0
Inheritance	8	37.5	62.5	0.0	100.0	100.0
Overall	696	38.6	61.4	71.4	28.6	100.0

Figure 5: Share of Sector* in the Total Wealth of the 400

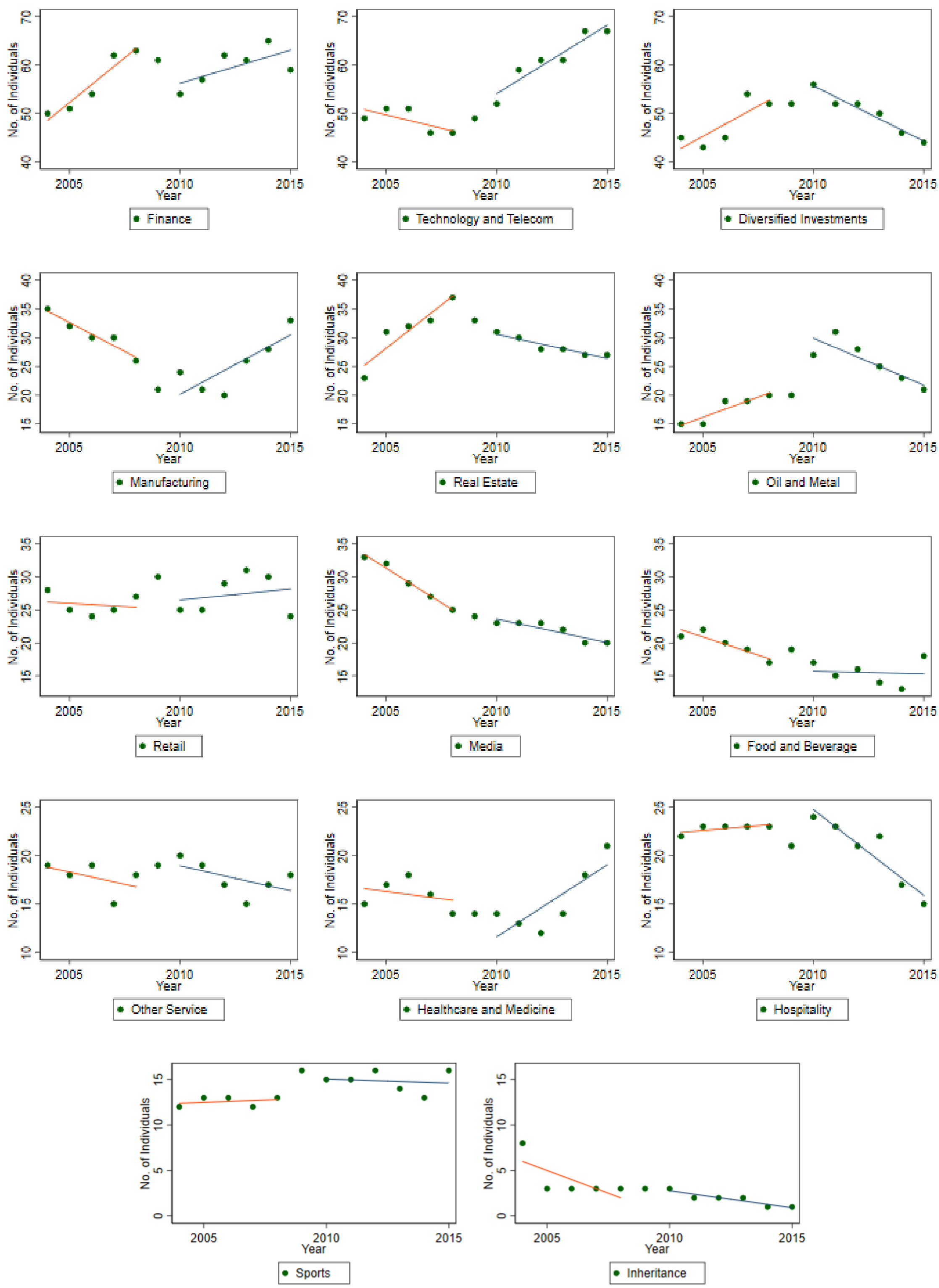
Linear Fit - Before 2009, After 2009



*The Agriculture sector is not displayed, since there is no one in this sector for certain years.

Figure 6: No. of Individuals by Sector*

Linear Fit - Before 2009, After 2009



*The Agriculture sector is not displayed, since there is no one in this sector for certain years.

2.4 Being "Self-Made"

An important aspect of American ideology (or mythology) is the notion that anyone can become successful through their own efforts. The main argument of Arnott et al. (2015) is that inherited wealth dissipates relatively rapidly, and that most of the large fortunes we see at present have been created in the recent past.

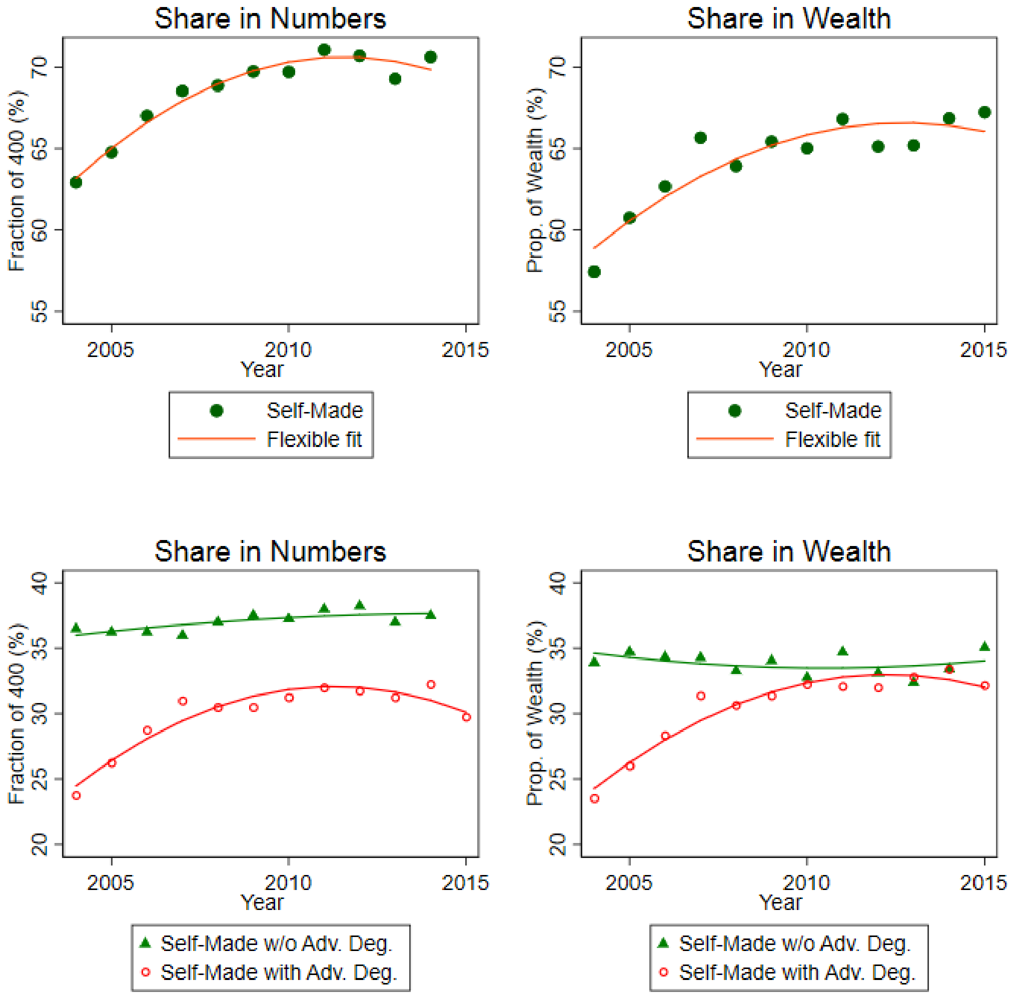
In line with the conceptual importance of personal success versus inheritance, the Forbes list reports a "self-made" score on a scale of 1-10. The scoring system is described in detail in a Forbes Magazine article by Fontevecchia (2014). The scoring uses information on whether, and to what extent, individuals were the beneficiaries of substantial inherited wealth. Of course, this does not distinguish among those who might still have come from wealthy or educated families, those from comfortable backgrounds (e.g., "upper middle class"), and those who may have started without any advantages in their socio-economic background.

We use a simpler version of the Forbes score, a binary variable which takes the value 1 for anyone with the score 6 or more, and 0 for others. By this classification, of the 696 unique individuals, there are 497 who are self-made and 199 who are not. Note that the number of individuals who are not self-made by this measure is larger than the number of individuals whose wealth is attributed prinarily to inheritance, in Table 2. Using our definition, as shown in the upper left panel of Figure 7, the annual proportion of the self-made in the Forbes list is high and it increased slightly over the dozen years of our sample. The increase coincided with the boom years prior to the financial crisis. The proportion stabilized at around 70% from 2009 on. The share in wealth of the self-made relative to the total wealth of the Forbes 400 displays a similar pattern, in the upper right panel, leveling at about 65% since 2009. The lower share of wealth as compared to the share of individuals reflects the fact that self-made individuals were slightly less wealthy on average than others in the list.

The pattern of increase in the first years of our sample, and stabilization thereafter, in the number of the self-made in the Forbes 400 is similar to that of the subset holding advanced degrees, as shown in the lower panels of Figure 7. In fact, self-made individuals are somewhat more likely to hold an advanced degree: among the 497 unique self-made individuals in the panel, 41% hold an advanced degree, while among the not self-made 199, only 32% do. The lower panel in Figure 7 divides the self-made into the two groups, those holding advanced degrees and others, and plots them separately. This figure shows that much of the increase in the number and share in wealth of the self-made in the early part of the sample is due to an increase in the number of the self-made who have advanced degrees.

Table 2 shows the proportion of self-made individuals by sector. As might be expected, human-capital intensive industries with likely low barriers to entry, such as Finance and Technology, have the highest rates of self-made wealthy individuals, while more capital intensive industries such as Hospitality and Agriculture have less than 50%.

Figure 7: "Self-Made" Shares over Time



Note: Flexible fit - best-fitting fractional polynomial after estimating many functional forms for y = g(x), where the powers of g(x) are searched in the range (-2, -1, -.5, 0, .5, 1, 2, 3).

2.5 Age

There are two perspectives we can take on age, which is calculated from the reported year of birth for each individual. We can look at the age profile of the individuals in our sample, irrespective of which years they appear in the list, and we can also examine the age profile of each year's list. The connection between the two depends on entry and exit, which is discussed in the next section. For example, a simple t-test over unique individuals shows that the younger individuals are more likely to have advanced degrees, and this can be related to the increased presence of the latter characteristic over the first years of the sample. The source of year of birth is the Forbes list, or other news articles where needed.

Figure 8 relates being self-made to the year of birth, rounded to the nearest 5 years. The fraction of unique individuals who are self-made, calculated for each 5-year interval, tends to be higher among younger individuals, although there is considerable variation around the line of best fit.

In Figure 9, we plot the proportion of unique individuals with advanced degrees by year of birth. Among those born up until 1970, we see a steady increase in the fraction with advanced degrees, This pattern reverses for the younger cohorts in our sample of individuals. To check whether there was a difference between the self-made and others in this regard, we plotted the fraction of those with advanced degrees separately for the self-made and for others in the right panel. The difference between the self-made and others is quite pronounced. For the self-made, the pattern is quite similar to the whole sample. The reversal for younger cohorts is now clearly attributed to them: those not self-made are all born before 1980. There is a large increase in the proportion with advanced degrees in the younger cohorts among those who are not self-made.

Next, we turn to the second perspective on age, by examining the age profile of individuals in each of the annual lists. The 400 does not age all that much over the sample period (see Figure 10). The group with advanced degrees is younger than their less educated counterparts, but the average age of this group increases slightly faster than their counterparts. This could be due to the mobility of those with advanced degrees, if they persist longer in the list before dropping off; but more likely this is due to the fact that there is an influx of new entrants without advanced degrees. The right hand panel of the figure displays a different pattern for new entrants: their average age declines over the sample period, though there is again convergence in the average age of those with and without advanced degrees.

Turning to the age profile of just the self-made over the sample period, in Figure 11, one sees that the average age of the self-made is increasing at about the same rate as for the overall sample, shown in the previous figure. The differences between those with and without advanced degrees for the self-made subsample are fairly similar to those in the whole sample. This similarity also hold for new entrants, as shown in the right hand panel of the figure.

Figure 8: Year of Birth and Self-Made

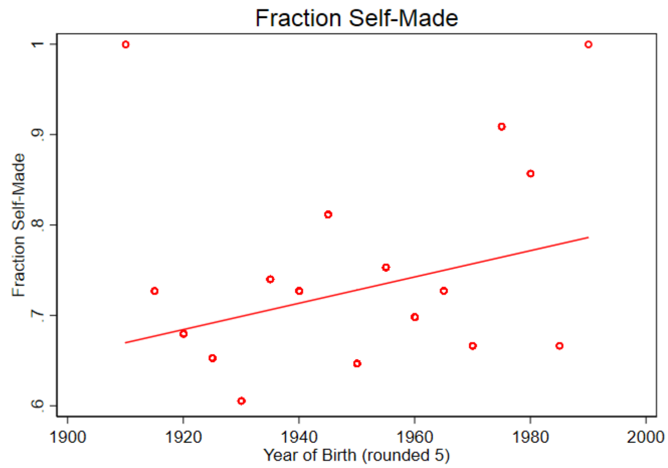
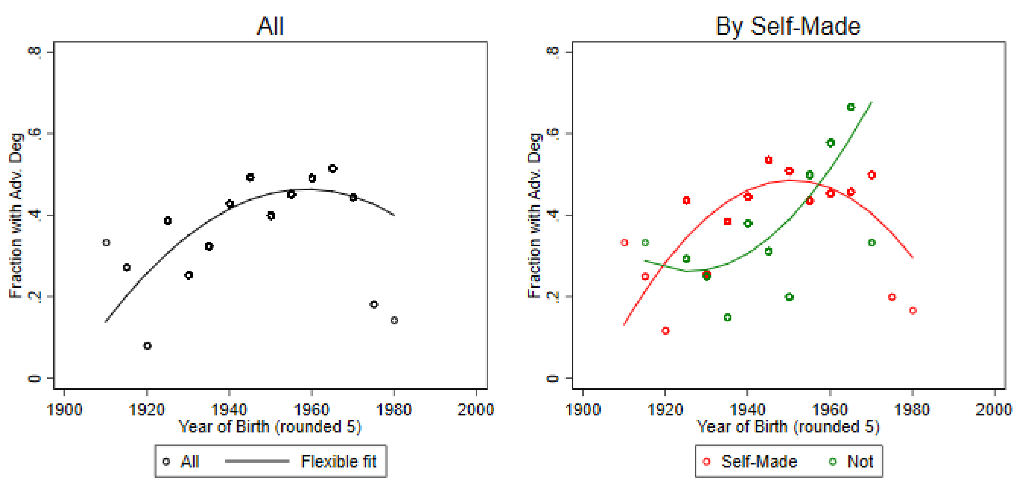


Figure 9: Year of Birth and Advanced Degrees



Note: Flexible fit - best-fitting fractional polynomial after estimating many functional forms for y = g(x), where the powers of g(x) are searched in the range (-2, -1, -.5, 0, .5, 1, 2, 3).

Figure 10: Average Age over Time

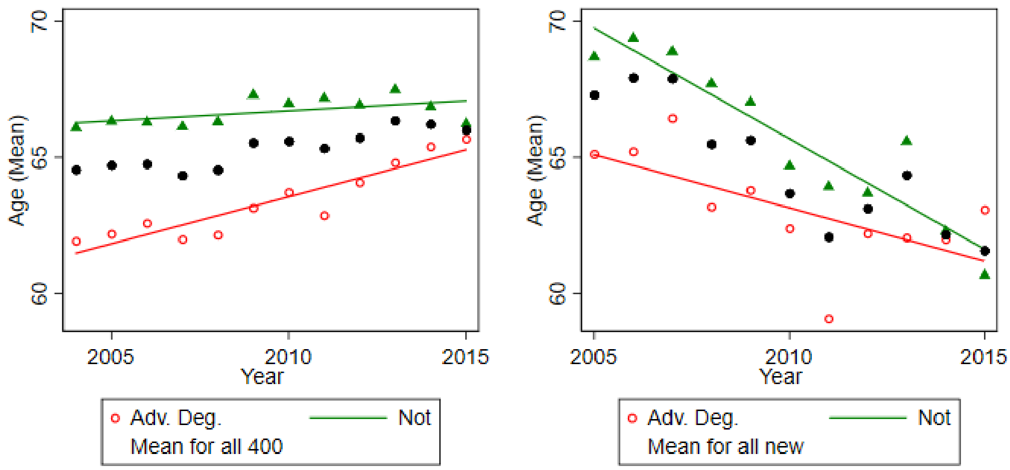
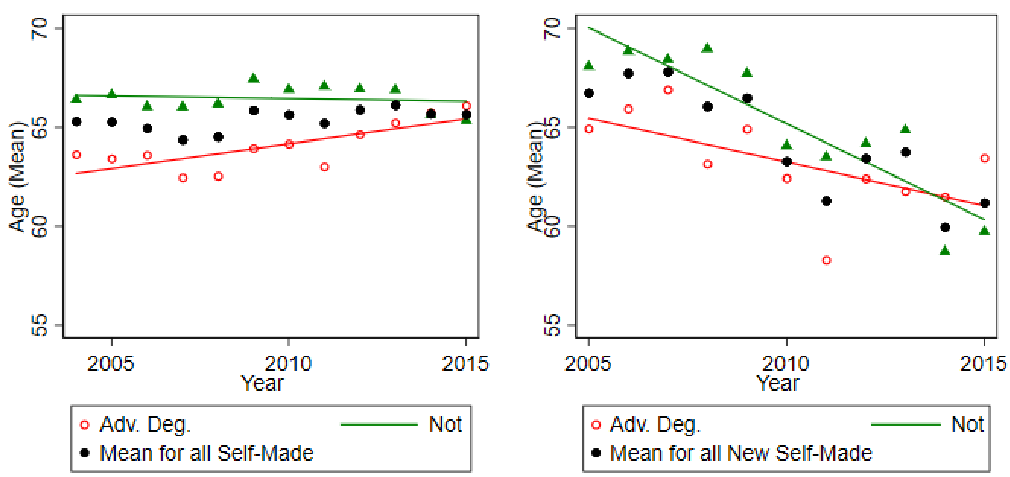


Figure 11: Average Age of the Self-Made over Time



3 Mobility: Entry and Exit

In this section, we analyze mobility or turnover within the Forbes 400, an issue explored by Arnott et al. (2015) in a somewhat different manner. While we have annual data, it is easier to observe noticeable changes at periods longer than a year, so we divide our sample into two periods, from 2004 to 2009, and 2009 to 2015. Thus, the two sub-periods are slightly unequal in length. The first sub-period includes the years up to and including the financial crisis, while the second period is one of slow recovery from the crisis. Our division of the sample period allows us to examine possible business cycle effects in the process of turnover among the Forbes 400.

3.1 New Entrants

Figure 12 provides different views of trends with respect to annual new entrants into the Forbes 400 over the sample period. In the top panels, the left hand plot displays the fraction of the Forbes 400 who are new entrants for each year. These vary considerably from one year to the next, but the fitted lines on either side of 2009 suggest that entry goes down after the financial crisis. The right-hand panel displays the proportion of the wealth of the Forbes 400 that is held by new entrants. This is smaller than the fraction of the 400 who are new entrants because, on average, the new entrants are less wealthy than the rest. The fraction of wealth does not seem to vary as much as the number of individuals.

The middle panels compare new entrants with and without advanced degrees. Interestingly, after the financial crisis, the number of new entrants with advanced degrees trends down, while the number without advanced degrees does not display this trend.

The bottom left panel plots the mean wealth for new entrants with and without advanced degrees. The mean wealth of the former group is always lower than the mean wealth of the latter group. The right hand panel displays the same patterns, but in this case for the per person average proportion of total wealth in each group.

Table 3 extends the breakdown of new entrants to examine whether they are self-made or not. Numbers are reported for each year. Most new entrants are self-made, but this is especially true of the boom years earlier in the sample period. In parallel, the number of self-made also increases in these boom years.

3.2 Turnover

Table 4 shows the pattern of turnover within the entire Forbes 400 for both the two chosen sub-periods (2004-09 and 2009-15). The data are aggregated by quartile, so that we capture movement between quartiles, as well as entry into and exit from the Forbes 400. Quartile 1 represents the richest quarter of individuals, quartile 2 the next richest group, and so on. The numbers do not equal 100 for each quartile because of ties in estimated wealth, and there are

Table 3: Number of New Entrants and Self-Made

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
New only	7	5	6	4	5	9	1	9	11	7	11
Self-Made only	214	224	217	236	237	244	255	255	253	255	253
Both	36	36	51	34	35	30	25	25	20	24	23
Neither	129	123	117	118	113	110	113	107	110	109	108
Total	386	388	391	392	390	393	394	396	394	395	395

also some missing observations, because we have omitted those for whom we do not have education data. The table can be read as follows. There are 383 individuals included in 2004 (505 minus 122 who are not in the 2004 list). Out of these, 115 were no longer in the list in 2009 (the sum of the first column): 20 of them because of death. Out of the 101 in the top quartile in 2004, 67 remained in that quartile in 2009. A total of 16 individuals dropped out of the list entirely, over the five year period. On the other hand, as one would expect, erosion was much higher at the lower end of the distribution: 50 out of 77 in the bottom quartile in 2004 had dropped out in 2009. Of the 107 individuals in the top quartile in 2009, 17 were new entrants. The numbers of new entrants were much higher in the other three quartiles (27, 43, 35). We can also observe movement within the list. Thus, 14 people went from the top quartile in 2004 to the second quartile in 2009, whereas 17 people made the reverse move between these years, climbing from quartile 2 to the top quartile. If we look at the bottom half of Table 2, we can see similar patterns for the second sub-period, from 2009 to 2015.

Table 5 presents the data in an identical format, but restricted to individuals with advanced degrees. In 2004, 142 (202 minus 60 in the final column) of the 383 individuals included in Table 4 had advanced degrees. The number with advanced degrees in 2009 was somewhat higher, at 164 (202 minus 38). There was a net increase of 22 in the number of individuals with advanced degrees in the Forbes 400 list, with 60 entering and 38 leaving. Since 3 exits were due to death, if we exclude these from the exit count, there was a net increase of 25 individuals with advanced degrees. This pattern was not replicated in the second sub-period, after the financial crisis. There was a net decrease of 3 in the later period: 42 individuals entering and 45 leaving (6 due to death, implying a net increase of 3 excluding those cases)the list between 2009 and 2015. The numbers who dropped out because of death were relatively small, so most of the turnover was from other causes.

In Table 6, we present the same data for the remainder of the list, those without an advanced degree. This designation therefore lumps together college graduates and those without college degrees. We can see that among this subset, there is very small net addition in the first sub-period of 2 people, if deaths are excluded (62 minus 77, adjusted for 17 deaths). But in the second sub period there is an appreciable addition of 35 (82 minus 74, adjusted for 27 deaths).

Comparing the groups with and without advanced degrees, the patterns of turnover are

Table 4: Transition Matrix, All Individuals

	Quartile in 2009					
Quartile in 2004	Not in the list	1	2	3	4	Total
Not in the list	0	17	27	43	35	122
1	16	67	14	2	2	101
2	14	17	27	29	10	97
3	35	2	16	29	26	108
4	50	4	8	8	7	77
Total	115	107	92	111	80	505
	Quartile in 2015					
Quartile in 2009	Not in the list	1	2	3	4	Total
Not in the list	0	12	31	35	46	124
1	14	73	11	9	0	107
2	14	13	27	27	11	92
3	38	6	20	24	23	111
4	53	1	6	7	13	80
Total	119	105	95	102	93	514

Between 2005 and 2009, 20 were dropped from the list after their death.
Between 2009 and 2015, 33 were dropped from the list after their death.

fairly similar for each of the two sub-periods. However, the proportion dropping out due to death is quite a bit higher among those without advanced degrees.

The most notable feature of the comparisons across level of education for each sub-period is that the period 2004-09 is different, because the number of individuals with advanced degrees increases over those years. But whether this is a transitory phenomenon, or a specific feature of the business cycle of that time, or something that reflects underlying trends in the relationship between higher education and extreme wealth (extending Kaplan and Rauhs observations) cannot be determined with this sample. These possibilities certainly deserve further investigation.

Table 5: Transition Matrix, Individuals with Advanced Degrees

		Quartile in 2009				
Quartile in 2004	Not in the list	1	2	3	4	Total
Not in the list	0	8	15	20	17	60
1	5	26	3	2	1	37
2	5	9	10	12	6	42
3	10	1	6	9	8	34
4	18	1	5	3	2	29
Total	38	45	39	46	34	202
		Quartile in 2015				
Quartile in 2009	Not in the list	1	2	3	4	Total
Not in the list	0	3	9	16	14	42
1	3	33	6	3	0	45
2	7	7	6	13	6	39
3	13	3	7	12	11	46
4	22	1	2	3	6	34
Total	45	47	30	47	37	206

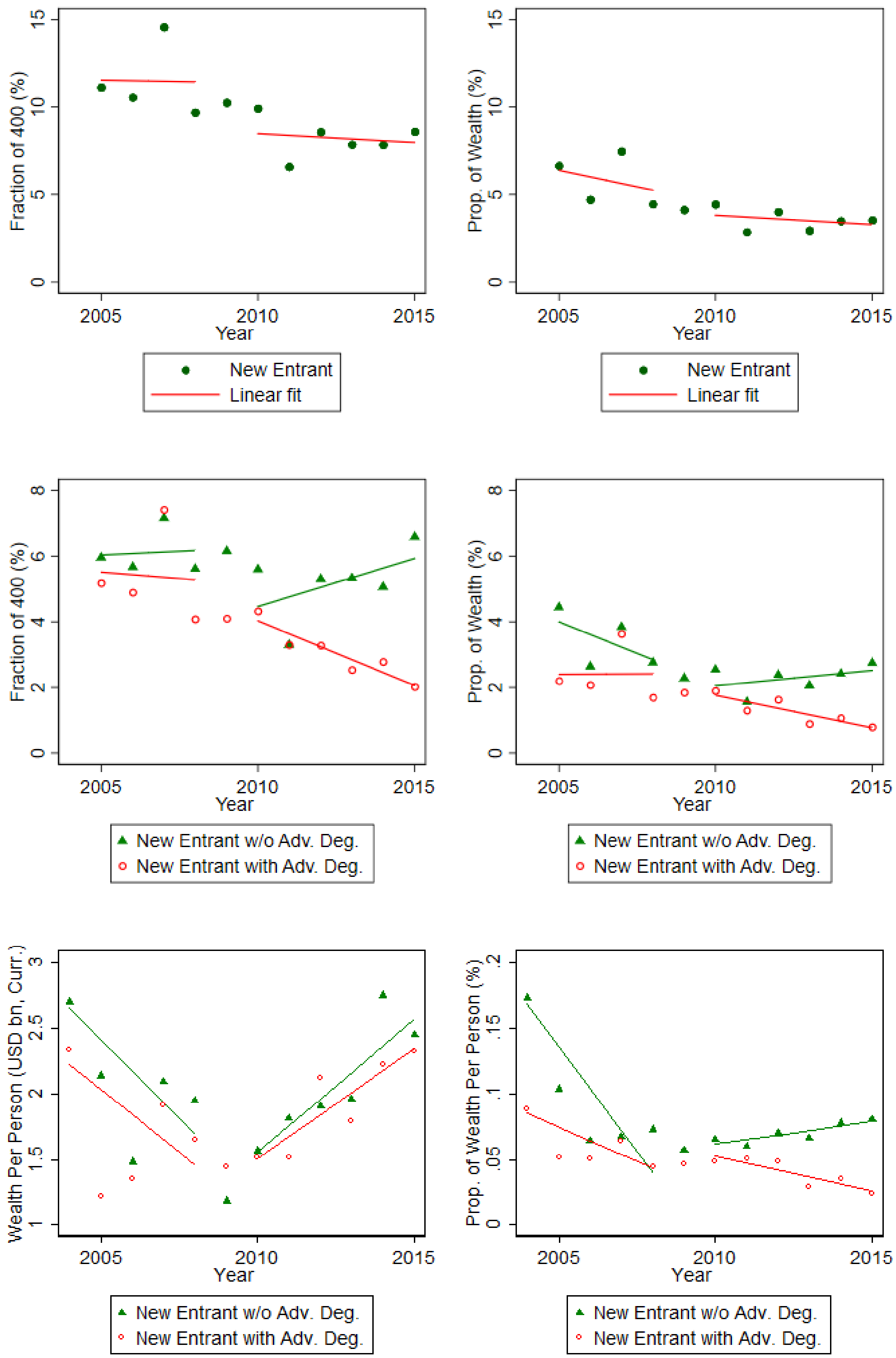
Between 2005 and 2009, 3 were dropped from the list after their death.
Between 2009 and 2015, 6 were dropped from the list after their death.

Table 6: Transition Matrix, Individuals without Advanced Degrees

		Quartile in 2009				
Quartile in 2004	Not in the list	1	2	3	4	Total
Not in the list	0	9	12	23	18	62
1	11	41	11	0	1	64
2	9	8	17	17	4	55
3	25	1	10	20	18	74
4	32	3	3	5	5	48
Total	77	62	53	65	46	303
		Quartile in 2015				
Quartile in 2009	Not in the list	1	2	3	4	Total
Not in the list	0	9	22	19	32	82
1	11	40	5	6	0	62
2	7	6	21	14	5	53
3	25	3	13	12	12	65
4	31	0	4	4	7	46
Total	74	58	65	55	56	308

Between 2005 and 2009, 17 were dropped from the list after their death.
Between 2009 and 2015, 27 were dropped from the list after their death.

Figure 12: New Entrants over Time



3.3 Keeping Wealth: Mobility Regressions

Table 7 presents the results of regressions to test the hypothesis that persistence in the list is related to having an advanced degree or being self-made.

In the first two columns, the observations are the 696 unique individuals, for whom we have education data. The dependent variable is the number of times each individual appears on the list in the 12 year period 2004-2015. The right hand side variable of interest is a dummy variable for whether the individual has an advanced degree. Column 1 reports the results of a simple regression, while column 2 controls for age as well as sector and year fixed effects. In either case, those who have advanced degrees appear significantly more often than those who do not, while self-made individuals appear less often.

In the next two columns the dependent variable is the probability of persisting in the list after being in it the previous year. In all these regressions we account for persons who have been dropped from the list after their death by including a dummy for being deceased as an explanatory variable.

Specifically, in columns 3 and 4, if a person was on the list in 2004, and is still the list in 2005, *Stay* assumes the value 1 for 2005. If the person is not on the list any more, *Stay* takes the value 0. If a person was not on the list in the previous year, the value is unassigned. The variable *Stay* cannot be estimated for the year 2004.[8]

In columns 5 and 6, we present a test of the hypothesis that the self-made or persons with advanced degrees improved their ranks more than their counterparts without advanced degrees. The dependent variable is a dummy for improvement of rank, which we explain with an example. Suppose a person appears in the list in the previous year, say 2004 at a rank say 100. If in the next year, 2005, their rank is below 100 the dummy takes the value 1. If they stay at the same rank or drop below 100 or drop out, the dummy takes the value 0. If a person is not in the list in the initial year (2004 in our example), the value for the dummy is unassigned or 'missing'. Like *Stay*, we can only estimate this variable for the years 2005-2015.

Since the dependent variables for these regressions are dummy variables we estimate panel probit models with random effects. While persons with advanced degrees are significantly more likely to appear on the list over the period of twelve years (columns 1 and 2), when examined year-by-year, columns 3-6 show that the difference is not significant at the 5% level. However, individuals with advanced degrees are more likely to improve their rank within the list than their counterparts without advanced degrees. Regarding those who are self-made, columns 3 and 4 confirm, as columns 1 and 2 suggested, that year after year being self-made is associated with less persistence. However, those that do persist in the list, rise up the ranks faster than those who are not self-made, thus being self-made is associated with improvements of rank over time.

[8]Thus, the number of observation in the estimation panel is smaller than in the entire panel.

Table 7: Persistence in the Forbes 400

	(1)	(2)	(3)	(4)	(5)	(6)
	No. Times in the List		Pr(Stay)		Pr(Rank Improves)	
Adv. Deg.	0.913**	0.846*	0.136	0.123	0.0745^{+}	0.0850*
	(0.323)	(0.334)	(0.0877)	(0.0901)	(0.0419)	(0.0422)
Self-Made	-1.012**	-0.965**	-0.404***	-0.393***	0.131**	0.141**
	(0.348)	(0.368)	(0.0958)	(0.101)	(0.0449)	(0.0465)
Deceased			-0.407*	-0.524**	-0.148^{+}	0.0121
			(0.160)	(0.168)	(0.0871)	(0.0884)
Year of Birth		Y		Y		Y
Sector-effect		Y		Y		Y
Year-effect				Y		Y
Observations	696	696	4716	4716	4716	4716

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The results in column 1 - 2 are from OLS.

The dependent variable for regressions in column 1 and 2: No of times the person appears in the list in the period 2004-15.

The results in column 3 - 6, are from a random-effects panel probit regression.

Column 3 and 4: The dependent variable is likelihood of staying in the list after being on it last year.

Column 5 and 6: The dependent variable is likelihood of rising up the ranks after appearing in it last year.

4 Wealth Dynamics

In this section, we study the short run dynamics of the wealth of the members of the Forbes 400 through panel regressions, controlling for characteristics of the individuals and the economic environment, and thereby formalizing some of the data analysis earlier in the paper. We begin by describing the general econometric approach to the problem. Then we present the basic regression results. Next, we extend the analysis to take account of possible estimation biases due to truncation, since some individuals drop out of the sample in particular years because they no longer meet the ranking criterion for inclusion. Finally, we consider specific sectors in isolation, to examine how different parts of the economy display different dynamics of wealth within this sample.

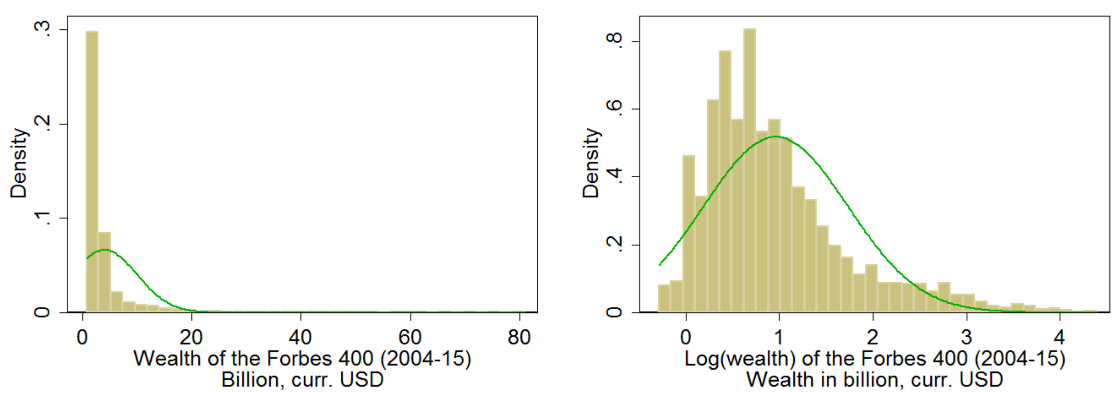
4.1 Econometric Modeling Approach

As usual, the subscript i will indicate an individual and t the year. For example, W_{it} is wealth of one person in a particular year, say, the wealth of Bill Gates in 2008. Lower case, w_{it}, represents the log of wealth. Information about whether a person is self-made, or their education level, does not change over time, so we drop t in such cases, Self-Made$_i$ and Adv. Deg$_i$.

The figure 13 shows the distribution of wealth (W_{it}), which is very skewed, as noted earlier, and the log of wealth (w_{it}). We will use the log transformation as the dependent variable for the rest of the analysis.

Figure 13: Distribution of the Variables Wealth and log(Wealth), 2004-15

Smooth line is the normal distribution with same mean and deviation, for comparison



Let us say that wealth depends on an array of independent variables X_{it}, including individual characteristics and indicators of economic conditions. In a panel of data, wealth in one period will be heavily dependent on wealth in the previous period, as in the following equation:

$$w_{it} = \beta_0 + \beta_1 w_{it-1} + \beta_2 X_{it} + u_{it} \tag{1}$$

However, it is more useful to estimate the equation in terms of the change in log wealth, which is the growth rate of wealth:

$$\Delta w_{it} = \beta_0 + \beta_1 w_{it-1} + \beta_2 X_{it} + u_{it}. \tag{2}$$

If we divide the variables X_{it} into those that are time-invariant – such as being self-made, having advanced degrees, and sector – and those that are not, the above model can be rewritten:

$$\Delta w_{it} = \beta_0 + \beta_1 U_i + \beta_2 V_{it} + u_{it}. \tag{3}$$

Generally, two kinds of methods are employed to estimate such a model, depending on the assumptions: random-effects or fixed-effects (Wooldridge 2010).

Random-effects models assume that there are no individual related-effects in the panel, and that all the unobserved characteristics are unrelated to the error term. In our case, this assumption is likely to be violated: individuals have many characteristics that contribute to wealth generation, other than the ones we can measure.

If there is a clear case for time-invariant individual effects in the panel, we can employ fixed-effect methods, in which we essentially remove the time-invariant individual fixed effects. This can be done by taking first differences, or alternatively by demeaning all the variables (Arellano and Bond 1991). Subtracting the mean removes the time-invariant individual fixed effects, so we will not be able to estimate the effect of time-invariant characteristics such as having advanced degrees or being self-made.

There are, however, some hybrid models[9] such as one proposed by Allison (2009) for estimating the within-effects in the random-effects model. These could be suitable for our analysis, other than the complication that we have time-persistence in our model. However, one can modify these methods to deal with that complication.

In the hybrid method proposed by Allison, we can decompose the time-varying variables into two parts: $V_{it} - \overline{V_i}$ and $\overline{V_i}$. Our model 3 can then be rewritten as:

$$\begin{aligned}
& \Delta w_{it} && = \beta_0 + \beta_1 U_i + \beta_2 (V_{it} - \overline{V_i}) + \beta_3 \overline{V_i} + u_{it}. \\
\Longrightarrow \quad & \Delta w_{it} && = \beta_0 + \beta_1 U_i + \beta_2 V_{it} + (\beta_3 - \beta_2) \overline{V_i} + u_{it}. \\
\Longrightarrow \quad & \Delta w_{it} && = \beta_0 + \beta_1 U_i + \beta_2 V_{it} + \beta_4 \overline{V_i} + u_{it}.
\end{aligned}$$

For implementation, we would include the means of time-varying terms for each individual as explanatory variables on the right-hand side and estimate this model with the random-effects assumption:

$$\Delta w_{it} = \beta_0 + \beta_1' U_i' + \beta_2 V_{it} + u_{it}. \tag{4}$$

Where, $U_i' = U_i + \overline{V_i}$.

[9] These are summarized by Schunck (2013).

A further issue is that the panel data has AR(1) errors, and lagged wealth is an explanatory variable, so the random-effects assumption that the error term u_{it} is uncorrelated with unobserved individual fixed-effects does not hold. To overcome this problem we implement the hybrid model through a two stage method proposed by Kripfganz and Schwarz (2013).[10] Very briefly, one estimates the GMM coefficients of the time-varying variables at the first stage. At the second stage, residuals from the first-stage analysis are used to estimate the coefficients of the time-invariant variables, with corrected standard errors.

4.2 Estimation Results

The results of the different regressions are displayed in Table 8. In each case, the dependent variable is the growth rate of wealth, measured as the difference of log wealth. In all the methods, the coefficient of lagged wealth is negative, indicating some wealth convergence. However, in the random effects and sequential Kripfganz-Schwarz methods, the magnitude of the coefficient is much smaller, and seems more plausible empirically. In general, as one would expect, the results for the random effects and hybrid models are closer to those of our preferred method, the two-stage or sequential K-S method, than the fixed effect estimates.

In all cases, the estimates display a strong business cycle effect, in that the GDP growth rate has a large and significant effect on the growth rate of wealth. Indeed, a one percentage point increase in the GDP growth rate translates into over 3 percentage points of growth in the wealth of those in the Forbes 400. At the aggregate economy level, this should not be surprising, although we will observe differences across sectors in disaggregated estimations in section 4.4.

There are some additional differences in the period before the onset of the financial crisis. Focusing on the results of the sequential K-S method, in column 4, the dummy associated with the pre-crisis period is negative, but interactions of this dummy with indicators for being self-made and having an advanced degree both have positive coefficients, which are also similar in magnitude, and together outweigh the negative coefficient on the pre-crisis dummy variable. In other words, this was a period in which individuals with these two characteristics were doing better in terms of growth in wealth than their counterparts without advanced degrees or those who were not self-made. However, the results for the second stage, in which time-invariant effects are estimated, show that the positive impact of being self-made on the growth of wealth continued after 2008, albeit at a much lower level than in the pre-crisis period, while the impact of having an advanced degrees no longer was perceptible.

[10] The implementation is done in the package STATA, using the command xtseqreg developed by Kripfganz.

Table 8: Growth in Wealth Full Panel Estimation Results

	(1) Fixed Effects	(2) Random Effects	(3) Hybrid	(4) Sequential K-S Method
First-stage	Dependent variable is Log(Wealth)_t - Log(Wealth)_{t-1}			
Method	GLS	GLS	GLS	GMM
Log(Wealth)_{t-1}	-0.389***	-0.036***	-0.280***	-0.023***
	(0.018)	(0.005)	(0.015)	(0.005)
Before 2008	0.214***	-0.023	-0.049***	-0.037***
	(0.020)	(0.014)	(0.015)	(0.013)
Before 2008 × Self-made	0.016	0.022	0.028	0.040***
	(0.020)	(0.016)	(0.018)	(0.014)
Before 2008 × Advanced	0.007	0.041**	0.016	0.041**
	(0.021)	(0.018)	(0.019)	(0.016)
GDP growth rate	0.123	3.603***	3.018***	3.688***
	(0.256)	(0.220)	(0.211)	(0.220)
Self-made	0.000	0.016*	0.060***	
	(.)	(0.009)	(0.014)	
Advanced	0.000	-0.002	0.010	
	(.)	(0.008)	(0.013)	
Age	0.047***	-0.005	-0.003	-0.004
	(0.008)	(0.004)	(0.003)	(0.004)
Age^2	-0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Mean of Log(Wealth)_{t-1}			0.299***	
			(0.016)	
Mean of Before 2008			-0.027	
			(0.040)	
Mean of Before 2008 × Self-made			-0.132***	
			(0.041)	
Mean of Before 2008 × Advanced			-0.007	
			(0.040)	
Mean of GDP growth rate			2.321**	
			(0.995)	
Constant	-2.502***	1.382***	0.806	0.128
	(0.293)	(0.482)	(0.506)	(0.123)
Second-stage	Dependent variable is residuals from the previous stage			
Method				GLS
Self-made				0.013**
				(0.006)
Advanced				-0.001
				(0.006)
Constant				0.011
				(0.012)
Sector-fixed effects	Yes	Yes	Yes	Yes
Observations	3900	3900	3900	3900

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.3 Dealing with Truncation

We also estimate a modified version of the two-stage Kripfganz method, which deals with the truncation issue arising from the data being restricted to the 400 wealthiest individuals in each year. Truncation leads to a potential selection bias, which is dealt with by methods that can be traced back to Heckman (1979), involving estimation of inverse Mills ratios to capture the effect of the selection bias. Of course, the original methodology was for simple cross-sections, and dynamic panel data requires considerably more sophisticated estimation. We follow Semykina and Wooldridge (2010),[11] who provide a method for estimation of the part of the error that is allowed to be systematically correlated with selection in a dynamic panel with endogenous explanatory variables. With some simplifying assumptions, the result of these correlations can be obtained and included in the primary equation to give consistent estimates of the primary regression coefficients. These extra terms are the inverse Mills ratios.

Here, our innovation is to combine the methods of Semykina and Wooldridge (2010) and Kripfganz and Schwarz (2013). First we estimate the inverse Mills ratios following the technique of Semykina and Wooldridge (2010), and then we use these inverse Mills ratios as an explanatory variable along with the other variables, using the implementation developed by Kripfganz.

The results for the resulting modification of the sequential K-S method are presented in the first column of Table 9. They are very similar to those in column 4 of Table 8, suggesting that the truncation problem is not a serious one. However, we provide further estimates to examine the robustness of the results to possible selection bias due to truncation. Column 2 of Table 9 applies the K-S method, but without the correction for selection, to a sample restricted to individuals who are in the Forbes 400 for each of the 12 years. Hence, there is no issue of individuals dropping out of this sub-sample in some years due to their rank falling below 400. The results are broadly similar to those of the two-stage K-S method, with and without the truncation correction.

Results of a further robustness check are reported in Table 10. Column 1 of the table applies the K-S method to the top 300 of our sample, excluding data for those individuals who remain in the top 400 in some years. Column 2 applies the selection correction to this sub-sample, as was done for the full sample in Column 1 of Table 9. The next two columns use the top 300 individuals, but we now include data for these individuals for years in which their rank is between 301 and 400, since this data is available to us. The idea here is that the truncation issue will be partially attenuated in this data set. Column 3 estimates the regression using the 2-stage K-S method, and column 4 further applies the truncation correction. Comparing across all four columns, we see that the impact of missing data is not severe, and the truncation correction does not change the results appreciably.

[11]That paper also provides a review of various prior analyses of how to tackle selection biases in various situations.

Table 9: Full Panel Estimation Effect of Truncation

	(1)	(2)	(3)
	K-S Modified	K-S	K-S
Panel subset	All	Always in 400	Always in 300
First-stage	Dependent variable is Log(Wealth)$_t$ - Log(Wealth)$_{t-1}$		
Method	GMM		
Log(Wealth)$_{t-1}$	-0.025***	-0.012**	-0.015**
	(0.005)	(0.005)	(0.006)
Before 2008	-0.001	-0.026	-0.045**
	(0.031)	(0.017)	(0.021)
Before 2008 × Self-made	0.037***	0.064***	0.089***
	(0.014)	(0.017)	(0.020)
Before 2008 × Advanced	0.042***	0.065***	0.074***
	(0.016)	(0.017)	(0.020)
GDP growth rate	4.186***	3.480***	3.300***
	(0.729)	(0.269)	(0.316)
Age	-0.005		
	(0.004)		
Age^2	0.000		
	(0.000)		
Constant	0.128	-0.047***	-0.030**
	(0.134)	(0.012)	(0.015)
Inverse Mills Ratios	Yes		
Second-stage	Dependent variable is residuals from the previous stage		
Method	GLS		
Self-made	0.013**	0.006	-0.001
	(0.006)	(0.011)	(0.014)
Advanced	-0.002	-0.001	0.003
	(0.006)	(0.011)	(0.013)
Constant	0.012	0.000	0.000
	(0.011)	(.)	(.)
Sector-fixed effects	Yes	Yes	Yes
Observations	3900	1947	1408

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Restricted Panel Forbes 300

	(1)	(2)	(3)	(4)
	K-S	K-S Mod.	K-S	K-S Mod.
Panel subset	Completely Truncated 300		Partially Truncated 300	
First-stage	Dependent variable is Log(Wealth)$_t$ - Log(Wealth)$_{t-1}$			
Method	GMM			
Log(Wealth)$_{t-1}$	-0.025***	-0.028***	-0.025***	-0.026***
	(0.005)	(0.005)	(0.005)	(0.005)
Before 2008	-0.048***	0.026	-0.036***	-0.014
	(0.015)	(0.037)	(0.013)	(0.026)
Before 2008 × Self-made	0.046***	0.044***	0.041***	0.038***
	(0.016)	(0.015)	(0.015)	(0.015)
Before 2008 × Advanced	0.036**	0.038**	0.041**	0.042***
	(0.017)	(0.017)	(0.016)	(0.016)
GDP growth rate	3.786***	2.873***	3.702***	4.260***
	(0.259)	(0.877)	(0.226)	(0.607)
Age	-0.004	-0.003	-0.004	-0.003
	(0.004)	(0.004)	(0.004)	(0.004)
Age^2	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.111	0.131	0.132	0.068
	(0.136)	(0.140)	(0.127)	(0.138)
Inverse Mills Ratios		Yes		Yes
Second-stage	Dependent variable is residuals from the previous stage			
Method	GLS			
Self-made	0.014**	0.014**	0.014**	0.014**
	(0.007)	(0.007)	(0.006)	(0.006)
Advanced	0.002	0.002	-0.002	-0.002
	(0.006)	(0.006)	(0.006)	(0.006)
Constant	-0.002	-0.002	0.011	0.011
	(0.012)	(0.012)	(0.012)	(0.012)
Sector-fixed effects	Yes	Yes	Yes	Yes
Observations	2985	2985	3768	3768

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.4 Sectoral Results

In this section, we examine how our results change when we restrict attention to sector-specific subsets of the overall Forbes 400. The entire group is spread across more than a dozen sectors (Table 2), so the numbers are relatively small for individual sectors, and there are no obvious cases for further combinations of sectors, beyond what we have done (Technology and Telecom, Healthcare, and Medicine). Therefore, we estimate the model for just the three most highly represented sectors, in terms of numbers of individuals. The results are reported in Table 11.

In none of the three top sectors is there any statistically significant evidence of convergence, since the coefficient of lagged wealth is statistically insignificant, even though it remains negative. In the case of Finance, only the impact of being self-made remains significant, although that is no longer true of any additional pre-2008 effect. The impact of the business cycle, as captured by the coefficient of the GDP growth rate, is positive, but no longer significant when the truncation correction is applied. For Technology and Telecom, the pre-2008 effect of having an advanced degree remains significant, but the impact of GDP growth changes sign when the truncation correction is applied. The case of Diversified Investments, which is not really a sector in the sense of the others, but represents the best description of the source of wealth of individuals in this category, has the most robust results with respect to GDP growth and the pre-2008 impact of having an advanced degree, but the other coefficients are no longer statistically significant.

At this stage, the best we can conclude from these sectoral results may be that wealth dynamics differ across sectors, and additional disaggregated analysis would be helpful. To perform such an analysis, a longer sample might be useful, by making it easier to disentangle longer-term trends (such as might be overwhelming business cycle impacts for Technology and Telecom in our results). On the other hand, longer samples would also introduce more challenges in terms of assumptions of parameter stability.

Table 11: Panel Estimation for Most Represented Sectors

	(1)	(2)	(3)	(4)	(5)	(6)
	K-S	K-S Mod.	K-S	K-S Mod.	K-S	K-S Mod.
Sector	Finance		Tech. & Telecom		Div. Invest.	
First-stage	Dependent variable is Log(Wealth)$_t$ - Log(Wealth)$_{t-1}$					
Method	GMM					
Log(Wealth)$_{t-1}$	-0.008	-0.010	-0.015	-0.014	-0.013	-0.013
	(0.012)	(0.012)	(0.009)	(0.010)	(0.013)	(0.012)
Before 2008	0.019	-0.254	-0.076**	0.201*	-0.015	-0.163
	(0.058)	(0.179)	(0.033)	(0.108)	(0.039)	(0.100)
Before 2008 × Self-made	0.074	0.063	0.005	0.011	0.039	0.047
	(0.053)	(0.054)	(0.036)	(0.033)	(0.045)	(0.045)
Before 2008 × Advanced	-0.025	-0.024	0.072*	0.084**	0.126***	0.122***
	(0.035)	(0.032)	(0.041)	(0.042)	(0.044)	(0.043)
GDP growth rate	2.187***	6.296	4.546***	-2.590*	4.129***	7.305***
	(0.640)	(5.061)	(0.426)	(1.482)	(0.570)	(2.295)
Age	0.002	0.009*	-0.018**	-0.013	0.004	0.015**
	(0.005)	(0.006)	(0.009)	(0.009)	(0.006)	(0.006)
Age^2	-0.000	-0.000*	0.000**	0.000	-0.000	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.010	-0.362	0.513**	0.561**	-0.195	-0.675***
	(0.172)	(0.276)	(0.261)	(0.275)	(0.202)	(0.203)
Inverse Mills Ratios		Yes		Yes		Yes
Second-stage	Dependent variable is residuals from the previous stage					
Method	GLS					
Self-made	0.036*	0.037*	0.025	0.024	0.001	-0.003
	(0.021)	(0.020)	(0.019)	(0.018)	(0.013)	(0.012)
Advanced	-0.013	-0.015	-0.023*	-0.018	0.008	0.007
	(0.017)	(0.016)	(0.013)	(0.013)	(0.010)	(0.010)
Constant	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)
Sector-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	569	569	537	537	510	510

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5 Conclusion

By analyzing a panel of 12 years of annual Forbes 400 data, spanning either side of the financial crisis, we are able to observe some interesting characteristics of the dynamics of membership in this group of the extremely wealthy. In particular, in the boom years leading up to the financial crisis, there was greater mobility in this group, and increased entry by those with advanced degrees and by those who could be characterized as "self-made". Furthermore, having an advanced degree and being self-made also contributed positively to the growth of wealth in this boom period. We find evidence of business cycle effects in the growth of wealth, which should not be surprising, but these are less clear when the analysis is restricted to individuals in particular sectors of the economy. It is possible that other, longer-term trends are being reflected in these differences across sectors.

For the average super-rich individual in the list, over the entire time-span, the rate of growth of wealth was slightly negatively related to the previous year's wealth, implying a mild degree of convergence. While the rate of growth of wealth slowed after 2008, as would be expected, the growth rate of wealth for this group was considerably higher than the GDP growth rate, by a factor of about three. However, the rate of growth of wealth was higher for the self-made relative to their counterparts both before and after 2008, although the lead narrowed after 2008. We also found that the self-made were more likely to improve their ranking within the Forbes 400, conditional on staying in the list.

As noted, for the overall panel we found business cycle effects in terms of the relationship between the GDP growth rate and the growth of wealth for the group, as well as positive boom-year impacts of being self-made and having an advanced degree. However, these results are not always robust to disaggregation by sectors, which suggests that wealth dynamics are quite complex, partly as a result of different sectors having different sensitivity to the business cycle, and partly due to the overlay of longer term trends on short term fluctuations. In particular, the technology and telecom sector differs in these patterns from the finance sector. On the other hand, the group whose wealth is in diversified investments displayed wealth growth patterns more similar to the overall sample. We hope our analysis will point the way to further investigation of these complex dynamics at the very top of the wealth distribution. The dynamics of inequality and its interaction with the growth of non-dynastic, self-made wealth also deserve further investigation over a longer time span.

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