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Worker Diversity and Wage Growth Since 1940

Makenzie Peake and [Guillaume Vandenbroucke](#)

Since 1940 the average worker has become older, more educated, more likely to be a woman, less likely to be White, and slightly less likely to be single. How has this evolution of the average worker affected wage growth, that is, the wage of the average worker? We conduct two sets of experiments: First, we decompose wage growth between a “growth effect” and a “distribution effect.” The former measures the effect of a change in the wage function, associating wages with worker types; the latter measures the effect of the changing distribution of worker types. Both effects contribute significantly to wage growth. Second, we evaluate the contribution of changing marginal distributions of these worker types one at a time: Aging and education enhanced wage growth, while the increased participation of women and non-White workers deterred wage growth—the latter effect being a direct implication of gender and racial wage gaps. (JEL J11, J21, J31)

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1 INTRODUCTION

The wage rate of the typical American worker is the subject of countless discussions in the press and academic circles. Growth of the wage rate is often associated with the performance of the labor market, and when compared with inflation it is an indicator of the purchasing power of workers. In this article, we take a long-run perspective and discuss the evolution of the real U.S. wage rate since 1940.

Figure 1 shows the real wage rate (i.e., labor earnings per hour, or hourly wages) for the average U.S. worker from 1940 to 2015. The average growth is 1.4 percent per year during this period, but it is not constant. The average wage rate slowed down (and even declined) at the start of the 1970s, which corresponds to the so-called “productivity slowdown.” It took two decades before the wage rate reached its 1970 value again. Another decline occurred between 2005 and 2010 and corresponds to the Great Recession. Figure 1 also emphasizes a

Makenzie Peake is a research associate and Guillaume Vandenbroucke is a research officer and economist at the Federal Reserve Bank of St. Louis. This article was originally circulated as “The Evolution of Wages Since 1940.” The authors thank Alexander Monge-Naranjo for useful comments and suggestions.

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Figure 1**Average Hourly Wage Rate**

SOURCE: IPUMS and authors' calculations.

long-lasting stagnation over recent decades: The wage rate more than doubled between 1940 and 1970, whereas in the 40 years after 1970 it increased by only 12 percent.

Our goal is to present a series of exercises to describe wage growth in the United States, or the lack thereof. We use the word “describe” on purpose: We do not seek to “explain” wage growth; that is, our analysis does not indicate causal factors behind changes in the real wage rate. Our motivation stems from the observation that the “average worker” paid the hourly wages represented in Figure 1 is not the same in the 2010s as the average worker in the 1980s or the 1940s. Specifically, we show the extent to which the average worker in the 2010s is older, more educated, more likely to be a woman, less likely to be White, and slightly less likely to be single than the average worker in the 1940s. Therefore, changes in the average hourly wages represented in Figure 1 reflect both changes in the hourly wages of various types of workers and changes in the type composition of workers. We quantify the contributions of these two components of wage growth.

We start with a description of the data in Section 2. We use data on the number of workers by type (i.e., by age, education, sex, race, and marital status), wage income, and hours worked. Our sources are the decennial U.S. Census and the American Community Survey. In Section 3, we present the distribution of worker types and discuss how it has changed over the years. We also present and discuss the evolution of the wage rate for each type of worker.

Our analysis and results are in Section 4. We first decompose wage growth between the contribution of the hourly wages per type and that of the distribution of types (Section 4.1). We call the former the growth effect and the latter the distribution effect. We find that both

effects play a noticeable role at different points in time: The growth effect tends to be the largest component of wage growth during periods of fast economic growth, while the distribution effect is the largest component during periods of slow economic growth. The distribution effect results, in part, from slow-moving demographic trends (e.g., aging) and is, therefore, quite stable over time. We apply the same decomposition to each sex-race subgroup and discuss the growth rate of wages across these subgroups. In Section 4.2 we present a different type of exercise to assess the effects of the changing distribution of worker types along specific margins. We ask, for example, what the evolution of the wage rate would have been if the age distribution of workers had remained at its 1940 values throughout the sample period. We repeat this analysis for the effects of education, sex, race, and marital status, respectively. We find that the increasing proportion of female workers dampened wage growth because women tend to be paid less than men; thus, as the average worker has become more likely to be a woman, average wage growth has been slowing down. Similarly, we find that wage growth has been enhanced as the average worker has become older and more educated and dampened as the average worker has become less likely to be White. The fact that the average worker has become slightly less likely to be single implies slightly higher wage growth.

Our article relates to a vast literature documenting and explaining wage inequality. If there were no inequality, say if men and women were paid exactly the same wages, then the increasing proportion of working women would have no effect on the hourly wages of the average worker. The same argument can be made for age, race, and marital status. Thus, the importance of the changing distribution of worker types for wage growth emanates directly from the presence of wage inequality across these characteristics. The point of our article is to quantify these effects and argue that they are of significance. For the interested reader, see the following (far-from-exhaustive) list of papers on inequality (with references to even more papers): Ben-Porath (1967) provides a theory of wage growth over the life cycle, thereby explaining wage inequality by age. Heckman, Lochner, and Taber (1998), Huggett, Ventura, and Yaron (2006, 2011), and Guvenen and Kuruscu (2010) also use the Ben-Porath model to discuss wage inequality and the college premium. Goldin (1992) analyzes the gender wage gap in earnings. Katz and Murphy (1992), Card and Lemieux (2001), and Bowlus and Robinson (2012) discuss wage differences across education groups. Restuccia and Vandenbroucke (2013) and Daly et al. (2017) discuss wage growth and Black-White inequality in the United States.

2 DATA

The analysis in this article is based on decennial U.S. Census data from 1940 to 2010 and from the American Community Survey (ACS) for the years 2005 and 2015. The data are available from the Minnesota Population Centers Integrated Public Use Microdata Series (IPUMS).¹

The data contain the following information for each individual: year, age, sex, race, employment status (*empstat*), marital status (*marst*), education (*educ*), and wage and salary income (*incwage*). The data also contain information on hours worked: *hrswork2* and *uhrswork*. The variable *hrswork2* corresponds to “hours worked last week.” It is intervalled and available from 1940 to 2000. The variable *uhrswork* corresponds to “usual hours worked per

week.” It is available starting in 1980. We build an hours-worked variable by using the middle point of each interval of hrswork2 from 1940 to 1990. For the years 2000, 2005, 2010, and 2015, we first construct intervals replicating the same intervals as the hrswork2 variable, then take the middle point.

Our analysis is restricted to employed (empstat = 1) individuals. The earnings variable (incwage) reports a person’s total pre-tax wage and salary income for the previous year. Top-coded observations are excluded, as well as observations with \$0 earnings. Earnings are converted to 2019 dollars using the consumer price index.

We create the following categories. For age we consider six groups: 18-24, 25-34, 35-44, 45-54, 55-64, and 65-74 years of age. We index age by $a \in \{1, \dots, 6\}$. For education, we consider six groups: (i) 8th grade or below ($\text{educ} \leq 2$); (ii) 9th to 11th grade ($3 \leq \text{educ} \leq 5$); (iii) 12th grade ($\text{educ} = 6$); (iv) one to three years of college ($7 \leq \text{educ} \leq 9$); (v) four years of college ($\text{educ} = 10$); and (vi) five or more years of college ($\text{educ} = 11$). We index education by $e \in \{1, \dots, 6\}$. For sex we consider two groups: (i) male ($\text{sex} = 1$) and female ($\text{sex} = 2$). We index sex by $s \in \{1, 2\}$. We consider three racial groups: (i) White ($\text{race} = 1$); (ii) Black ($\text{race} = 2$); and (iii) other ($\text{race} > 2$). We index race by $r \in \{1, 2, 3\}$. Finally, for marital status, we consider three groups: (i) married ($\text{marst} = 1, 2$); (ii) separated, divorced, or widowed ($\text{marst} = 3, 4, 5$); and (iii) single ($\text{marst} = 6$).² We index marital status by $m \in \{1, 2, 3\}$.

We use the notation $N_t(a, e, s, r, m)$ to denote the number of workers in year t in a particular age, education, sex, race, and marital status cell. Similarly, we use $E_t(a, e, s, r, m)$ to refer to annual earnings of such workers (in 2019 U.S. dollars) and we use $H_t(a, e, s, r, m)$ to refer to weekly hours. We define hourly earnings, which we refer to simply as wages, as

$$W_t(a, e, s, r, m) = \frac{E_t(a, e, s, r, m)}{50 \times H_t(a, e, s, r, m)}.$$

3 THE DISTRIBUTION OF WORKERS AND WAGES

In this section, for each year, we construct the distribution of worker types and compute the wages of each worker type.

The proportion of workers of type (a, e, s, r, m) in year t is

$$(1) \quad F_t(a, e, s, r, m) = \frac{N_t(a, e, s, r, m)}{\sum_{\{a, e, s, r, m\}} N_t(a, e, s, r, m)}.$$

The marginal distribution of age at date t is

$$(2) \quad A_t(a) = \sum_{\{e, s, r, m\}} F_t(a, e, s, r, m).$$

We compute, similarly, the marginal distribution of education, $E_t(e)$; sex, $S_t(s)$; race, $R_t(r)$, and marital status, $M_t(m)$ (Table 1). Panel A of Figure 2 shows the distribution of workers by age group. Consider, for instance, the proportion of workers 18-24 years of age. The general downward trend is a manifestation of the aging of the U.S. population and its workforce. The

Figure 2

Marginal Distributions

NOTE: Each figure indicates the proportion (in percent) of a particular category of workers in the employed population. The data for these figures are presented in Table 1.

SOURCE: IPUMS and authors' calculations.

Table 1**The Distribution of Workers by Categories (percent)**

Year	Age						Education			
	18-24	25-34	35-44	45-54	55-64	65-74	No HS	HS graduate	Some college	College graduate
1940	19.7	29.8	23.0	16.5	8.5	2.5	65.7	21.1	6.8	6.3
1950	15.1	24.9	22.2	19.6	13.8	4.4	57.0	25.4	9.3	8.2
1960	14.0	23.1	25.3	21.4	13.0	3.2	50.1	29.3	10.7	9.9
1970	17.7	22.3	21.4	21.4	14.1	3.0	36.2	36.8	13.9	13.2
1980	20.4	29.2	20.2	16.5	11.6	2.2	20.9	39.7	20.1	19.4
1990	15.0	29.9	26.4	16.9	9.4	2.3	11.5	33.4	31.0	24.1
2000	13.3	24.3	27.6	22.3	10.2	2.4	9.9	39.3	23.2	27.6
2005	13.0	22.6	25.1	23.7	12.8	2.7	8.8	37.2	24.2	29.8
2010	12.7	22.2	22.6	23.8	15.3	3.3	7.8	33.6	26.6	32.1
2015	13.0	23.1	21.5	21.8	16.4	4.2	7.0	32.6	26.4	34.0

Year	Sex		Race			Marital status		
	Men	Women	White	Black	Other	Married	Separated	Single
1940	72.7	27.3	90.3	9.4	0.3	62.1	6.4	31.5
1950	67.2	32.8	90.0	9.6	0.4	63.6	14.9	21.5
1960	66.8	33.2	89.3	9.9	0.8	73.5	9.8	16.7
1970	61.8	38.2	89.0	9.8	1.2	72.2	10.6	17.2
1980	57.5	42.5	87.6	9.8	2.6	64.4	13.0	22.6
1990	54.5	45.5	83.0	10.1	6.8	61.0	14.4	24.6
2000	53.3	46.7	79.4	10.6	10.0	58.0	16.0	26.0
2005	53.3	46.7	76.7	10.9	12.3	57.8	15.5	26.8
2010	51.8	48.2	76.4	11.1	12.5	54.6	15.7	29.7
2015	52.3	47.7	74.5	11.8	13.7	52.0	15.0	33.0

NOTE: "Other" means neither White nor Black; "Separated" means either separated, divorced, or widowed.

SOURCE: IPUMS and authors' calculations.

interruption in this trend, notably by the peak in 1980, results from the Baby Boom, which implies an abnormal abundance of young workers 18-24 years of age.³ Panel B shows the distribution of workers by educational attainment. The general increase in the educational attainment of the U.S. population implies that the proportion of workers with a college degree increased, while the proportion of workers without a high school degree decreased. Panel C shows that women account for an increasing fraction of workers during this period, reflecting an increase in the labor force participation of women.⁴ Panel D shows that the fraction of

Figure 3

Hourly Wages by Categories of Workers

A. Wage by age

B. Wage by education

C. Wage by sex

D. Wage by race

E. Wage by marital status

NOTE: The data for these figures are presented in Table 2.

SOURCE: IPUMS and authors' calculations.

Table 2**Hourly Wages (2019, USD)**

Year	Age				Education			
	All	18-34	35-54	55-74	No HS	HS graduate	Some college	College graduate
1940	9.2	7.3	11.2	10.5	8.1	9.4	11.7	16.2
1950	12.4	10.9	13.6	12.7	11.1	12.9	14.2	17.5
1960	17.5	14.9	19.2	18.3	15.2	17.3	19.9	26.7
1970	22.0	18.3	25.0	23.0	18.5	20.7	23.1	34.0
1980	20.6	16.8	24.7	23.8	16.8	18.8	20.5	28.7
1990	22.0	17.0	26.2	25.9	14.9	17.9	20.8	32.6
2000	24.3	17.6	28.2	28.4	14.5	18.8	22.3	37.2
2005	24.9	17.5	29.0	29.2	13.8	18.7	22.4	38.1
2010	24.7	16.9	28.7	29.4	13.4	18.1	21.2	37.3
2015	25.5	16.9	29.9	31.1	14.4	18.2	20.8	38.3

Year	Sex		Race			Marital status		
	Men	Women	White	Black	Other	Married	Separated	Single
1940	10.2	6.3	9.7	3.9	5.6	10.6	7.1	6.7
1950	13.8	9.4	12.9	7.6	8.9	13.6	10.1	10.3
1960	20.2	11.9	18.2	10.7	15.0	19.0	13.2	13.1
1970	26.2	15.1	22.7	15.6	20.0	24.1	18.0	15.5
1980	24.8	15.1	21.1	16.9	19.7	23.1	18.9	14.6
1990	25.7	17.6	22.8	18.1	19.1	24.8	20.8	15.8
2000	27.9	20.1	25.2	19.6	21.7	27.6	22.8	17.6
2005	28.3	21.2	26.1	19.8	22.1	28.9	23.4	17.4
2010	27.8	21.4	25.7	20.1	22.9	29.1	23.6	17.1
2015	28.7	22.0	26.6	19.7	24.4	31.1	24.4	17.1

NOTE: "Other" means neither White nor Black; "Separated" means either separated, divorced or widowed.

SOURCE: IPUMS and authors' calculations.

White workers has been declining since 1940, and Panel E shows that the proportion of workers that are single first decreased from 1940 to 1970 and then rose. The main message from Figure 3 is that the average worker has noticeably changed since 1940. To be precise, the average worker is older, more educated, more likely to be a woman, less likely to be White, and slightly less likely to be single.

Figure 3 shows average wages by categories of workers (the percentages of workers are in Table 2). Older workers tend to earn more than younger workers (Panel A), more-educated workers earn more than less-educated workers (Panel B), men earn more than women

(Panel C), White workers earn more than workers of other races, and Black workers earn the least (Panel D). Finally, and perhaps less well known, married workers tend to earn more than single or separated workers (Panel E). Note, in all panels, that the 1970 slowdown was a turning point. Panel A reveals that after 1970 wage growth mostly benefited older workers, while wage growth stagnated for younger workers. Similarly, Panel B reveals that the wages of college-educated workers kept growing after the 1970s, while wages for the least-educated workers stagnated or even decreased. Women's wages appear to have recovered better than men's wages after the 1970s, indicating a closing of the gender wage gap (see Panel C). Black workers' wages did not decrease during the slowdown (see Panel D), unlike wages for other races. In the 2000s, however, Black workers' wages diverge from those of White and other non-White workers. Finally, the gap between single and married workers widens after the 1970s, accelerating in the 2000s.

4 ANALYZING THE EVOLUTION OF WAGES

4.1 The Growth and Distribution Effects

The average hourly wage shown in Figure 1, denoted ω_t , is given by

$$(3) \quad \omega_t = \sum_{a,e,s,r,m} W_t(a,e,s,r,m) F_t(a,e,s,r,m).$$

In this section, we ask how much of the growth in ω_t can be ascribed to changes in $W_t(a,e,s,r,m)$ —the growth effect—and how much can be ascribed to changes in $F_t(a,e,s,r,m)$ —the distribution effect.

To understand our decomposition, it simplifies notations to write ω_t as $\omega_t = T(W_t, F_t)$, where T is the mean operator applied to the function W_t against the distribution F_t . Note the following identities:

$$\begin{aligned} \omega_{t+1} - \omega_t &= T(W_{t+1}, F_{t+1}) - T(W_{t+1}, F_t) + T(W_{t+1}, F_t) - T(W_t, F_t), \\ &= T(W_{t+1}, F_{t+1}) - T(W_t, F_{t+1}) + T(W_t, F_{t+1}) - T(W_t, F_t). \end{aligned}$$

Summing these two lines, rearranging, and dividing by ω_t yields a decomposition of the growth rate of the average hourly wage:

$$(4) \quad \frac{\omega_{t+1} - \omega_t}{\omega_t} = \underbrace{\frac{1}{2\omega_t} \left[\overbrace{\left(T(W_{t+1}, F_{t+1}) - T(W_{t+1}, F_t) \right)}^A + \overbrace{\left(T(W_t, F_{t+1}) - T(W_t, F_t) \right)}^B \right]}_{\text{Distribution effect}} + \underbrace{\frac{1}{2\omega_t} \left[\overbrace{\left(T(W_{t+1}, F_t) - T(W_t, F_t) \right)}^C + \overbrace{\left(T(W_{t+1}, F_{t+1}) - T(W_t, F_{t+1}) \right)}^D \right]}_{\text{Growth effect}}.$$

Figure 4**The Decomposition of Wage Growth**

NOTE: The height of each bar indicates the annualized growth rate of the average wage during the corresponding period. The two colors indicate the contributions of the change in the distribution of workers by types (the distribution effect) and the change in the wage rate given worker types (the growth effect), respectively. The horizontal red line indicates the average growth rate (over the period 1940-2015) of the wage rate of the entire population of workers.

SOURCE: IPUMS and authors' calculations.

In this expression, the term A indicates the change in ω_t that can be ascribed to a change in the distribution of types from F_t to F_{t+1} , holding the wage function (i.e., the wage per type) constant at its date- $t+1$ value. The term B measures the effect of a change in the distribution of types, but this time holding the wage function constant at its date- t value. The average of the two terms A and B constitutes the effect of F , that is, the distribution effect. The same logic applies to the effect of W , that is, the growth effect.

Figure 4 shows our results. The height of each bar indicates the annualized growth rate of ω_t during each period. Note how different wage growth was before and after 1970: The first three decades of the sample period were times of fast wage growth, while the rest were marked by slow wage growth. The negative growth rates during the 1970-80 and 2005-10 periods correspond to the decline in ω_t visible in Figure 1. The two colors indicate the contributions of the change in the distribution of worker types (the distribution effect) and the change in the wage rate given worker types (the growth effect). The main message from Figure 4 is that both effects contribute significantly to the growth rate. During the first three decades, 1940-50, 1950-60, and 1960-70, the distribution effect accounted for 15, 12, and 6 percent of the growth in wages, respectively.⁵ During the periods 1980-90, 1990-2000 and 2000-05, it accounted for 80, 27, and 84 percent, respectively.

Figure 5
The Decomposition of Wage Growth

NOTE: The height of each bar indicates the annualized growth rate of the average wage during the corresponding period. The two colors indicate the contributions of the change in the distribution of workers by types (the distribution effect) and the change in the wage rate given worker types (the growth effect). The horizontal red line indicates the average growth rate (over the period 1940-2015) of the wage rate of the entire population of workers.

SOURCE: IPUMS and authors' calculations.

Table 3**Hourly Wages (2019, USD) and Annualized Rate of Growth (percent) by Sex-Race Subgroup**

A. Hourly wages (2019, USD)						
Year	White men	Black men	Other men	White women	Black women	Other women
1940	10.7	4.6	5.7	6.9	2.7	5.1
1950	14.3	8.7	9.0	9.9	5.8	8.5
1960	21.0	12.6	16.5	12.5	7.9	11.6
1970	27.0	18.2	23.3	15.5	12.6	15.2
1980	25.4	19.0	22.9	15.1	14.8	15.6
1990	26.8	19.6	20.9	17.8	16.7	16.6
2000	29.2	21.1	23.7	20.5	18.3	19.1
2005	29.9	21.3	23.9	21.8	18.6	19.8
2010	29.1	21.3	24.6	21.9	19.1	21.0
2015	30.1	20.8	26.5	22.5	18.8	21.9

B. Annualized rate of growth (percent)						
Years	White men	Black men	Other men	White women	Black women	Other women
1940-50	2.9	6.5	4.5	3.6	7.6	5.1
1950-60	3.8	3.7	6.1	2.3	3.0	3.1
1960-70	2.5	3.7	3.4	2.2	4.7	2.7
1970-80	-0.6	0.4	-0.2	-0.2	1.6	0.3
1980-90	0.5	0.3	-0.9	1.6	1.2	0.6
1990-2000	0.9	0.7	1.2	1.4	0.9	1.4
2000-05	0.5	0.1	0.2	1.2	0.3	0.7
2005-10	-0.5	0.0	0.6	0.1	0.6	1.1
2010-15	0.7	-0.5	1.5	0.6	-0.3	0.9

NOTE: "Other" means neither White nor Black.

SOURCE: IPUMS and authors' calculations.

It is interesting to note that the growth effect is noticeably more variable than the distribution effect. Thus, during a period of strong economic growth, as in the first three decades, the growth effect plays the dominant role. As the economy slows down, however, the distribution effect changes little and, therefore, its contribution becomes relatively more important. This occurs because the growth effect reflects economic conditions likely to change faster than the trends, some of them demographic, underlying the distribution effect. The distribution effect does not reflect only demography, however. The increasing labor force participation of women, for example, resulted from economic considerations (see Greenwood, Seshadri, and Yorukoglu, 2005), but these are likely to be slow-moving changes, hence the relative stability of the distribution effect.

In Figure 5 we present the results of calculations similar to those in Figure 4, for each sex-race subgroup instead of all workers simultaneously. We first compute wages and the distribution of workers by age, education, and marital status for each sex-race subgroup; we then decompose wage growth as described by equation (4). Table 3 reports wages and their annualized growth rates for each subgroup. In the Figure 5 decomposition, the distribution effect, therefore, is the joint effect of education, age, and marital status on a given sex-race subgroup, and a few points emerge. First, the general pattern observed for the average wage (see Figure 4) is repeated in each subgroup. Namely, the contribution of the growth effect is the strongest in periods of fast economic growth. Second, the first part of the sample period—before 1970—was a period of fast wage growth for all and, in particular, for non-White workers: The wage growth of non-White workers equaled or exceeded that of White workers during the 1940-1970 period. Since the wages of non-White workers had been, on average, below those of White workers (see Panel D of Figure 3), this was a period during which wage inequality across races must have decreased. Note also that since the 1970s, White and Black men have not experienced wage growth above 1 percent. The sex-race subgroups experiencing the highest average wage growth since the 1970s is non-Black women: 0.8 percent per year for both White women and women of other races.

The decomposition just described comes with a word of caution: Our assessment of the distribution effect, for instance, comes from holding the wages per worker type constant and computing the effect of changing only the distribution of worker types (equation (4)). We do not know, however, if the distribution of worker types would have changed as it actually did had the wages per type not changed. For instance, would women have entered the labor force as they did if wages had not changed? Would workers have acquired the education they did? Similarly, when we assess the growth effect, we hold the distribution of worker types fixed and change only the wages per type. We do not know if holding the distribution of worker types fixed would have affected the wages per type. Absent a theory of wage determination as well as education choices, labor force participation, etc., we cannot answer these questions. Thus, the results presented in Figure 2 should be viewed as indicative of the respective strengths of the growth and distribution effects, not definite measurements.

4.2 Counterfactual Experiments

The message from Section 4.1 is that changes in F_t played a significant role in the evolution of the average wage rate over the years. But what are the contributions of specific marginal distributions? In this section, we propose a set of counterfactual experiments to answer this question.

We start by computing the distribution of education, sex, race, and marital status conditional on age. We denote this distribution $Q_t^A(e, s, r, m | a)$, which is given by

$$Q_t^A(e, s, r, m | a) = \frac{F_t(a, e, s, r, m)}{A_t(a)}.$$

Similarly, we compute the distribution of age, sex, race, and marital status conditional on education as

$$Q_t^E(a, s, r, m | e) = \frac{F_t(a, e, s, r, m)}{E_t(e)},$$

and likewise for Q_t^S , Q_t^R , and Q_t^M . Recall that the average wage in year t is ω_t (see equation (3)). We now compute the average wage that would have prevailed if the age distribution had remained at its 1940 values:

$$\omega_t^A = \sum_{\{a, e, s, r, m\}} W_t(a, e, s, r, m) A_{1940}(a) Q_t^A(e, s, r, m | a).$$

Note that, by construction,

$$\omega_{1940} = \omega_{1940}^A$$

since $A_{1940}(a) Q_{1940}^A(e, s, r, m | a) = F_{1940}(a, e, s, r, m)$. For any year $t \neq 1940$, the difference between ω_t and ω_t^A is due to the marginal age distribution remaining fixed at its 1940 values in the computation of ω_t^A . Suppose, for instance, that ω_t is above ω_t^A in year $t \neq 1940$. This can be interpreted as a positive effect of the changing age distribution on the average wage in year t : The actual wage ω_t is above ω_t^A because the age distribution is not the same in year t as in 1940.

Figure 6 plots $100 \times (\omega_t / \omega_t^A - 1)$ in Panel A, $100 \times (\omega_t / \omega_t^E - 1)$ in Panel B, etc. In Panel A, the trend in wages is increasing and above 0; that is, the average wage since 1940 has been higher than what it would have been if the age distribution had remained at its 1940 values. This can be understood by noting, as Panel A shows, that older workers tend to earn higher wages than younger workers. Since the working population is on average becoming older, this is a force toward the average wage getting higher. Holding the age distribution fixed from 1940 to 2015 at its 1940 values implies that the average worker remains younger and therefore earns less. Quantitatively the effect is not negligible: If the age distribution was fixed, all else equal, the wage rate of the average worker would have been 9 percent lower in 2015.

As shown in Panel A, notably, from 1960 to 1980 the actual wage, ω_t , tended toward the counterfactual wage, ω_t^A . This is the effect of the Baby Boom: The inflow of an abnormally large number of young workers lowered the average wage. Note also that in 1980 the two wages ω_t and ω_t^A are almost at the same levels as in 1940. Contrary to 1940, however, the equality between ω_t and ω_t^A in 1980 is not by construction. It results because the proportions of young workers were almost the same on these two dates, as shown in Panel A of Figure 3.

Figure 6 plots $100 \times (\omega_t / \omega_t^E - 1)$ in Panel B. The trend in wages is increasing. That is, the average wage since 1940 has been higher than it would have been if the education distribution had remained at its 1940 values. This results because educational attainment has increased over time (see Panel B of Figure 2), and more-educated workers tend to earn more than less-educated workers (see Panel B of Figure 3). In addition, in the counterfactual experiment, more than 60 percent of workers do not have a high school diploma in 2015. (The actual number is less than 10 percent.) Similarly, in the counterfactual, there are fewer high school graduates and college graduates in 2015 than in the data; as a result, the actual average wage in 2015 is 50 percent above the counterfactual.

Figure 6 plots $100 \times (\omega_t / \omega_t^S - 1)$ in Panel C. The trend in wages based on the sex distribution is decreasing; that is, the average wage since 1940 has been lower than what it would have

Figure 6

Counterfactual Experiments

A. Effect of age

B. Effect of education

C. Effect of sex

D. Effect of race

E. Effect of marital status

SOURCE: IPUMS and authors' calculations.

been if the sex distribution of workers had remained at its 1940 values. To understand this, recall that Panel C of Figure 2 shows an increasing proportion of female workers: Slightly over 25 percent of workers were female in 1940, while almost 50 percent were in 2015. Panel C of Figure 3 also shows that female workers receive lower wages than male workers. Thus, in the counterfactual experiment, the average wage is higher than in the data because the average worker in the counterfactual is more likely to be a male and to earn a higher wage. Note that the negative impact the changing sex distribution has on wages decreases after 1980, even though the proportion of female workers is not slowing down. The average wage in 1980 is about 6.5 percent below what it would have been under the counterfactual of a fixed (25 percent) proportion of female workers; by 2010, however, the gap is about 5 percent smaller. Thus, Panel C indicates a closing of the gender wage gap after 1980.

Figure 6 plots $100 \times (\omega_t / \omega_t^R - 1)$ in Panel D. As for the sex distribution, the trend in wages based on race is decreasing; that is, the average wage since 1940 has been lower than what it would have been if the race distribution had remained at its 1940 values. Panel D of Figure 2 shows that the proportion of White workers has fallen from 90 percent in 1940 to just over 70 percent in 2018 and that the proportions of Black workers and workers of other races have increased over the same period. This data, coupled with the data from Panel D of Figure 3 that shows that White workers tend to make the most money of all races, shows the progression of racial diversity in the distribution of workers is consistent with a lower average wage. Holding the race distribution fixed at 1940 implies that the average workers would remain more likely to be White and would earn more. Note, however, that the negative impact of the change in the race distribution has been lessening since the early 2000s.

Lastly, Figure 6 plots $100 \times (\omega_t / \omega_t^M - 1)$ in Panel E. The effect of holding the marital status distribution at its 1940s values is non-monotonic—because changes in the marital status distribution are not monotonic, as Figure 2 reveals. Since married workers tend to have higher wages (Panel E of Figure 3), and since the average worker was more likely to be married in 1970 than in 1940, the effect of the marital status distribution is positive and increasing through 1970. To put it differently, the actual wage was higher than the counterfactual wage because the average counterfactual worker was more likely to be single than the actual average worker between 1940 and 1970. The same logic applies in the opposite direction after 1970: The average worker is becoming more likely to be single—like the average worker in 1940.

The conclusions we draw from Figure 6 are subject to the same qualifications noted for Figures 4 and 5. Take the comparison between ω_t and ω_t^A , for example. We interpret ω_t^A as the wage that would have prevailed if neither the age distribution nor the wage function had changed after 1940. It is, however, possible that the wage function would have changed, that is, that workers of a given type would have been paid differently in a world where the Baby Boom had not occurred. Once again, the results presented in Figure 6 should be viewed as indicative rather than definitive measurements.

5 CONCLUDING REMARKS

We presented an analysis of the average wage rate (labor earnings per hour) from 1940 to 2015. We emphasized that the average worker's characteristics changed significantly during this period, and we proposed simple calculations that are informative about the effects of such changes. Our findings are as follows. First, the growth rate of wages can be decomposed between a "growth effect" and a "distribution effect." The former measures the effect of a change in the wage function that associates wages with worker types; the latter measures the effect of the changing distribution of worker characteristics. We find that both effects contribute significantly to overall wage growth. Second, we evaluate the contributions of different aspects of the changing distribution of worker characteristics. The average worker is (i) older, which contributes to higher wage growth; (ii) more educated, which also contributes to higher wage growth; (iii) less likely to be a man, which contributes to lower wage growth; (iv) less likely to be White, which contributes to lower wage growth; and (v) only slightly less likely to be single, which contributes to slightly higher wage growth.

Our findings should be viewed as indicative rather than definitive measurements—because we assume that the wage function and the distribution of workers are independent objects. In other words, we have neither a theory of wage determination nor a theory of worker characteristics (female labor force participation, educational attainment, etc.). ■

NOTES

- ¹ Steven Ruggles, Katie Genadek, Ronald Goeken, Josiah Grover, and Matthew Sobek. Integrated Public Use Microdata Series: Version 7.0. Minneapolis: University of Minnesota, 2017; <https://doi.org/10.18128/D010.V7.0>.
- ² Single is equivalent to never married.
- ³ The peak of the Baby Boom was in the late 1950s. Thus, by the late 1970s there was an abnormal abundance of workers in their early 20s.
- ⁴ Note that the increased labor force participation of women is not what Panel C shows. Labor force participation includes, by definition, the unemployed. Panel C refers only to employed workers; but an increased rate of participation of women also implies an increased proportion of women among employed individuals.
- ⁵ Take, for example, the 1940-50 decade: ω grew at annual rate of 3.5 percent between 1940 and 1950. The growth effect was 3 percent, and the distribution effect was 0.5 percent. Thus, the contribution of the distribution effect was $0.5/3.5 \approx 15$ percent.

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The College Wealth Divide: Education and Inequality in America, 1956-2016

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Using new long-run microdata, this article studies wealth and income trends of households with a college degree (college households) and without a college degree (noncollege households) in the United States since 1956. We document the emergence of a substantial *college wealth premium* since the 1980s, which is considerably larger than the *college income premium*. Over the past four decades, the wealth of college households has tripled. By contrast, the wealth of noncollege households has barely grown in real terms over the same period. Part of the rising wealth gap can be traced back to systematic portfolio differences between college and noncollege households that give rise to different exposures to asset price changes. Noncollege households have lower exposure to the equity market and have profited much less from the recent surge in the stock market. We also discuss the importance of financial literacy and business ownership for the increase in wealth inequality between college and noncollege households. (JEL I24, E21, D31)

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1 INTRODUCTION

It is a well-documented fact that the college wage premium has increased substantially since the 1980s (see, e.g., Levy and Murnane, 1992; Katz and Autor, 1999; and Goldin and Katz 2007). This trend can be traced back to differences in the growth of the demand for and the supply of college-educated workers that are driven by skill-biased technical change, socio-demographic factors, and institutional features (Card and Lemieux, 2001, and Fortin, 2006). Recent work has begun to analyze the relationship between college education and wealth inequality (Emmons, Kent, and Ricketts, 2018, and Pfeffer, 2018) and demonstrates an increasing association between college education and wealth.

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In this article, we take a long-run perspective on college and noncollege income and wealth over almost the entire post-WWII period. We use a novel household-level dataset, the “SCF+”, which combines the post-1983 Survey of Consumer Finances (SCF) with data from historical surveys going back to 1949. To ensure consistent coding of education groups, our analysis starts in 1956. Kuhn, Schularick, and Steins (forthcoming) have harmonized the data across the historical survey waves. The combined data provide long-run household-level information on income, assets, debt, and demographics. The SCF+ closes an important gap, as high-quality microdata were not previously available over longer time horizons. For instance, the Panel Study of Income Dynamics (PSID), which is one of the most important sources of household-level wealth data in the United States, has included questions on family wealth only since 1984 (see Pfeffer et al., 2016).

Our analysis confirms a strong increase in the college income premium since the early 1980s. The average income of college households has increased by about 50 percent in real terms since then. However, the increase of the college income premium is dwarfed by that of the college wealth premium. The wealth of college households has increased by a factor of three between 1983 and 2016, while that of noncollege households has barely grown at all. A substantial part of the widening of the wealth gap between college and noncollege households is driven by strong wealth gains within the top 10 percent of the wealth distribution. Moreover, the share of noncollege households making it to the top 10 percent of the wealth distribution has declined over time. We also document that households with two college-educated spouses have enjoyed particularly large gains in wealth. However, this trend is not driven by assortative matching, but by the overall growth in college education. Consistent with previous findings of Eika, Mogstad, and Zafar (forthcoming), assortative mating appears to have decreased among college graduates over time.

An important question raised by our findings is why the ratio of college to noncollege wealth has grown so much more than the income gap. The workhorse economic models of wealth accumulation imply tight comovement of income and wealth differences, as income is the sole determinant of wealth. We demonstrate that college and noncollege households exhibit systematic differences not only in the size of their asset holdings, but also in the composition of their portfolios. College households own a higher share of stocks and mutual funds. As a consequence, college and noncollege households are differentially exposed to asset price changes. College households reap disproportionately high capital gains during stock market booms. Importantly, such capital gains are unrelated to income. This is consistent with the decoupling of the evolutions of the college income and college wealth premiums since the 1980s (see also Kuhn, Schularick, and Steins, forthcoming).¹ We also find some indication that business ownership matters for the increase in the college wealth premium, especially since the late 1990s. The fact that the college wealth premium is associated with equity holdings and business ownership may be related to higher levels of financial literacy and entrepreneurial skills among college households. We discuss the role of these factors and their potential to affect wealth via portfolio composition and differential returns.

While this article documents a sharply rising college wealth premium in recent decades, it is important to note that causality can run in both directions. College graduates may hold

more wealth due to their higher educational attainment, but there is also evidence that it is easier to obtain college degrees when coming from a wealthy family. Wealthy families can afford more investment in their offsprings' educational careers. The cost of college has increased considerably since the 1980s, which constitutes an obstacle for children from poorer households (see, e.g., Haveman and Smeeding, 2006). Beyond providing a basis for *inter vivos* transfers, wealth may have an insurance function as a “safety net” (Pfeffer, 2018). In this sense, it can work as a “catalyzer,” facilitating human capital investment in early life. This will typically lead to higher wealth, which may be augmented by gifts and bequests. The process can accumulate across generations, creating a succession of college-educated households with ever more wealth (Pfeffer and Killewald, 2018).² Our SCF+ data consist of repeated cross sections and therefore remain silent on intergenerational wealth links. At the same time, the wealth information in the PSID is less detailed than that in the SCF+, and in particular the coverage of wealth at the top is not comprehensive (Pfeffer et al., 2016). New data sources are needed to address these questions.

The paper begins with a description of the data in Section 2. In Section 3, we present our empirical results. Section 4 focuses on the role of asset prices and business ownership in college wealth growth. Section 5 discusses potential transmission mechanisms, and Section 6 concludes.

2 DATA

Our analysis is based on a newly compiled resource for inequality research, the SCF+. The modern SCF is conducted every three years by the Board of Governors of the Federal Reserve System (see Bricker et al., 2017). It is one of the most widely used datasets for the study of distributional issues in the United States. The modern waves cover the period since 1983. However, a predecessor of the modern surveys was conducted at an annual frequency by the Survey Research Center of the University of Michigan from 1947 to 1971 and again in 1977. Based on the original codebooks, Kuhn, Schularick, and Steins (forthcoming) extract the historical data. They match and harmonize variables across the historic and modern waves to create rich microdata that allow study of the joint distribution of income and wealth, along with key demographic variables, over the period 1949–2016. Bartscher et al. (2019) use the data to examine the post-war U.S. household debt boom. Following these papers, we pool the annual historic waves over three-year windows.

Missing data in the old waves were inferred by using multiple imputation methods such as predictive mean matching (cf. Schenker and Taylor, 1996), and historical data are reweighted to account for nonresponses at the top of the income and wealth distributions. These adjustments are described in detail in Kuhn, Schularick, and Steins (forthcoming). To assure representativeness along socio-demographic dimensions, the data were reweighted to match demographic targets from the U.S. Current Population Survey (CPS) and decennial census. Specifically, the data were post-stratified to match the age structure of the population, the share of households with a Black household head, the share of households whose head has at least obtained some college education, and the homeownership rate.³ For the new waves, the

survey weights and data are the ones provided on the website of the Board of Governors of the Federal Reserve System. The only amendment we made is to post-stratify the original 1983 weights to match the CPS homeownership rate. This is done for better consistency with the modern waves, which match the homeownership rate closely.

The key advantage of the dataset is that it combines rich information on economic and financial data with key socio-demographic variables. Kuhn, Schularick, and Steins (forthcoming) exploit this feature of the data to study another key stratifying dimension of inequality, namely race. They find that income and wealth gaps between Black and White households have hardly narrowed since the pre-civil rights era: The median Black household only had about half the income and one-tenth of the wealth of the median White household. By 2016, the income ratio of the median Black to median White household had increased by only 10 percentage points and the wealth gap had remained almost unchanged. We will abstain from a joint analysis of education and race due to low numbers of observations when slicing the data along both dimensions in the early years.

Total household income in the SCF+ data includes income from wages and salaries, professional practice and self-employment, rental income, interest, dividends, business and farm income, as well as transfer payments. Assets comprise liquid assets (certificates of deposit and checking, saving, call, and money market accounts), housing and other real estate (net of debt), bonds, stocks, mutual funds, corporate and noncorporate equity, and defined-contribution retirement accounts. Total debt sums housing debt on primary residences, car loans, education loans, loans for consumer durables, other nonhousing debt, and credit card debt. Wealth is computed as total assets net of total debt. All monetary variables were transformed to 2016 dollars using the U.S. consumer price index (CPI) for all urban consumers from the Macroeconomic History Database (Jordà, Schularick, and Taylor, 2017). This is also the source for the stock price data used in Section 4.

Figure 1 compares the share of households headed by a college graduate in the SCF+ with data from the CPS, which are available since 1962. For the earlier period, we rely on linearly interpolated data from the decennial census. Throughout the article, college households are households whose head has obtained at least a bachelor's degree. Householders with "some college" are included in the group of noncollege households.⁴ The distinction between households with some college versus a college degree was not made in the earliest surveys, and there are notable differences in the portfolios and incomes of these groups (Table 2). Therefore, we decided to discard the first two three-year windows and let our sample begin with the 1956 window (1954-56).

While a close match to targeted census shares is a good test of the reweighting procedure, it does not necessarily imply that the aggregated microdata match macroeconomic variables. Yet Kuhn, Schularick, and Steins (forthcoming) demonstrate that the SCF+ data closely match aggregate trends in income, wealth, housing, financial and nonfinancial assets, and housing and nonhousing debt. In addition, they demonstrate that the data exhibit a close fit to top income shares from Piketty and Saez (2003) using IRS tax data, and top wealth shares from Piketty and Saez (2003) using IRS data and the capitalization method.

Figure 1**Comparison to Census Data**

NOTE: The figure shows the share of households with a college-educated head in the SCF+ data compared with the shares obtained from the CPS for 1962-2016 and from the U.S. decennial censuses for 1950 and 1960. Intermediate data points were obtained by linear interpolation.

3 SIX DECADES OF COLLEGE INCOME AND WEALTH PREMIA

Going beyond previous research, the SCF+ data allow us to document income and wealth differences between college and noncollege households over the long run. As discussed above, much of the previous literature has focused on wage differences between college and noncollege individuals. Instead of looking at wages at the individual level, we consider total income and wealth at the household level, with a particular focus on the college wealth premium, the ratio of college to noncollege wealth.

3.1 Income and Wealth Growth

Figure 2 shows the development of average household income and wealth for college and noncollege households. The two groups evolved similarly until the 1970s and diverged thereafter. In Figure 2, we normalize the data to 1971 to track the divergence since the 1970s. Figure 2A reveals that income has grown at, by and large, similar rates for both groups until the 1970s. Thereafter, the real income of noncollege households stagnated, while the real income of college households has risen by around 50 percent. In other words, our data confirm a secular rise in the college income premium.

The differential growth of college and noncollege income is considerable, but it is dwarfed by the discrepancy in wealth. As with income, wealth evolved similarly for both groups until the 1970s and stagnated for noncollege households thereafter. The only exception is the period prior to the Financial Crisis of 2007-09, when noncollege households increased their wealth

Figure 2

Wealth and Income Levels

A. Income

B. Wealth

NOTE: The figure shows the average income and average wealth, respectively, of college and noncollege households normalized by each group's level in 1971.

Figure 3

Wealth-to-Income Ratios

NOTE: The figure shows the ratios of average net wealth to average income of college and noncollege households, respectively.

to around 1.5 times its 1971 level. Consistent with the results of Kuhn, Schularick, and Steins (forthcoming), this was mainly due to the short-lived effects of the house price boom in the 2000s. As we document below, housing constitutes a particularly large share of total wealth for noncollege households (see Figure 12). While noncollege households were treading water in terms of wealth, college households have increased their net worth by a factor of three compared with 1971. As average wealth has increased by more than average income for both college and noncollege households, wealth-to-income ratios have expanded as well.⁵ However, the increase has been much larger for college households due to their massive surge in wealth. Their wealth-to-income ratio has roughly doubled, from around 4.4 in 1971 to 8.5 in 2016, as shown in Figure 3. The corresponding growth for noncollege households was only 26 percent, from around 3.7 to 4.7. Figure A2 in the appendix shows that the gap between the two groups is somewhat reduced when excluding pension wealth. Yet the difference still remains substantial: While college households would still have experienced an increase in their average wealth-to-income ratio by a factor of approximately 1.6 (from 4.4 to 7.1) without pensions, noncollege households would not have experienced any increase in wealth relative to income apart from the house-price-boom period prior to 2007.

3.2 Decomposing Wealth Growth

In the next step, we explore wealth growth for three different wealth groups. Within each of these wealth groups, we distinguish between college and noncollege households. In the middle group, which we define as the 50th to 90th percentiles of the wealth distribution, college and noncollege wealth has to comove closely by construction, as it is limited both from below and above. What can change for this group is the shares of college and noncollege households who belong to the group. Figure 4 shows wealth growth for all three wealth groups, stratified by education. It reveals that the widening of the college wealth gap has been pronounced within the top 10 percent of the aggregate wealth distribution, whereas college and noncollege households have evolved similarly within the bottom 50 percent and the middle 50-90 percent.⁶ As Kuhn, Schularick, and Steins (forthcoming) point out, households in the top 10 percent of the aggregate wealth distribution are more heavily invested in equity and business wealth. We will discuss the role of these factors in more detail in Sections 4 and 5. The graphs for the different parts of the aggregate wealth distribution in Figure 5 relate to Figure 2B via the following decomposition:

$$(1) \quad \frac{\bar{W}_{e,t}}{\bar{W}_{e,71}} = \frac{\sum_{i=1}^3 s_{e,i,t} \bar{W}_{e,i,t}}{\bar{W}_{e,71}} = \sum_{i=1}^3 s_{e,i,t} \frac{\bar{W}_{e,i,71}}{\bar{W}_{e,71}} \frac{\bar{W}_{e,i,t}}{\bar{W}_{e,i,71}} \quad e = c, nc.$$

$\bar{W}_{e,t}$ denotes average wealth of education group $e \in \{c, nc\}$ at time t , where c means college and nc means noncollege. The index $i \in \{1, 2, 3\}$ refers to the three groups of the aggregate wealth distribution, and $s_{e,i,t}$ is the share of households in education group e and wealth group i out of all households in education group e at time t . Hence, the widening of the college wealth gap in Figure 2B depends on three factors: initial conditions in the base period, the development of the share $s_{e,i,t}$ over time, and the wealth growth in each education-wealth group depicted

Figure 4**Wealth Growth Along the Wealth Distribution**

NOTE: The figure shows the average wealth growth of college and noncollege households in the bottom 50 percent, middle 50-90 percent, and top 10 percent of the aggregate wealth distribution over time, respectively, relative to 1971.

Figure 5**Wealth Growth Counterfactuals****A. Counterfactuals: College** **B. Counterfactuals: Noncollege**

NOTE: Figure 5A shows three counterfactuals for college households. In Counterfactual 1, college households from the top 10 percent of the aggregate wealth distribution are assigned the average wealth growth of their noncollege counterparts, $\bar{W}_{nc,top10,t}/\bar{W}_{nc,top10,71}$. In Counterfactual 2, the share of college households in each wealth group i is fixed at its 1971 level, $s_{c,i,71}$. Counterfactual 3 combines the previous two counterfactuals. Figure 5B presents the analogous exercise for noncollege households.

Figure 6**Shares Within Education Group**

NOTE: The figure shows the shares of households belonging to the bottom 50 percent, 50-90 percent, and top 10 percent of the aggregate wealth distribution for college households (Figure 6A) and noncollege households (Figure 6B) over time.

in Figure 4, $\frac{\bar{W}_{e,i,t}}{\bar{W}_{e,i,71}}$. Based on this decomposition, Figure 5A presents three counterfactuals.

The first one assigns the average wealth growth of noncollege households in the top 10 percent of the aggregate wealth distribution, $\frac{\bar{W}_{nc,top10,t}}{\bar{W}_{nc,top10,71}}$, to their college counterparts. The second one holds the share of college households in each wealth group i fixed at its 1971 level, $s_{c,i,71}$. The third counterfactual combines the two previous counterfactuals. Figure 5B presents the analogous “converse” counterfactuals for noncollege households. For college households, a substantial part of their wealth growth was driven by faster wealth growth within the top 10 percent of the wealth distribution, whereas compositional effects across wealth groups barely mattered. By contrast, both compositional effects and wealth growth in the top 10 percent played an important role for lower wealth growth of noncollege households.

Surprisingly, at first glance, compositional effects across wealth groups played only a minor role in accounting for aggregate wealth growth. To understand why, Figure 6 shows the shares of households belonging to the bottom 50 percent, the middle 50-90 percent, and the top 10 percent of the aggregate wealth distribution within the group of college households (Figure 6A) and noncollege households (Figure 6B). The finding that compositional changes contribute little to college wealth growth is reflected in the fact that the shares have remained remarkably stable over time. Among college households, on average, around 23 percent belong to the top 10 percent of the aggregate wealth distribution, 45 percent to the middle 50-90 percent, and 32 percent to the bottom 50 percent. We observe only small fluctuations around these averages over time. For noncollege households, the corresponding shares are 6 percent,

Figure 7**Shares of College and Noncollege Households by Wealth Group**

NOTE: The figure shows the shares of college and noncollege households in the entire population and in each group of the aggregate wealth distribution.

38 percent, and 56 percent, but there is a visible trend toward a smaller top 10 percent share and a larger bottom 50 percent share, which is reflected in the results of Figure 5B.

The relative stability of the shares within the group of college households also has important implications for the discussion of education as a means of financial mobility. Our results suggest that obtaining a college degree does not increase the probability of finding oneself in the upper parts of the wealth distribution. A college degree seems to help households to keep pace, but not to climb the wealth ladder.

While Figure 6 slices the data by educational attainment, Figure 7 shows the shares of college and noncollege households within each group of the wealth distribution as well as the full cross section. The overall share of households with a college-educated head has quadrupled

from 8.1 percent in 1956 to 34 percent in 2016. We find that this increase was distributed evenly across wealth groups, so this trend is consistent with Figure 6. Between 1956 and 2016, the college share rose from 5 percent to 21 percent in the bottom 50 percent of the aggregate wealth distribution, from 9.1 percent to 39.5 percent in the middle 50-90 percent, and from 19.8 percent to 76.8 percent in the top 10 percent. In other words, it has roughly quadrupled in each group, implying that obtaining a college degree does not necessarily go hand in hand with mobility toward the top of the wealth distribution. The college share is largest in the top 10 percent of the wealth distribution, but having a college degree is not a sufficient condition to reach the top. It is noteworthy that the increase in average college income and wealth, documented above, has taken place while the group of college households grew larger. Accordingly, the total cake has grown faster than the amount of people sharing it. These developments also imply that college households have appropriated larger and larger shares of total wealth and income over time. While noncollege households still accounted for 78 percent of total wealth and 83 percent of total income in 1956, these shares had fallen to 26 percent and 39 percent, respectively, by 2016. As we show next, the wealth and income advantages are particularly large for households in which both spouses hold a college degree (dual-college households).

3.3 The Role of Marriage Patterns in Wealth and Income Growth

The share of dual-college households has risen over time. Using Census data, previous research has investigated the importance of assortative mating for income inequality (Eika, Mogstad, and Zafar, forthcoming, and Greenwood et al., 2014 and 2015). Positive (negative) assortative mating refers to a situation when people with the same level of education marry more (less) frequently than what would be expected if marriage patterns were random. The existing studies suggest that positive assortative mating helps to explain cross-sectional income inequality, but hardly contributes to changes of income inequality over time. The SCF+ data allow us to shed light on the role of marriage patterns and assortative mating for wealth in addition to income inequality.

The data show that dual-college households have experienced particularly large increases in income and wealth. In Figure 8A, we see that dual-college households have increased their average income by a factor of around two between 1965 and 2016, while income stagnated for households in which both partners hold only a high school diploma and decreased for households in which both spouses have each completed less than 12 years of schooling.⁷ A qualitatively similar but quantitatively even more pronounced picture emerges for wealth in Figure 8B. Dual-college households have more than quadrupled their wealth, while households without any college-educated spouse have experienced very meager wealth growth.

Figure 8C shows that while dual-college households appropriated only 8 percent of all nonsingle households' income in 1965, the share increased to 49.7 percent in 2016.⁸ However, because the population share of this group also increased over that period, from 4.2 percent to 26.4 percent, the income share of dual-college households relative to their population share hardly changed. A similar result pertains to wealth (Figure 8D). In this sense, the increasing share of total income and wealth accruing to (dual-)college households has not been disproportionate.

Figure 8**Average Income and Wealth by Education of Spouses****A. Average income** **B. Average wealth** **C. Income shares (both college)** **D. Wealth shares (both college)**

NOTE: Figure 8A shows average income of households in which *both* partners have less than 12 years of schooling, a high school diploma, or a college degree, respectively, over time. The thick black line depicts average income for all nonsingle (married or living with partner) households. The male partner was defined as the household head. Figure 8B shows analogous results for net wealth. Figure 8C shows the share of total income of nonsingle households appropriated by dual-college households, once in percent (black line, left axis), and once relative to this group's population share (gray dashed line, right axis). Figure 8D shows analogous results for net wealth.

The data also document that dual-college households have appropriated larger shares of income and wealth over time but that this has little to do with assortative mating. Table 1 compares actual marriage patterns with those that would have been observed under random matching based on marginal frequencies. We find that assortative mating has actually *decreased* for college-educated individuals, whereas it has increased for low-educated individuals. Our

Table 1**Marriage Patterns in Selected Years—Actual Data Versus Random Matching**

Head/spouse	Data				Random			Ratio		
	(1)	(2)	(3)	Sum	(1)	(2)	(3)	(1)	(2)	(3)
1965										
<12 Years (1)	36.6	14.6	0.4	51.6	23.5	24.9	3.2	1.6	0.6	0.1
High school (2)	8.6	26.8	1.6	37.0	16.8	17.9	2.3	0.5	1.5	0.7
College (3)	0.3	6.9	4.2	11.4	5.2	5.5	0.7	0.1	1.3	5.9
Sum	45.5	48.3	6.2	100						
1977										
<12 Years (1)	20.2	13.1	0.7	34.0	9.7	19.1	5.3	2.1	0.7	0.1
High school (2)	7.7	32.7	4.7	45.1	12.8	25.3	7.0	0.6	1.3	0.7
College (3)	0.5	10.3	10.2	21.0	6.0	11.8	3.3	0.1	0.9	3.1
Sum	28.4	56.1	15.6	100						
1989										
<12 Years (1)	11.8	10.7	0.7	23.2	4.4	14.4	4.4	2.7	0.7	0.2
High school (2)	6.6	38.9	5.2	50.7	9.6	31.5	9.5	0.7	1.2	0.5
College (3)	0.6	12.5	12.9	26.0	4.9	16.1	4.9	0.1	0.8	2.6
Sum	19.0	62.1	18.8	100						
1998										
<12 Years (1)	6.9	7.6	0.2	14.7	1.7	9.2	3.8	4.0	0.8	0.1
High school (2)	4.3	44.4	7.4	56.1	6.6	35.1	14.5	0.7	1.3	0.5
College (3)	0.5	10.5	18.3	29.3	3.4	18.3	7.6	0.1	0.6	2.4
Sum	11.7	62.5	25.9	100						
2007										
< 12 Years (1)	6.7	6.3	0.3	13.3	1.5	7.8	4.0	4.4	0.8	0.1
High school (2)	4.4	41.0	8.2	53.6	6.1	31.4	16.1	0.7	1.3	0.5
College (3)	0.3	11.2	21.6	33.1	3.8	19.4	10.0	0.1	0.6	2.2
Sum	11.4	58.5	30.1	100						
2016										
<12 Years (1)	5.4	6.1	1.0	12.5	1.2	6.5	4.8	4.5	0.9	0.2
High school (2)	3.8	35.2	11.0	50.0	4.9	26.0	19.2	0.8	1.4	0.6
College (3)	0.5	10.7	26.4	37.6	3.6	19.6	14.4	0.1	0.5	1.8
Sum	9.7	52.0	38.4	100						

NOTE: The table shows the relative size (in percent) of marriage groups defined by education of the head and spouse over time. The reference totals are all nonsingle households (married or living with a partner) with information on the educational attainment of both spouses: (1) means less than 12 years of schooling, (2) means high school diploma, and (3) means a college degree. Rows refer to the head, columns to the spouse. The male partner was defined as the household head. The "Data" columns of the table shows each group's relative size in the data. The "Random" columns show the corresponding shares if matching were random. The "Ratio" columns show the ratio of the shares in the data to the shares that would have been obtained with random matching. The counterfactual was computed from marginal frequencies. Reading example: In 1965, 4.2 percent of households had both a head and spouse with a college degree; 6.2 percent of all spouses and 11.4 percent of all heads had a college degree. The share of dual-college households was 5.9 times as large as it would have been with random matching.

Figure 9**Wealth and Income Ratios: College/Noncollege**

NOTE: The graph shows the ratios of college to noncollege wealth (black line) and income (gray dashed line), respectively, each relative to its level in 1971.

results are both qualitatively and quantitatively consistent with the findings of Eika, Mogstad, and Zafar (forthcoming), who use U.S. data from the March CPS for 1962-2013.⁹ In other words, the fact that we see a larger share of dual-college households nowadays can mainly be attributed to increases in educational attainment, especially among females, rather than changes in preferences and sorting. While there were around 11.4 percent male college graduates in 1965, the share of college graduates among the female partners was only 6.2 percent. The shares increased to 37.6 percent for males and 38.4 percent for females in 2016.

4 PORTFOLIO COMPOSITION AND ENTREPRENEURSHIP

The previous section has presented evidence that college households have improved their wealth position substantially compared with noncollege households, which we referred to as an increase in the college wealth premium. In this section, we investigate potential drivers of this development in more detail.

Figure 9 contrasts the increase in the college wealth with the college income premium.¹⁰ The ratio of college to noncollege income was roughly stable until the late 1970s. The ratio of college to noncollege wealth fluctuated somewhat more over this period but did not show any trending behavior. In the early 1980s, both ratios embarked on a largely uninterrupted upward trend. The only exceptions were the early-1990s recession and the burst of the “dot-com bubble” in 2001. The wealth premium has increased considerably more than the income premium, namely by around 135 percent versus 50 percent for the income premium between 1971 and 2016.

Figure 10**Middle-Class Wealth and Income Levels by Decade**

NOTE: The figure shows average income and wealth, respectively, for college and noncollege households, respectively, from the middle 50-90 percent of the aggregate *income* distribution. Data were averaged across decades and normalized to the 1980s.

The discrepancy in the development of income and wealth becomes even more explicit when we consider only the middle class (50-90 percent) of the *income* distribution and average the data by decade.¹¹ The results are shown in Figure 10. Even for middle-class households who, by construction, had almost identical income paths, the increase of the college wealth premium since the 1980s stands out. While wealth has doubled for college households, noncollege households with the same income trends saw their wealth increasing only by 25 percent. Which role do demographic shifts play for the observed phenomena? So far, we have looked at unconditional averages. To obtain an estimate of the “college wealth effect” net of potential confounders such as demographics, we estimate the following micro-level regression:

$$(2) \quad W_{it} = \beta_0 + \beta_1 c_{it} + \sum_{t > 1956} \beta_{2,t} \mathbb{I}_{[year=t]} \cdot c_{it} + \sum_{t > 1956} \beta_{3,t} \mathbb{I}_{[year=t]} + \Gamma' X_{it} + \xi_{it}.$$

W_{it} denotes wealth of household i in survey wave t , $\mathbb{I}_{[year=t]}$ are survey wave fixed effects for $t = \{1959, 1962, \dots, 2016\}$, and c_{it} is an indicator for whether the head has a college degree. The control vector X_{it} includes total household income, a full set of age dummies, a dummy for whether the household includes children, and an indicator for whether the head is married. As a baseline specification, we estimate this regression on the entire sample. As a robustness check, we also estimate it on a restricted sample that is limited to households in the 50-90 percent group of the aggregate income distribution. This restriction can be interpreted as an additional nonparametric way of controlling for income.

Figure 11 illustrates the results, and the underlying coefficient estimates are summarized in Table B3. The college wealth effect ($\beta_1 + \beta_{2,t}$) is clearly visible from the 1980s on. The figure also illustrates that college wealth tends to be hit more severely in recessions, which tend to reduce the college wealth premium. For the middle-class income sample, the college wealth

Figure 11**Regression Evidence**

NOTE: The graph shows the advantage of having a college degree ($\beta_1 + \beta_2$) over time. The black line refers to the baseline in (2). The dashed line presents the results for a restricted sample including only households from the middle 50-90 percent of the aggregate income distribution. The gray bars indicate recessions as determined by the National Bureau of Economic Research.

effect is smaller in size but still clearly visible since the 1980s. Indeed, the college wealth effect is strongest for the top 10 percent of the income distribution but also visible for the bottom 90 percent (Figure A3 in the appendix). By contrast, the college income effect is much smaller and entirely driven by the top 10 percent of the aggregate income distribution.

4.1 Portfolio Heterogeneity

In workhorse models of wealth inequality following the early work of Huggett (1993) and Aiyagari (1994), wealth growth depends on the amount of savings, so that changes in income inequality translate into changes in wealth inequality. However, it is a well-established fact that wealth inequality exceeds income inequality. Economic theory highlights the role of the life cycle, bequests, entrepreneurship, and differential returns on assets to explain this finding (see, e.g., Cagetti and De Nardi, 2008; De Nardi and Fella, 2017; and Benhabib, Bin, and Luo, 2017). Kuhn, Schularick, and Steins (forthcoming) provide further empirical substance to the important role of differences in portfolio choice and associated returns. They illustrate how differences in household portfolios along the wealth distribution, combined with differential asset price growth, can lead to a “decoupling” of the growth of income and wealth.

The SCF+ data allow us to examine the portfolio composition of households with different educational attainment. Figure 12 illustrates that the average portfolios of college and non-

Figure 12**Portfolio Shares of College and Noncollege Households**

NOTE: Figure 12A shows the portfolio composition of college households. Figure 12B shows the portfolio composition of noncollege households. Housing includes nonresidential real estate. Stocks include mutual fund holdings and other managed assets.

college households do not merely differ in size, but also in composition. In particular, the share of nonfinancial assets is substantially larger for noncollege households. Table B2 in the appendix shows that this high share is mainly accounted for by housing. For instance, the housing portfolio share of noncollege households was 53 percent in 2007, compared with 37.3 percent for college households. By 2016, these shares had slightly decreased to 46.9 percent and 30.9 percent, respectively. By contrast, college households tend to hold larger shares of business wealth and equity than noncollege households.

Kuhn, Schularick, and Steins (forthcoming) show how portfolio differences give rise to differential exposure to asset price changes. In the case of college households, their higher equity portfolio share allowed them to reap higher capital gains due to increasing stock prices over the past 30 years. Figure 13 shows that real equity prices, taken from the Macrohistory Database, have more than tripled since 1989. The figure also illustrates that the increase in stock prices has moved hand in hand with the ratio of college to noncollege equity holdings over this period. As capital gains from asset price changes are unrelated to the development of income, they can help to explain why the college wealth premium has increased substantially more than the college income premium. Indeed, the estimated college wealth advantage is reduced when we control for stock market exposure in our micro regressions (Figure 14). We measure stock price exposure via the portfolio share of equity s^e and the real average

Figure 13**Stock Market Exposure and Equity Prices**

NOTE: The solid line shows the ratio of average college to average noncollege household equity. The dashed line shows the average stock price from the Macrobistory Database, transformed to 2016 dollars. Both series were indexed to 1989. Stocks include mutual fund holdings and other managed assets.

Figure 14**Controlling for Stock Market Exposure**

NOTE: The graph shows the advantage of having a college degree ($\beta_1 + \beta_{2,t}$). The solid line repeats the baseline from (2) as a reference. The short-dashed black line presents the results for regression (3); the dashed gray line presents the results for regression (4); and the long-dashed, light-blue line includes the additional controls from both (3) and (4).

equity price P^e , included in levels, interacted with each other and interacted with college. More precisely, we estimate the following regression:

$$(3) \quad W_{it} = \beta_0 + \beta_1 c_{it} + \sum_{t>1956} \beta_{2,t} \mathbb{I}_{[year=t]} \cdot c_{it} + \sum_{t>1956} \beta_{3,t} \mathbb{I}_{[year=t]} \\ + \beta_4 s_{it}^e + \beta_5 s_{it}^e \cdot c_{it} + \beta_6 s_{it}^e \cdot P_t^e + \beta_7 s_{it}^e \cdot P_t^e \cdot c_{it} + \Gamma' X_{it} + \epsilon_{it}.$$

Figure 14 shows that controlling for stock price exposure reduces the college wealth premium substantially, especially during the stock market booms in the 1960s and since the 1990s. The high correlation of college to noncollege equity growth with stock price growth since the 1990s stock market boom suggests that differential stock market exposure via direct stock and mutual fund holdings played a key role for the rapid increase in the college wealth premium since the 1980s.

4.2 Business Ownership

While stock price exposure can account for an important share of the observed college wealth premium, there still remains an unexplained wealth growth differential between college and noncollege households. In a second step, we explore the role of business ownership for the observed trends. Motivated by the fact that business wealth has gained importance in the portfolio of college households in recent years, and that business assets, just like equity, are an asset class that is primarily held by the top 10 percent of the aggregate wealth distribution (Kuhn, Schularick, and Steins, forthcoming), we look at the effects of controlling for business ownership.

In equation (3), we included the portfolio share of equity and mutual funds. Fangereng et al. (2018) point out that entrepreneurial skills may affect the whole portfolio via differential returns. Therefore, we include a more general dummy for business ownership, bus_{it} , instead of the portfolio share of business wealth in this specification. Since there is no general market price for business assets, we interacted the dummy with year fixed effects to allow for variation across time. Apart from these slight changes, the specification follows that in equation (3)

$$(4) \quad W_{it} = \beta_0 + \beta_1 c_{it} + \sum_{t>1956} \beta_{2,t} \mathbb{I}_{[year=t]} \cdot c_{it} + \sum_{t>1956} \beta_{3,t} \mathbb{I}_{[year=t]} + \beta_4 bus_{it} + \beta_5 bus_{it} \cdot c_{it} + \\ \sum_{t>1956} \beta_{6,t} \mathbb{I}_{[year=t]} \cdot bus_{it} + \sum_{t>1956} \beta_{7,t} \mathbb{I}_{[year=t]} \cdot bus_{it} \cdot c_{it} + \Gamma' X_{it} + \epsilon_{it}.$$

The dashed gray line (+ Bus. ownership) in Figure 14 shows the resulting coefficients β_1 and $\beta_{2,t}$. Moreover, we estimate a specification of the regression in which we include the additional controls from (3) and (4) jointly. This specification is shown as the long-dashed, light-blue line (+ Stock exposure & bus. ownership) in Figure 14. The estimations suggest that also business ownership has contributed to the increase in the college wealth premium. Yet our regressions only show conditional correlations and cannot lay claim to causality. In the following section, we discuss potential underlying mechanisms for the observed correlations.

Figure 15**Financial Literacy**

NOTE: Figure 15A shows the shares of college and noncollege households, respectively, who answered all three questions on financial literacy correctly in the 2016 SCF, by wealth group. Figure 15B shows the shares stratified by stock and business ownership instead of wealth.

5 FINANCIAL LITERACY AND RETURNS ON WEALTH

Our results suggest that stock market exposure and business ownership are driving forces behind the rise in the college wealth premium. In the following, we explore potential reasons why these factors are important, pointing to promising directions for future research. In particular, we ask which role financial literacy plays for portfolio composition and for differential returns on wealth.

5.1 Financial Literacy and Portfolio Composition

One reason why college households hold different assets may be financial literacy. Previous research has consistently established that higher educational attainment is associated with higher levels of financial literacy (see Lusardi and Mitchell, 2011; Lusardi and Mitchell 2014; and Lusardi, Michaud, and Mitchell, 2017).¹² Higher financial literacy can, for example, affect wealth growth through portfolio composition. Typically, financial literacy is measured via three questions that elicit the understanding of compound interest, inflation, and risk diversification (see Lusardi and Mitchell, 2011). Since the 2016 wave, these questions are also part of the SCF. Figure 15A shows the shares of households who answered all three questions correctly, stratified by wealth and education. The figure reveals that financial literacy increases with wealth, and is clearly higher for college than for noncollege households in all wealth groups. Moreover, Figure 15B shows that stock owners do on average have a higher level of financial literacy than nonowners. The same is true for business owners. In a study of Dutch household survey data, Von Gaudecker (2015) shows that low financial literacy leads to return losses due

to underdiversification in financial assets (unless households seek financial advice). Indeed, the question on risk diversification is the financial literacy question that respondents find most challenging across a wide range of countries (see Lusardi and Mitchell, 2014). In the 2016 SCF, the difference between college and noncollege households is most pronounced for the risk diversification question, with an average share of correct answers of 75.9 percent for college and 55.9 percent for noncollege households.¹³ Moreover, while we have only looked at direct stock market exposure, this may also impact indirect exposure via pension plans. Lusardi, Michaud, and Mitchell (2017) stress the heightened importance of financial literacy in the United States due to the movement from defined-benefit to defined-contribution plans, such as 401(k)s. This transition started in the 1980s, coinciding with the timing of the widening college wealth premium.

To explore the role of financial literacy, we estimate a regression analogous to the baseline in equation (2) for 2016. When we included the SCF financial literacy measure (which equals 1 if all three questions were answered correctly and zero otherwise) and its interaction with the college indicator, the estimated college effect was reduced by around 40 percent. Yet this result is only suggestive. Further research is necessary to investigate the robustness of the finding and potential transmission mechanisms.

5.2 Returns on Wealth

College education might affect wealth accumulation not only through its effect on portfolio allocation across different asset classes, but also via higher returns *within* a given asset class. For instance, college households might be savvier in picking investments with high returns or low fees. Fagereng et al. (2018) demonstrate that persons with higher levels of education, and especially those with an economics-related college degree, earn higher returns on their wealth and financial assets even *conditional on* portfolio composition. This suggests that our estimate of the effect of differential asset price exposure from Section 4 might be conservative, given that we applied the average rate of return on stocks for all households.

Apart from financial savvy, Fagereng et al. (2018) also point to entrepreneurial skills as a source of differential returns. Moreover, borrowing constraints can induce entrepreneurs to save substantial amounts and thus become very wealthy (Cagetti and De Nardi, 2006). There is evidence that business ownership is associated with higher education (see, e.g., Hurst and Lusardi, 2004). Consistently, the share of business owners in the SCF+ is higher among college households than among noncollege households in all waves (and conversely, the share of college households is disproportionately high among business owners).

Fagereng et al. (2018) use administrative individual-level data from Norway to construct a measure of returns to financial wealth. To this end, they add income from safe and risky assets and divide it by the average stock of financial and business assets.¹⁴ Due to the panel structure of their data, they can use the average of beginning- and end-of-period assets as the denominator, in order to account for changes in the stock of assets over the current period. This is not possible with the SCF, as it consists of repeated cross sections. Moreover, income is reported for the year previous to the survey year.

For these reasons, a similar measure constructed from SCF data is likely to include more measurement error. Keeping this in mind, we construct an analogous proxy for returns based

Figure 16**Returns to Financial and Business Wealth****A. Returns to financial and business wealth** **B. Returns to business wealth** **C. Returns to financial wealth by education** **D. Returns to financial wealth by ownership**

NOTE: Figure 16A shows the proxy for the returns to financial and business wealth by education and business ownership status. Figure 16B shows a similar proxy for business wealth only by education. Figure 16C shows analogous results for a proxy based on financial wealth only by education. Figure 16D shows the latter measure by business ownership status instead of education. See the text for additional details.

on the modern SCF data, which include detailed information on different components of income.¹⁵ For the numerator, we use information on income from farming and business, income from other businesses, rents, trusts or royalties, income from nontaxable investments such as municipal bonds, dividend income, capital gains and losses, and other interest income. For the denominator, we add the amount of stocks, liquid assets and certificates of deposit, bonds, mutual funds, other managed and financial assets, the cash value of life insurances, defined-contribution pension wealth, and business wealth.

Fegereng et al. (2018) exclude persons with less than \$500 in financial wealth and winsorize the bottom and top 0.5 percent of the returns distribution. We also exclude households with less than \$500 in financial wealth and drop returns below the 0.5th and above the 95th

Figure 17**College Business Ownership**

NOTE: The figure shows the shares of college households in the bottom 50 percent, middle 50-90 percent, and top 10 percent of the business wealth distribution (conditional on owning a business).

percentile. The larger trimming region at the top was chosen to take into account that we observe wealth at only one point in time and with a certain lag compared with income. If a household sold most of its financial assets in the year prior to the survey, it would have had high capital income in that year and a relatively low amount of financial assets when surveyed, which would lead to an upward bias in the returns proxy. As Fagereng et al. (2018) report that their results are insensitive to applying an age limit of 20 to 75 year of age, we include households of all ages. Like them, we use real variables before taxes.

The results are presented in Figure 16A. On average, business owners earn higher returns on their financial assets than nonowners. However, the difference between college and non-college households is limited. Figure 16B presents a similar returns proxy for business wealth only, that is, with income from farming, business, other businesses, rents, trusts or royalties in the numerator, and business wealth in the denominator. While college households had higher returns to business wealth as measured by the proxy until the mid-1990s, the advantage disappears afterward and is even reversed after 2004.

The same comparison for financial wealth is presented in Figure 16C, using the complementary set of income measures in the numerator. Importantly, there is no advantage for college households with respect to this measure, and even a disadvantage in the 1980s. Finally, Figure 16D shows the proxy for returns to financial wealth by business ownership status instead of education. We find that business owners earn slightly higher returns on their nonbusiness wealth as well, in line with the hypothesis of Fagereng et al. (2018) that entrepreneurs' "talent to manage and organize their business" (p. 5) enables them to generate higher returns in general.

However, while our return proxies are necessarily coarse due to the measurement issues described above, it appears that the return differences between college and noncollege households are small. Yet it is important to keep in mind that a similar rate of return can translate into large level differences if the difference in the underlying asset values is large. Figure 17 shows the shares of college households in the bottom 50 percent, middle 50-90 percent, and top 10 percent of the business wealth distribution, conditional on owning a business. The college share is particularly high in the top 10 percent group, and has increased from slightly below 50 percent to almost 80 percent between 1983 and 2016.

Based on the existing literature and our explorative results presented in this section, it seems plausible that the interaction of educational attainment, financial literacy, and business acumen has played an important role in shaping the differential development of college and noncollege wealth. However, portfolio composition, not differential returns between college and noncollege households in the same asset class, appears to play the dominant role.

6 CONCLUSION

This article documents the evolution of U.S. college and noncollege income and wealth over six decades using newly compiled long-run data at the household level. We corroborate that the college income premium has increased substantially since the 1980s. Yet, though the college income premium has increased substantially, the college wealth premium has risen even more. Since the 1980s, college households have outpaced noncollege households by a factor of 2.5 in terms of wealth growth. We provide evidence that especially households with two college-educated spouses could appropriate large amounts of wealth. However, we confirm previous evidence that this is not related to assortative mating, but rather to rising educational attainment. We find that portfolio choices and the resulting exposure to asset price changes played a crucial role for the observed trends. Using the asset information in the SCF+, we uncover systematic differences in the size and composition of college versus noncollege household portfolios. Building on insights from previous research, we study the combined role of portfolio choices and asset price changes for the evolution of the wealth distribution. Our results suggest that college households could reap large capital gains from stock market booms owing to the higher equity share in their portfolios. This explanation is consistent both with the fact that college wealth grew faster than noncollege wealth, and that college wealth grew faster than college income, since capital gains from asset price changes are not directly related to other sources of income. Moreover, we provide suggestive evidence that the increase in the college wealth premium is related to business ownership.

In the last part of the article, we discuss potential reasons for the importance of differential asset price exposure and capital gains such as financial literacy and entrepreneurial skills. Both can affect wealth accumulation via portfolio choice and differential returns. These factors also interact with institutional features such as the change from defined-benefit to defined-contribution pension plans. Further research will be needed to disentangle different hypotheses for the rising college wealth premium and establish causal relationships. ■

APPENDIX

A. Supplementary Figures

Figure A1

Comparison to Census Data

NOTE: The figure shows the share of households in the SCF+ data whose head has at least obtained some college education compared with the share in the CPS for the period 1962-2016 and the share from the U.S. decennial censuses for 1950 and 1960. Intermediate data points were obtained by linear interpolation.

Figure A2

Wealth-to-Income Ratios Excluding Pensions

NOTE: The figure shows the ratio of average net wealth to average income for college and noncollege households. The solid lines replicate the baseline from Figure 3 for comparison. The dashed lines show average net wealth net of pensions relative to average income.

Figure A3**Regression Coefficients: Advantage of College Within Income Groups**

NOTE: The figure shows the advantage of having a college degree ($\beta_1 + \beta_{2,t}$) within the bottom 50 percent, 50-90 percent, and top 10 percent of the aggregate income distribution over time. The dependent variable is wealth for the left panels and income for the right panels.

*B. Supplementary Tables***Table B1****Comparison of Households with College versus Some College**

	1956 (\$)			1959 (\$)		
	Some college	College	% Δ	Some college	College	% Δ
Liquid assets + bonds	39,740.9	45,956.4	15.6	35,207.0	44,010.8	25.0
Houses	98,765.5	116,740.2	18.2	94,597.0	105,928.8	12.0
Other nonfinancial assets	9,340.6	10,496.2	12.4	7,366.8	8,061.5	9.4
Housing debt	23,698.3	26,688.1	12.6	25,827.2	30,477.1	18.0
Nonhousing debt	5,806.7	6,712.7	15.6	5,471.3	6,000.0	9.7
Total income	74,855.2	89,300.1	19.3	72,960.7	85,590.3	17.3

NOTE: College indicates households whose head has obtained at least a bachelor's degree; some college indicates households whose head has at least one year of college. The columns "% Δ" show the difference between the two groups in percent.

Table B2**Portfolio Shares for College and Noncollege Households (percent)**

	Other nonfinancial assets	Housing	Business	Equity	Liquid assets + bonds	Other financial assets
A. College						
1956	2.0	22.8	33.3	32.9	9.0	—
1965	1.3	28.0	26.1	34.2	10.5	—
1977	2.9	42.7	20.1	24.5	9.8	—
1989	4.6	41.8	20.9	9.5	10.7	12.5
1998	3.9	32.6	20.5	18.3	7.3	17.5
2007	2.7	37.3	22.5	15.3	6.4	15.8
2016	2.4	30.9	22.0	20.3	7.1	17.2
B. Noncollege						
1956	3.2	33.2	32.4	21.1	10.1	—
1965	3.0	39.6	23.5	26.0	7.8	—
1977	4.1	47.4	32.4	5.2	10.9	—
1989	6.4	50.1	18.1	4.0	12.4	9.0
1998	6.5	46.0	14.7	11.2	8.6	13.1
2007	5.6	53.0	16.6	6.1	6.1	12.6
2016	6.4	46.9	17.1	6.6	6.6	16.4

NOTE: Equity includes mutual fund holdings and other managed assets.

Table B3**Regression Results: College Effect ($\beta_1 + \beta_{2,t}$) by Year**

	Baseline	Middle-class sample	+ Stock exposure	+ Business ownership	+ Stock & business
1956	7.82 (0.126)	4.41* (0.053)	2.66 (0.559)	2.02 (0.634)	-3.81 (0.292)
1959	-9.26 *** (0.007)	-0.12 (0.943)	-9.83 *** (0.003)	-8.37 *** (0.003)	-9.43 *** (0.001)
1962	7.95 (0.203)	8.11 (0.159)	-6.93 (0.218)	8.05 (0.145)	-7.35 (0.137)
1965	3.67 (0.695)	-1.05 (0.645)	-10.71 (0.210)	0.83 (0.897)	-14.85 *** (0.005)
1968	15.26 ** (0.049)	1.95 (0.304)	-12.22 ** (0.037)	5.91 (0.391)	-22.78 *** (0.000)
1971	3.09 (0.579)	3.85 (0.278)	-14.68 *** (0.003)	-1.27 (0.759)	-20.25 *** (0.000)
1977	3.08 (0.589)	3.29 (0.167)	-3.26 (0.541)	0.00 *** (0.000)	0.00 *** (0.000)
1983	11.05 ** (0.015)	0.27 (0.868)	8.46 * (0.053)	0.61 (0.843)	-1.77 (0.543)
1989	12.69 ** (0.028)	4.52 (0.141)	6.53 (0.233)	4.21 (0.274)	-2.55 (0.483)
1992	10.76 ** (0.011)	7.03 *** (0.001)	4.77 (0.218)	2.08 (0.502)	-4.42 (0.110)
1995	15.39 *** (0.001)	8.88 *** (0.000)	3.42 (0.408)	2.54 (0.478)	-9.45 *** (0.003)
1998	25.78 *** (0.000)	9.96 *** (0.000)	-4.55 (0.309)	7.91 ** (0.046)	-22.28 *** (0.000)
2001	41.09 *** (0.000)	15.64 *** (0.000)	13.81 ** (0.019)	16.11 *** (0.002)	-11.99 *** (0.005)
2004	39.02 *** (0.000)	9.01 *** (0.006)	18.15 *** (0.002)	13.62 *** (0.003)	-6.94 * (0.068)
2007	52.75 *** (0.000)	20.38 *** (0.000)	30.92 *** (0.000)	18.62 *** (0.000)	-1.60 (0.713)
2010	43.56 *** (0.000)	20.24 *** (0.000)	28.60 *** (0.000)	14.17 *** (0.003)	-0.09 (0.983)
2013	42.17 *** (0.000)	21.06 *** (0.000)	17.89 *** (0.001)	17.14 *** (0.000)	-7.11 * (0.051)
2016	56.91 *** (0.000)	20.24 *** (0.000)	26.01 *** (0.000)	22.29 *** (0.000)	-7.57 * (0.061)
N	89,571	34,297	86,154	89,571	86,154
R ²	0.255	0.135	0.264	0.270	0.278

NOTE: The dependent variable is net wealth. The controls include survey wave fixed effects, total household income, a full set of age dummies, a kids dummy, and an indicator for marital status. The "Baseline" columns refer to the specification in (2), and the "Middle-class sample" column presents the same regression for the middle 50-90 percent of the aggregate income distribution. The specification "+ Stock exposure" includes the additional controls from (3); "+ Business ownership" includes the additional controls from (4); and "+Stock & business," which is stock exposure plus business ownership, includes the additional controls from both (3) and (4). Multiply imputed observations were averaged for the regressions. p -values are given in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

NOTES

- ¹ Note that total household income in the SCF+ is defined net of capital gains.
- ² Parental income and wealth may even affect educational outcomes beyond assistance to tap one's full skill potential. Looking at the income of U.S. households, Reeves and Howard (2013) find evidence of "glass floors" in educational outcomes: Children from high-income households tend to do better in terms of education and income than their skills would suggest. The authors stress that wealth is likely to play an important role beyond income. Certainly, the persistence of education and wealth across generations and their interaction are important topics for further research.
- ³ Throughout the paper, demographic information will always refer to the household head, if not otherwise stated. In the case of married couples, the household head is typically male.
- ⁴ As noted, the reweighting was done based on the share of households with *at least some* college. A comparison of the SCF+ and census data with respect to this measure is provided in Figure A1.
- ⁵ The ratios reported throughout the article are ratios of averages (as opposed to averages of ratios).
- ⁶ By contrast, the college wealth gap has increased in all parts of the aggregate income distribution. The corresponding decomposition is available from the authors upon request.
- ⁷ Information on the spouse's educational attainment is only available since 1965.
- ⁸ Nonsingle households comprise marriage and cohabitation. We find very similar results when only considering married households.
- ⁹ Eika, Mogstad, and Zafar (forthcoming) demonstrate the robustness of these patterns to accounting for sorting by age and changes in the probability of marriage by education level, as well as to different measures of assortative mating.
- ¹⁰ Note that Figure 3 showed wealth-to-income ratios.
- ¹¹ Note that our results in the following sections always refer to the full sample and not the "middle class" sample unless explicitly stated otherwise.
- ¹² Lusardi, Michaud, and Mitchell (2011) demonstrate that this can actually be an individually optimal outcome, as households with different levels of education have different life-cycle income paths, which entail different incentives to save. Given that financial knowledge helps to earn higher returns on savings, this creates different incentives to invest in financial literacy.
- ¹³ The corresponding share for the question on interest compounding are 86 percent and 73 percent, respectively, and for the question on real interest rates 86.7 percent and 72.9 percent, respectively.
- ¹⁴ They consider the following income components: interest income earned on bank deposits and bond yields, yields from risky assets held abroad and outstanding claims and receivables, yields from mutual funds, yields from directly held listed shares (dividends and accrued capital gains), and yields from all private equity holdings (distributed dividends and the individual share of retained profits). Financial wealth includes bank deposits, money market funds, bond mutual funds, government and corporate bonds, stocks and mutual fund shares, the value of shares in private businesses and other unlisted shares, and the value of risky assets held abroad and of outstanding claims and receivables.
- ¹⁵ Fagereng et al. (2018) also construct a proxy for returns to net worth. As this measure requires information on interest payments on all debt, which is so far neither included in the SCF+ nor the readily available extracts of the modern SCF, we decided to focus on returns to financial and business wealth.

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The Geography of Housing Market Liquidity During the Great Recession

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Using detailed micro data at the ZIP code level, this article explores the regional variation in housing market performance to account for the severity of the Great Recession. The granularity of the data, relative to a more traditional analysis at the county level, is useful for evaluating the performance of the housing market because credit and local macroeconomic variables are tied to housing valuations. The deterioration of the ability to transact (buy and sell) housing units, often referred to as *housing liquidity*, is an important link that connects housing outcomes with real and credit variables. The data indicate that the timing, severity, and duration of the recession varied across regions and was closely connected with the behavior of the housing market. The deterioration in housing liquidity was uniform across all house price tiers (i.e., bottom, middle, and upper end). Furthermore, there was correlation across areas between the magnitude of the declines in housing liquidity and the severity of the deterioration in house prices and macroeconomic conditions. (JEL D31, D83, E21, E22, G11, G12, G21)

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I. INTRODUCTION

The historic deterioration of housing markets during the Great Recession was characterized by plummeting home values and skyrocketing foreclosure rates. Although almost no place in the United States escaped unscathed, significant heterogeneity emerged across both time and space with regard to the housing market collapse. An important aspect missing in many theoretical and empirical studies of this episode is the role of liquidity in local housing markets as manifested in homes taking longer to sell.

Examining the dynamics of ZIP-code-level data reveals that the severity, timing, and length of the Great Recession varied across regions and is linked to housing liquidity. Throughout this article, our main measure of housing liquidity is time on the market (TOM), the

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number of days between listing a property and selling a property. A mismatch between the number of sellers and buyers changes the transactability of houses beyond house prices. Housing liquidity responds to changing macroeconomic conditions, resulting in selling delays. During the Great Recession, the deterioration in housing liquidity along with falling prices generated an imbalance between assets and liabilities, creating a debt overhang. To rebalance their portfolios, households needed to adjust their spending, liquidate leveraged assets (i.e., housing), and in some instances enter foreclosure, which in turn induced lenders to contract credit.

The National Bureau of Economic Research classifies the Great Recession as occurring from December 2007 to June 2009. However, the national housing market experienced a severe downturn nationally from at least 2006 to 2011. House prices deteriorated and mortgage delinquency increased as early as 2005 in the regions first affected by the crisis. The earlier start date for the housing crisis is not unexpected, because the subprime mortgage crisis was an important catalyst of the financial recession that followed. Besides starting earlier than the accepted recession dates, the housing market did not fully recover to pre-crisis levels until several years after the official end of the recession: Most areas did not see house prices, liquidity, or income recover to pre-recession levels until after 2011.

Within this window of 2005 to 2011, the various regions of the United States experienced different timing of the start, trough, and end of the housing crisis. For example, the state of California witnessed fairly early declines in housing market indicators but recovered more rapidly than many other regions. Meanwhile, states in the Sunbelt, particularly Florida, Arizona, and Nevada (hereafter called the Sunbelt states), also witnessed early large declines in house prices and increases in illiquidity and mortgage delinquency. These Sunbelt states did not recover until well after the official end date of the recession. Documenting the regional variation in housing market responses (and in particular housing liquidity) during the Great Recession is one of the main goals of this article.

The use of granular data is crucial to the study of housing. Housing markets by nature are disaggregated, as there can be significant variation within counties or metropolitan statistical areas (MSAs). The use of granular data is particularly important when looking at regional variation in the United States. Many western states have significantly larger counties by area than eastern states. Aggregating data to the MSA level, or even to the county level, causes any empirical analysis to ignore significant variation within counties. To alleviate these concerns, the analysis in this article uses ZIP-code-level data.

Several different empirical specifications establish a strong link between explanatory housing market variables (house prices and liquidity) and local outcomes for the credit market (mortgage delinquency) and macroeconomy (income). Moreover, categorizing the geography of the housing crisis into three large regions (California, the Sunbelt states, and the other states) generates heterogeneous effects that substantially differ from those at the national level. For example, in California, house prices declined by more than the national average and mortgage delinquency increased far more than the national average. However, liquidity and income declined by less than the national averages. Although the trough was later in the Sunbelt states, income declined by large amounts and homes' TOM and mortgage delinquencies increased.

The regression models exploit regional time windows to arrive at (non-causal) estimates of changes in house prices and liquidity on these outcomes. In all cases, the effects were highly statistically and economically significant. For example, at the national level, a one-month increase in TOM is associated with approximately a 1 percent decline in real income. To put these estimates into perspective, a 10 percent decline in house prices is associated with approximately a 1.8 percent decline in real income. For the Sunbelt states, the liquidity effects are slightly larger. Housing liquidity also has strong implications for the mortgage delinquency rate. In California, a one-month increase in TOM is associated with a 2.0 percent increase in the mortgage delinquency rate. Given this observed increase in TOM, the estimate for California predicts a 13.5 increase in mortgage delinquency. For the Sunbelt states, the estimate is 17 percent.

We also estimate alternate specifications of the models by dividing the United States into regions by housing supply elasticity rather than by geography. These estimates provide a counterfactual to the regional analysis and support the claim that liquidity was a highly significant factor in areas with a low housing supply elasticity. We also find that in areas with relatively high housing supply elasticity, liquidity was significant but had a smaller effect on outcomes. We detail in Section VI a brief theory of the interaction of housing liquidity and elasticity.

II. LITERATURE: HOUSING, THE MACROECONOMY, AND THE GREAT RECESSION

Traditionally, the role of housing in the macroeconomy was limited to exploring its role over the business cycle through various channels such as residential investment (i.e., Davis and Heathcote, 2005; Leamer, 2007; Fisher and Yavas, 2007; Rupert and Wasmer, 2014; and Boldrin et al. 2013), collateral constraints (i.e., Iacoviello, 2005; Iacoviello and Neri, 2010; and Liu, Wang, and Zha, 2013), and nominal mortgage contracts (i.e., Garriga, Kydland, and Sustek, 2017 and 2019).¹ These papers measure the importance of housing to high-frequency movements of the economy but were not designed to address large and broad swings in house prices across markets and their interaction with the macroeconomy.

There is a growing literature that focuses on this issue and has been summarized by Garriga and Hedlund (forthcoming). The evidence constructed by Jordà, Schularick, and Taylor (2015), who study large movements in housing and equity markets in 17 countries over the past 140 years, appears to be conclusive. Periods with easy credit fueled asset price booms, in particular in housing markets, which increase the risk of a financial crisis. Upon collapse, these episodes tend to be followed by deeper recessions and slower recoveries of key macroeconomic variables.

In the postwar period in the United States, movements in house prices until 2000 can be explained by increases in housing quality and construction costs (1950-70) or regulatory restrictions (1979-95). These facts are documented in Poterba (1984), Himmelberg, Mayer, and Sinai (2005), Shiller (2007), Glaeser, Gyourko, and Saks (2005), and Chambers, Garriga, and Schlagenhaut (2016). During this period, the interaction between housing markets and macroeconomic aggregates was limited, as aggregate house prices always grew in real terms.

In the 2000s, the boom-bust was fueled by an expansion and subsequent contraction of the credit supply along with changing expectations about future house price appreciation.² For example, Campbell et al. (2009) find that for the period 1997–2007, movements in price-rent ratios can be attributed more to time variation in the housing premium and less to expectations of future rent growth. The collapse of the housing market and the implications for the macroeconomy, in particular aggregate employment and consumption, has been a growing research topic. Boldrin et al. (2013) use a dynamic multisector model with production linkages where a decline in housing demand propagates through the rest of the economy, thereby reducing aggregate output and employment. Garriga, Manuelli, and Peralta-Alva (2019) develop a macroeconomic model of market segmentation that generates sizable movement in house values driven by current and future credit conditions. The endogenous collapse of house prices induces a large and persistent recession through the deleveraging process and decline in aggregate consumption. In addition to debt deleveraging, large declines in house values also generate a large negative wealth effect that propagates to aggregate consumption (i.e., Iacoviello and Pavan, 2013; Huo and Ríos-Rull, 2016; and Berger et al., 2017).

The collapse of the housing market can also spill over to the credit market in the form of a spike in mortgage delinquencies and foreclosures, such as occurred during the Great Recession (see Mian and Sufi, 2009; Anenberg and Kung, 2014; and Mian, Sufi, and Trebbi, 2015). These issues have also received attention in the macro structural literature. The complexity of the problem often requires that house prices be exogenous in the model, to allow study of the determinants of mortgage default (see Guler, 2015; Corbae and Quintin, 2015; Campbell and Cocco, 2015; Hatchondo, Martinez, and Sanchez, 2015; and Gerardi et al., 2018). Other papers explore the spillover effects of foreclosure on house prices by making both objects endogenous (i.e., Garriga and Schlagenghauf, 2009; Chatterjee and Eyigungor, 2015; and Arslan, Guler, and Taskin, 2015).

One of the challenges for this literature is to acknowledge that periods with large declines in house values also coincide with an impaired ability to transact housing units, particularly for sellers.³ In short, the magnitude and duration of these crises partially depend on the decline and recovery of housing liquidity. These issues have been documented and formalized using a structural general equilibrium model, including by Hedlund (2016 and 2018) and Garriga and Hedlund (2018 and 2019). Their analysis suggests that the deterioration in house prices and liquidity—transmitted to consumption via balance sheets that vary in composition and depth—is central to explaining the observed aggregate and cross-sectional patterns of macro and housing variables. More specifically, large declines in housing liquidity in an area are correlated with declines in house prices and macroeconomic conditions in that area.

III. DATA DESCRIPTION

To study the relationship among housing, credit, and macroeconomic conditions, this article uses transaction-level data from the Multiple Listing Services® (MLS) from CoreLogic, individual-level credit data from the Federal Reserve Bank of New York Consumer Credit Panel based on Equifax credit report data (FRBNY CCP/Equifax), and adjusted gross income

Table 1**National Summary Statistics (2006-11)**

	Obs.	Mean	SD	10th	Median	90th
Income (%Δ)	9,356	-6.3	11.1	-15.8	-5.9	1.7
House prices (%Δ)	9,425	-33.4	20.9	-61.4	-32.6	-6.7
Months' supply (ΔMonths)	9,425	3.1	7.4	-3.7	3.1	10.5
TOM (ΔDays)	9,425	47.4	35.2	9.8	42.5	93.6
Mortgage delinquency rate (Δpp)	9,410	4.7	4.4	0.8	3.3	10.5

NOTE: The table reports ZIP-code-level statistics. Obs., observations. SD, standard deviation. 10th, 10th percentile. 90th, 90th percentile. pp, percentage points.

SOURCE: Income: IRS SOI deflated by personal consumption expenditures (PCE). House prices, months' supply, TOM: CoreLogic's MLS. House prices are deflated by PCE. Mortgage delinquency rate: FRBNY CCP/Equifax.

(hereafter income) data from the Internal Revenue Service (IRS) measured at the ZIP code level. In addition to the closing price and date, the MLS dataset contains the listing date, asking price, and property location. Because the data are at the listing level, both failed and successful listings are observed, making it possible to track whether a seller delists and relists a house (for example, to move up the queue of online search results). The coverage of the MLS is broad, covering approximately 74 percent of the U.S. population in 2006 (16,954 ZIP codes) and over 85 percent of the population (20,109 ZIP codes) in 2011. The analysis of the housing variables is restricted to single-family homes and condominiums. The credit variables track several measures of mortgage payment status: delinquent, seriously delinquent, and “severely derogatory” loans (see the appendix for further details). We define the mortgage delinquency rate as the ratio of the total number of all three of these statuses to the outstanding number of mortgages. The FRBNY CCP/Equifax and MLS data are aggregated to the ZIP code level for comparison in many of the analyses that follow. For macroeconomic conditions, the IRS data provide detailed information of income at the ZIP code level as well as distributions across different brackets and the number of individuals filling. The analysis uses the mean value in every ZIP code. Table 1 provides national summary statistics for these variables during the period 2006-11.⁴ Table 2 provides regional mean statistics for the individual most-adverse time windows from 2005-2012 for the three regions studied.

The statistics in Table 1 illustrate the depth and duration of the Great Recession's impact on housing markets nationally. House prices in the MLS data declined on average over 33 percent, which is consistent with broad house price indices based on repeated sales, such as the Federal Housing Finance Agency and S&P/Case-Shiller indices. Table 2 reveals that declines in house prices were more severe in California and the Sunbelt states: All experienced declines larger than the national average. As shown in Table 1 for the nation, the magnitude of the decline for the bottom of the distribution was particularly large, with some ZIP codes experiencing house price declines in excess of 60 percent. Contemporaneously, the average days needed to sell a house, that is, the TOM, increased 40 percent, from 117 days to 164 days. The size of the increase is symmetric, with a 39 percent increase in the bottom 10th percentile and

Table 2**Regional Summary Statistics (Mean Values)**

	California (2005-09)	Sunbelt (2005-11)	Other (2006-10)
Income (%Δ)	-5.2	-15.2	-3.0
House prices (%Δ)	-47.7	51.7	-20.1
Months' supply (ΔMonths)	3.0	5.2	5.4
TOM (ΔDays)	42.1	92.9	34.8
Mortgage delinquency rate (Δpp)	9.3	9.8	3.1

NOTE: The table reports ZIP-code-level statistics. Sunbelt, the Sunbelt states of Arizona, Nevada, and Florida. Other, all other states. pp, percentage points.

SOURCE: Income: IRS SOI deflated by PCE. House prices, months' supply, TOM: CoreLogic's MLS. House prices are deflated by PCE. Delinquency rates: FRBNY CCP\Equifax.

41 percent increase in the top 90th percentile. Units that used to sell twice as fast as the national average became very illiquid during the Great Recession.

The comparison of the national statistics with the regional statistics reveals the housing crisis was more severe in specific regions of the United States. In particular, comparing the average mortgage delinquency rates of California and the Sunbelt states at the height of their local crises with those in the 90th percentile of the national statistics demonstrates that these regions were far more adversely affected by the housing crisis than most regions. As a counterfactual, Table 2 includes a column for all other states in their most adverse period. At their worst, the other states experienced only a 3.1 percent increase in the mortgage delinquency rate, confirming that a large portion of delinquent mortgages were concentrated in California and the Sunbelt states.

The findings of Table 2 demonstrate that the housing crisis had heterogeneous effects across regions that would be missed when looking at national statistics. National statistics show a large increase in housing market illiquidity, a decline in real house prices and incomes, and an increase in mortgage delinquency rates. However, these effects were not uniform. In California, house prices declined by more than the national average and the mortgage delinquency rate increased by far more than the national average, while housing liquidity and income declined by less than the national averages. In the Sunbelt states, income declined a staggering 15.2 percent, TOM increased to nearly 93 days (almost double the national average), and the mortgage delinquency rate increased nearly 10 percent. All other states experienced a recession, with income decreasing 3 percent and house prices falling near 20 percent, but conditions did not deteriorate to the extent witnessed in the Sunbelt states.

These trends are also evident in heat maps. Specifically, Figure 1 plots percent changes in house prices and income and mortgage delinquency rates by ZIP code. The period used is 2006-2011, to reflect the national statistics and to show that, although Table 2 reports specific time windows for the highlighted regions, the general findings do not change materially when using the same period across regions. It is evident that house prices deteriorated the most in

Figure 1**Macroeconomic Conditions During the Great Recession**

SOURCE: Income: IRS SOI. Mortgage delinquency rates: FRBNY CCP\Equifax. House prices: CoreLogic's MLS.

metropolitan areas in California, Arizona, Florida, and Nevada (especially Las Vegas). Furthermore, these plots show house prices had not recovered by 2011, a full two years after the end of the recession. These same areas also seem to be where the mortgage delinquency rate increased most dramatically, with Florida a particularly stark case (see Figure 1). The depth of the recession in these areas becomes most clear when comparing the maps of house prices and mortgage delinquency rates to that for income. By 2011, many areas in the country such as Texas and large swaths of the South and Midwest had fully recovered and income exceeded 2006 levels. The areas where the housing markets deteriorated the most, such as California and the Sunbelt states of Arizona, Nevada, and Florida, had lower real incomes in 2011 than they had in 2006.

It is convenient to explore two complementary measures of housing liquidity over time. One is TOM, the number of days between listing a property and selling a property. As such,

Figure 2

Housing Liquidity During the Great Recession

SOURCE: TOM, months' supply: CoreLogic's MLS.

this liquidity measure is constructed from individual transactions. The other is months' supply, a market-level measure of housing liquidity that comes from dividing the stock of unsold listings by the number of houses sold in a given geography and month. To be consistent with other measures of months' supply,⁵ we calculate annual months' supply at the ZIP code level by averaging over each year the monthly measures calculated from the MLS.⁶ Whether using TOM or months' supply, analyzing housing liquidity shows that, analogously to house prices, the national housing market did not recover to pre-recession levels until well after the Great Recession.

The heat maps in Figure 2 illustrate how measures of liquidity evolved in specific ZIP codes over time and reveal that national housing market conditions remained depressed during the Great Recession and beyond. The left-hand panels show the evolution of TOM and the right-hand panels the evolution of months' supply.

Measures of illiquidity remained elevated for at least five years after the initial housing bust. Nationally, this corresponded to about an additional month to sell a house or more than an additional three months' supply of housing stock. A reduction in housing liquidity during this period is critical to understanding the housing crisis because the inability to sell homes significantly worsened national macroeconomic conditions, as indicated by the regressions in Section V. These trends further demonstrate the heterogeneous effect the housing crisis had on regions in the United States, with California and the Sunbelt states having more illiquid markets earlier in the crisis.

IV. CHANGES IN HOUSING LIQUIDITY WITHIN LOCAL MARKETS

An important issue is whether the composition of housing units for sale in the market had different characteristics or qualities during the Great Recession relative to the boom period. To address this issue, this section provides additional evidence of the change of housing liquidity *within* each regional market.

For the period 2005-11, the density of TOM for the nation, California, the Sunbelt states, and all other states are depicted in Figure 3. The national plot suggests that liquidity reached its worst levels between 2008 and 2011. However, the regional plots suggest that this was not a uniform trend. California and the Sunbelt states experienced significant rightward shifts in their liquidity distributions earlier in the crisis, primarily in 2007 and 2008. The other regions did not display liquidity changes of those magnitudes until the later years of the crisis, such as 2011. Interestingly, California and the Sunbelt states saw a partial recovery in housing liquidity by 2009 and 2011, respectively. In contrast, the other regions of the United States largely saw slower liquidity declines during this period, but the declines were generally monotonic, with the worst years for housing liquidity occurring between 2008 and 2011.

Besides the temporal differences in these distributions of liquidity, the magnitudes of the changes in liquidity density varied across regions. The Sunbelt states experienced a more severe shock than the rest of the nation—including California. California experienced an early shock to liquidity, but its TOM measure never reached that for the Sunbelt states and its TOM measure recovered more quickly. Analyzing the levels of housing liquidity is useful

Figure 3**Housing Liquidity Kernel Density Plots (TOM, 2005-11)**

NOTE: Sunbelt, the Sunbelt states of Arizona, Nevada, and Florida. Other, all other states. The right tail is truncated at 490 days on the market. Any value over this threshold is included in the tail. Kernel density plots of housing liquidity (2005-11).

SOURCE: CoreLogic's MLS.

insofar as it can differentiate relatively liquid and illiquid regional housing markets. A factor that made the housing crisis particularly severe in California and the Sunbelt states was the change in liquidity during this period. In 2005, a larger portion of the homes in these regions were selling in under three months compared with the other regions of the United States (see Figure 3). The liquidity shocks of the housing crisis caused larger percentage reductions in liquidity in these regions compared with the rest of the United States.

To measure statistically how liquidity changed over time, we calculate measures of statistical significance and uniformity in trends; more specifically, we use a Kolmogorov-Smirnov test. The test is performed on all the density distributions, finding them all statistically different and significant at the 1 percent level. Across all regions, the number of homes sold in under three months dramatically decreased from 2005 levels. Starting in 2006, liquidity decreased

Figure 4**TOM Distributions (2000-16)**

NOTE: Sunbelt, the Sunbelt states of Arizona, Nevada, and Florida. Other, all other states.

SOURCE: CoreLogic's MLS.

in all housing markets, but the timing and height of the peak of housing illiquidity varies among regions.

In addition to regional effects, we analyze how segments of housing markets within regions responded to the liquidity shock of the Great Recession. In particular, it is important to determine whether the housing crisis caused already hard-to-sell homes to become more illiquid or if it impacted all houses uniformly. Figure 4 plots the mean, median, 25th-75th percentile, and 10th-90th percentile measures of TOM for each of the regions over time. Plotting the percentiles of the housing market captures how different local markets responded to the housing crisis and whether there were composition effects that account for the trends, such as illiquidity build-ups in specific segments of the market.

As shown in Figure 4, there were little to no composition effects in determining the trends in liquidity during this period. The different percentiles of the housing market in each region received negative liquidity shocks at approximately the same time and experienced similar percent declines in liquidity levels.

Figure 5**House Price Distributions Deflated by Personal Consumption Expenditures (2000-16)**

NOTE: Sunbelt, the Sunbelt states of Arizona, Nevada, and Florida. Other, all other states.

SOURCE: CoreLogic's MLS.

As discussed by Mian and Sufi (2009), the vast majority of housing markets saw severe price declines during the Great Recession. A reasonable question is whether the widespread collapse had uneven effects on different tiers of the housing market. To address this issue, Figure 5 plots different moments (namely, the mean, median, 25th-75th percentiles, and 10th-90th percentiles) of the distribution of real house prices in each region over time. Across all regions, a negative shock occurs starting in 2005, 2006, or 2007, depending on the region. In a manner analogous to liquidity, the timing, levels, and severity of the declines in house prices vary greatly across regions. California and the Sunbelt states saw the earliest and steepest declines in house prices. Furthermore, California experienced a recovery in house prices years earlier than the rest of the nation. Figure 5 also suggests that national house prices had yet to recover to their pre-2005 levels a full decade after the start of the crisis. For the Sunbelt states, the decline in real house prices persisted long after the crisis and did not begin to recover until more than five years after the official end date of the Great Recession.

Figure 6**ZIP Code Correlations of House Prices, Income, and Mortgage Delinquency Rates**

NOTE: MDR, mortgage delinquency rate. Sunbelt, the Sunbelt states of Arizona, Nevada, and Florida. The periods used are 2006-11, 2005-09, and 2005-11, respectively, for the nation, California, and the Sunbelt. These periods were chosen to reflect the most consistently adverse time windows for each region from a housing perspective. Correlations are weighted by population of the start year. Each bubble is an individual ZIP code, where the diameter is indicative of population.

SOURCE: House prices: CoreLogic's MLS. Mortgage delinquency rates: FRBNY CCP\Equifax. Income: IRS SOI.

Figure 7

ZIP Code Correlations of TOM, Income, and Mortgage Delinquency Rates

NOTE: Sunbelt, the Sunbelt states of Arizona, Nevada, and Florida. MDR, mortgage delinquency rate. The periods used are 2006-11, 2005-09, and 2005-11, respectively, for the nation, California, and the Sunbelt. Correlations are weighted by population of the start year. Each bubble is an individual ZIP code, where the diameter is indicative of population.

SOURCE: TOM: Corelogic's MLS. Mortgage delinquency rates: FRBNY CCP\Equifax. Income: IRS SOI.

While the magnitudes of house price changes vary across housing tiers (see Armesto and Garriga, 2009, for a more detailed analysis across U.S. cities for the period 1995:Q3-2009:Q3), the figure illustrates relatively uniform patterns across the different percentiles of the distributions. The aggregate housing price decline impacted the bottom quartile (which includes starter homes) as well as the top quartile of the housing stock (which includes luxury homes). Similar patterns emerge across all tiers of the regional housing markets. The timing of the decline of house prices across tiers is strikingly uniform and points to a truly macroeconomic shock to prices. In other words, during these episodes, when the aggregate, national price moved, all segments of the housing market changed.

The performance of housing markets is also connected to macroeconomic developments at a granular level. This point has been empirically made by Mian and Sufi (2014) and more formally, using structural models, by Boldrin et al. (2013); Herkenhoff and Ohanian (2019); and Garriga and Hedlund (forthcoming), who emphasize housing liquidity. The scatter plots of Figure 6 demonstrate that the shock to house prices in 2006 was correlated with outcomes in the macroeconomy (income) and the credit market (the mortgage delinquency rate).

Nationally, at the ZIP code level, income and house prices are correlated with a coefficient of approximately 0.40. This relationship weakens somewhat for specific regions but still exists for California and the Sunbelt states. The relationship between mortgage delinquency rates and house prices is consistent across all regions and has a coefficient of -0.53 for the nation. This implies that the housing market shocks shown had potentially large spillovers on the U.S. economy during this period.

The performance of the local housing market is described both by the dynamics of house prices and the behavior of housing liquidity. In the data, housing liquidity proves to be an important factor determining the impact housing markets had on macroeconomic outcomes such as income.

Figure 7 plots by ZIP code for the nation, California, and the Sunbelt states the changes in TOM (liquidity) relative to changes in income and the mortgage delinquency rate, respectively. At the national level, there is a weakly negative relationship between the changes in liquidity and income during the crisis period. This relationship is consistent with the predictions of the structural model in Garriga and Hedlund (2019). At a more disaggregated level, the sign of the correlation varies by region and once we add additional controls, as in Section V, the results are more consistent with the national correlation. Similarly, the correlation coefficient of mortgage delinquency rates and liquidity at the national level is 0.15, representing a decline from that of house prices and mortgage delinquency.

The heterogeneity of these regional relationships is notable. Nationally, changes in house prices and liquidity appear nearly uncorrelated, as they have a correlation coefficient of merely -0.01 . However, California exhibits a stronger negative relationship for this measure, with a correlation coefficient of -0.05 , implying it had a number of areas where liquidity increased and house prices decreased, the expected relationship predicted in Garriga and Hedlund (forthcoming). For the Sunbelt states, the correlation coefficient is 0.10, implying they had some places where prices and liquidity moved together. These correlations highlight the regional variation in housing market relationships during the period. We explore a potential explanation of this heterogeneity in Section V.

V. HOUSING LIQUIDITY, GEOGRAPHY, AND MACRO PERFORMANCE

To more formally establish the statistical significance of housing liquidity on macroeconomic variables during the Great Recession, we perform a series of regression analyses in the same spirit of Mian et al. (2013) and Mian and Sufi (2014). The basic idea is to explore how the addition of measures of housing liquidity improves the understanding of the channels that connect housing markets and the broader economy. Changes in housing liquidity depress housing demand, but decreased liquidity is ultimately correlated with negative macroeconomic performance. The advantage of using granular data is that it allows capture of measures of housing liquidity in finer terms.

The regressions use ZIP-code-level data from the MLS for house prices and liquidity, FRBNY CCP/Equifax for mortgage delinquency rates, and the IRS statistics of income (SOI) for income. MLS data are the result of manual entry by listing and selling agents, so mistakes and outliers can occur. To correct for this, we winsorize the top and bottom 10 percent of the liquidity change measures. This method allows us to preserve large values, which are plausible given the severity of the housing crisis, but corrects for extreme outliers and data errors.

The basic model of the regressions in this section uses ordinary least squares, with observations weighted by population calculated as the number of tax returns in a ZIP code in the IRS SOI data. We choose 2006 as the year for the weights, but this is arbitrary. The IRS SOI data consistently provide exceptional coverage of the United States, so choosing a specific year does not reduce the number of observations. Furthermore, the number of tax returns (the proxy used for population) is stable over time and approximates the cardinal ranking of ZIP codes by population.

The model form is given by

$$(1) \quad \Delta \text{Outcome}_{t-(t-1)}^i = B_0 + B_1 \Delta \text{Liquidity}_{t-(t-1)}^i + B_2 \Delta \text{HousePrice}_{t-(t-1)}^i,$$

where $\Delta \text{Outcome}_{t-(t-1)}^i$ is either the change in real income during the period or the change in the mortgage delinquency rate. The mortgage delinquency rate is calculated as noted above for each ZIP code. The change in mortgage delinquency and the change in income are each expressed as a percent change from the start to the end of the period. The change in liquidity is the number of days difference between the TOM at the start and the end of the period. The change in house prices is a percent change in real house prices from the start to the end of the period.

All regression models use the same periods for variables within regions, but as previously shown in Section III, the timing of house price and liquidity shocks varied across geographic regions. Therefore, each region uses a specific time window to reflect its housing crisis period: the nation, 2006-11; California, 2005-09; the Sunbelt states of Arizona, Nevada, and Florida, 2005-11; and all other ZIP codes, 2006-10. The results of these regressions for income and mortgage delinquency are found in Tables 3 and 4, respectively. As previously shown in Sections II and III, these windows are somewhat arbitrary, as regional housing markets were consistently adversely affected for the entirety of the sample period.

For the time windows selected to approximate the regional troughs of the Great Recession, almost all the coefficients for both the changes in house prices and in housing liquidity are highly significant, economically sizable, and in the expected direction. For the national regression, with income as the dependent variable, a one-month increase in TOM is associated with approximately a 1 percent decline in real income, and a 10 percent decline in house prices is associated with approximately a 1.8 percent decline in real income. For the Sunbelt states, the liquidity effects are slightly larger; for California, the price effect is smaller and the liquidity effect is insignificant. To put these results into perspective, for the nation, the average decline in house prices was over 33 percent and the increase in TOM was 47.4 days, with the decline in house prices corresponding to an estimated –5.9 percent decline in income and the increase in TOM (decline in liquidity) to a –1.7 percent decline in income, for a total estimated decline in income of 7.6 percent for a representative ZIP code during 2006–11. The representative ZIP code saw its income actually decline 6.3 percent during this same period, so these estimates are in the historical range of income declines. The same decomposition yields estimated declines of 9.3 percent and 2.0 percent of income for house prices and liquidity, respectively, for the Sunbelt states (using the average declines in house prices and liquidity during this period). These simple regression models emphasize a strongly statistically and economically significant relation between housing variables and income.

When estimating the effects of the housing crisis on one specific indicator of housing market health—the mortgage delinquency rate—the effects are more dramatic. In this case, all variables are significant at the 1 percent level and in the expected direction. Even California has a strong correlation between the increase in TOM and the decline in house prices. For this region, a one-month increase in TOM is associated with a 2.0 percent increase in the mortgage delinquency rate. Between 2005 and 2009 in California, house prices declined 47.4 percent, TOM increased 42.1 days, and the mortgage delinquency rate increased from 0.3 percent to 9.7 percent. Using these averages, the regression in Table 4 estimates a 13.5 percent increase in mortgage delinquency. Analogous calculations for the Sunbelt states estimate a 17 percent increase in mortgage delinquency. Given the size and significance of both house prices and liquidity in the regional regression models, we conclude that both are critical factors to consider when estimating housing market outcomes.

The results of this empirical analysis strongly imply that house prices and liquidity were important factors for macroeconomic outcomes during the Great Recession. However, it should be noted this analysis uses ordinary least-square regression models that do not imply causality of the housing variables on the dependent variables used. These tests demonstrate that housing outcomes were highly correlated during this period with the decline in income and an increase in mortgage delinquency, but this analysis cannot say with any certainty to what extent the deterioration of housing markets caused the macroeconomic conditions experienced during the Great Recession, due to endogeneity of the dependent and independent variables. To more definitively state how much the illiquidity buildup of this period caused a decline in national income, some control for endogeneity would be required.

Table 3

Regressions for Income with ΔAGI as the Dependent Variable (Number of Returns 2006 Weighted)

	National	California	Sunbelt	Other
ΔTOM	-0.035*** (0.006)	0.026 (0.016)	-0.021* (0.011)	-0.020** (0.008)
$\Delta Price$	0.180*** (0.008)	0.055*** (0.017)	0.150*** (0.021)	0.079*** (0.012)
Constant	1.966*** (0.422)	-3.767*** (1.01)	-5.232*** (1.685)	-0.098 (0.436)
Observations	9,356	951	864	7,312
R^2	0.053	0.013	0.056	0.007

NOTE: AGI, adjusted gross income. Sunbelt, the Sunbelt states of Arizona, Nevada, and Florida. Other, all other states. ZIP-code-level data have many outliers in the MLS. To control for these and limit their impact, the bottom and top 10 percent of changes in liquidity were winsorized. This applies to all regressions displayed in this article. Standard errors are in parentheses. Time windows for national, California, the Sunbelt, and other are 2006-11, 2005-09, 2005-11, and 2006-10, respectively. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

SOURCE: TOM, house prices: CoreLogic's MLS. Income: IRS SOI.

Table 4

Regressions for Mortgage Delinquency with ΔMDR as the Dependent Variable (Number of Returns 2006 Weighted)

	National	California	Sunbelt	Other
ΔTOM	0.043*** (0.001)	0.066*** (0.007)	0.073*** (0.006)	0.020*** (0.001)
$\Delta Price$	-0.125*** (0.002)	-0.224*** (0.008)	-0.198*** (0.011)	-0.075*** (0.002)
Constant	-1.527*** (0.083)	-4.183*** (0.466)	-6.966*** (0.892)	1.039*** (0.057)
Observations	9,410	971	879	7,334
R^2	0.446	0.504	0.317	0.262

NOTE: MDR, mortgage delinquency rate. Sunbelt, the Sunbelt states of Arizona, Nevada, and Florida. Other, all other states. Standard errors are in parentheses. Time windows for national, California, the Sunbelt, and other are 2006-11, 2005-09, 2005-11, and 2006-10, respectively. *** $p < 0.01$.

SOURCE: TOM, house prices: CoreLogic's MLS. Mortgage delinquency: FRBNY CCP\Equifax.

VI. HOUSING LIQUIDITY AND HOUSING SUPPLY ELASTICITY

The empirical analysis presented thus far has established that there were significant differences between regional housing markets during the Great Recession. Important questions to consider are these: What drove these regional differences, and why did the magnitudes of the house price and liquidity effects vary between regions? Obvious housing differences exist among California, the Sunbelt states, and many other regions of the United States. Perhaps the most notable regional housing difference is the age and amount of building development. Parts of California and the Sunbelt states are populated with relatively newly developed cities with broad city limits and an abundance of undeveloped land to use for future building. This regional feature differs from the older, more densely developed metropolitan areas in the Northeast. Possible explanations for the regional heterogeneity in response to the Great Recession are the differences in land availability and housing supply elasticity.

Even within the regions in this analysis, there is significant variation in local housing markets. Few would deny there are large land constraint and population density differences between San Francisco and San Bernardino counties. By grouping ZIP codes into geographic regions instead of categories based on some other economic similarity, our baseline analysis may be obscuring the effect of housing liquidity on macroeconomic outcomes. In particular, the variation of local housing supply elasticities is a natural candidate for grouping by ZIP code to analyze the responsiveness of the economy to shocks during the Great Recession. Saiz (2010) analyzes satellite footage of the United States to calculate housing supply elasticities based on land availabilities in MSAs. He finds that areas with little opportunity for land development due to land constraints were often the most housing supply inelastic. We use his MSA-level estimates of housing supply elasticity and assign an MSA-level value to each ZIP code found within a given MSA. We label ZIP codes in the highest quartile of elasticities (above 2.34) as “high elasticity” and in the lowest quartile (below 1.2) as “low elasticity.”

It is well established in the literature that house prices respond more strongly to shocks in less-elastic markets. We would expect the same to be true for the response of housing liquidity. In particular, if housing demand increases and there is little ability to build new houses, prospective buyers will bid up prices and cause properties to sell more quickly. The reverse process would likely occur during a downturn, especially if it is assumed that house prices are sticky or that agents do not wish to sell their homes for a low price unless constrained to do so in cases such as bankruptcy. When homeowners are unlikely or unwilling to sell for low prices or are not required to do so, the time it takes to sell properties increases. This loss-aversion behavior in real estate markets has been documented in previous studies such as Genesove and Mayer (2001), and we expect it to affect low-elasticity markets. However, it is not yet known how local supply elasticity affects the transmission of changes in house prices and liquidity to macroeconomic and credit variables.

To test for heterogeneity in the housing transmission mechanism by the local supply elasticity, we re-estimate the model in equation (1) and group by elasticity rather than region. We estimate these regressions over the period 2005-11 to encompass the entirety of the national housing crisis. The results of the regressions are in Tables 5 and 6.

Table 5

Saiz Elasticity Regressions for Income with ΔAGI_{05-11} as the Dependent Variable (Number of Returns 2006 Weighted)

	National	High elasticity	Low elasticity
ΔTOM_{05-11}	-0.037*** (0.003)	-0.031*** (0.008)	-0.087*** (0.006)
$\Delta Price_{05-11}$	0.195*** (0.004)	0.127*** (0.008)	0.194*** (0.010)
Constant	2.703*** (0.222)	-0.256 (0.388)	6.402*** (0.581)
Observations	6,118	1,638	1,503
R^2	0.286	0.130	0.306

NOTE: AGI, adjusted gross income. Elasticity groups are given in the column headers. Standard errors are in parentheses. *** $p < 0.01$.

SOURCE: TOM, house prices: CoreLogic's MLS. Mortgage delinquency: FRBNY CCP\Equifax. Income: IRS SOI. Saiz elasticities: Saiz (2010).

Table 6

Saiz Elasticity Regressions for Mortgage Delinquency Rates with ΔMDR_{05-11} as the Dependent Variable (Number of Returns 2006 Weighted)

	National	High elasticity	Low elasticity
ΔTOM_{05-11}	0.044*** (0.001)	-0.001 (0.002)	0.071*** (0.003)
$\Delta Price_{05-11}$	-0.107*** (0.002)	-0.039*** (0.002)	-0.170*** (0.005)
Constant	-1.215*** (0.097)	1.384*** (0.110)	-4.772*** (0.295)
Observations	6,146	1,643	1,521
R^2	0.453	0.141	0.552

NOTE: MDR, mortgage delinquency rate. Elasticity groups are given in the column headers. Standard errors are in parentheses. *** $p < 0.01$.

SOURCE: TOM, prices: CoreLogic's MLS. Mortgage delinquency: FRBNY CCP\Equifax. Income: IRS SOI. Saiz elasticities: Saiz (2010).

For ZIP code MSAs with an inelastic housing supply, a one-month increase in TOM yields an estimated 2.6 percent decline in income, and a 10 percent decline in house prices yields an estimated 1.9 percent decline in income. At the national level, the estimated declines are a 1.1 percent and 1.9 percent, respectively. Thus, the housing transmission mechanism for both prices and liquidity to income is stronger in low-elasticity areas. By contrast, in high-elasticity areas, a one-month increase in TOM yields only an estimated 0.9 percent decline in income, and a 10 percent decline in house prices only an estimated 1.3 percent decline in income.

Switching focus to the mortgage delinquency rate, the results are similarly stronger in low-elasticity areas. Specifically, a one-month increase in TOM yields an estimated 2.1-percentage-point increase in the mortgage delinquency rate compared with no statistically significant effect in high-elasticity areas and a 1.3-percentage-point increase nationwide. The price effect is also strongest in low-elasticity areas. The lesson that emerges by comparing Tables 3 and 4 with Tables 5 and 6 is that grouping by elasticity shows starker differences in the transmission from housing to the rest of the economy than does grouping by geographic region.

VII. CONCLUSION

The empirical findings in this article demonstrate that there was significant variation in the timing and magnitude of the housing market collapse across the United States. The more disaggregated analysis at the transactional and ZIP code level relative to previous studies at the county level indicates that, in addition to house prices, housing liquidity was strongly associated with the deterioration of macroeconomic outcomes during this period. Grouping the United States into areas of low and high elasticity of the housing supply confirms that the magnitude of the effect of liquidity is at least partially dependent on characteristics of local housing markets. ■

APPENDIX: DATA SOURCES

MLS Data

The MLS data are part of the CoreLogic Real Estate Database in the RADAR Data Warehouse (DW), which contains property-level data on deed and mortgage transactions, foreclosure actions, tax assessors' characteristics, and sale listings for residential properties around the United States. The MLS data include listings for properties that are on the market for sale or for rent. The data come from real estate boards, organizations of real estate agents who enter properties into an electronic MLS system in order to market them. The focus of our analysis is properties for sale, so we drop the rental properties information. The data include a large array of fields but most fundamentally cover things such as the date the property went on the market; the asking price; and a description of the properties features such as the square footage of living area, the number of bedrooms and bathrooms, and other attributes. The dataset provides information about the street address; ZIP code; and identifiers for the MSA, country, and state. The dataset is dynamic, as it tracks changes in the listing over time, in particular whether the property is pulled off the market, is relisted, or has its price adjusted.

The analysis is restricted to ZIP code level, but we also conduct robustness tests at the county level. For the analysis, the observations with a missing ZIP code or Federal Information Processing System code are dropped. The analysis is restricted to single-family homes and condominiums. The unit of measure for TOM is daily (sometimes referred to as days on the market), and the observations with negatives entries, exceeding 1,460 days, or missing information are eliminated. Properties with inconsistent information, such as a closed status but categorized as active, accepting backup offers, contingent, deleted, on hold, off market, pending sale, or pending, are eliminated.

The reported variable of TOM gets reset if the property is relisted with a different realtor. For example, a property could be listed with realtor A for six months without selling, pulled off the market for two months, and then relisted with realtor B and sold within two months. The data would report a failed listing of six months and a successful listing of two months. In the absence of major improvements to the dwelling, our view is that the property has taken at least eight months to sell. To capture the effective time that properties are listed before selling or being pulled off the market, we reconstruct the variable TOM by following the property from the initial listing to a complete sale or withdrawal from the market, allowing relistings or withdrawal from the market for less than three months. This three-month threshold seems to capture more than 75 percent of such incidences.

IRS Data

The main macroeconomic variable available at the ZIP code level is adjusted gross income (income) provided by the IRS. The IRS gathers tax receipts and creates tables by ZIP codes for individual states, including various tax and income-related statistics. In particular, the IRS reports income. A ZIP code is included by the IRS only if the area has more than 10 tax receipts. A tax receipt is an individual's gross income minus tax adjustments. The analysis uses data for the years 2004-15. In the file, there are different income classes given by the IRS.

The mean income across classes is added up and divided by the total number of returns, giving the average income for a ZIP code for a given year. The data are made real using the personal consumption expenditures index and multiplying by 100.

FRBNY CCP/Equifax Data

This dataset contains individual-level data on households' credit reports, and it is available in the RADAR Data Warehouse. The data are a representative 5 percent sample of individuals in the United States with a credit report and Social Security number and are reported on a quarterly basis. For the purposes of this project, the universe of data was aggregated annually at the ZIP code level on a few variables from this vast dataset. In particular, data gathered included several measures of mortgage payment status: the number of current mortgages in a ZIP code and several variables that disaggregated past-due mortgages into buckets by timing. The summary tables and the analysis uses the flags provided by Equifax to remove duplicated individuals during aggregation. The variable defined as the mortgage delinquency rate aggregates the number of mortgages 90 days past due (delinquent), between 90-120 days past due (seriously delinquent), and "severely derogatory." Severely derogatory mortgages have no clear definition from Equifax, but Equifax and other sources suggest that these are mortgages that are at least 120 days past due and also include mortgages in the process of foreclosure, collection, or repossession. The variable for total mortgages is calculated using the measures described above along with current mortgages and mortgages less than 90 days past due. The summary statistics and the regressions report the rate that is calculated as the ratio of mortgages 90+ days past due (plus those severely derogatory) over the stock of mortgages in a given year.

ZIP-Code-Level Data

The ZIP-code-level data are from the U.S. Census Bureau's 2010 Decennial Survey of the United States. If a given ZIP Code has population missing from this survey, it is replaced by data from the 2000 Census if possible. These data are used to weight the summary statistics and scatter plots in Figures 6 and 7.

INFORMATION ON WEIGHTING

ZIP Code Regressions

The ZIP code regressions are weighted using the number of tax returns in each ZIP code in 2006 as a proxy for population. This proxy is also used in the regressions with the mortgage delinquency rate and mean income as dependent variables.

Summary Statistics

The summary statistics use weights as well. For the ZIP code summary statistics, 2000 and 2010 Census population data are used as the weights. Because population is fixed per ZIP code and does not vary per year, the static populations of the ZIP codes are used to weight these statistics.

ENDNOTES

- ¹ An extensive summary of the state of this literature is provided by Davis and Van Nieuwerburgh (2015) and Piazzesi and Schneider (2016).
- ² There is a growing literature that measures the extent to which the housing boom was driven by expectations/ beliefs or credit conditions. Plenty evidence indicates that homeowners tend to have overoptimistic expectations about future appreciation. Case and Shiller (2003) found that up to 95 percent of homebuyers in the year 2003 thought that housing prices would appreciate by an astonishing annual average of 9 percent over the next decade. Davis and Quintin (2014) show that during boom-bust periods household expectations adjust sluggishly and households fail to anticipate changes in the value of their home relative to the market value. These notions have been incorporated in models to rationalize boom episodes (i.e., Glaeser, Gottlieb, and Gyourko, 2013; Glaeser and Nathanson, 2015; Adam, Kuang, and Marcet, 2012; Kahn, 2009; and Gelain, Lansing, and Natvik, 2018). Another strand in the macro-housing literature explores the impact of changes in housing finance (i.e., reductions in mortgage rates, relaxation of loan-to-value constraints, and innovations in mortgage lending) on house prices (i.e., Ortalo-Magné and Rady, 2006; Kiyotaki, Michealides, and Nikolov, 2011; Landvoigt, Piazzesi, and Schneider, 2015; and Favilukis, Ludvigson, and Van Nieuwerburgh, 2017).
- ³ Formalizing the role of frictions in housing transaction is becoming more standard. There is an extensive literature that uses random-matching search techniques from the labor literature (i.e., Wheaton, 1990; Krainer, 2001; Novy-Marx, 2009; Ngai and Tenreyro, 2014; and Caplin and Leahy, 2011). More recently the selling behavior evidence provided by Merlo, Ortalo-Magne, and Rust (2015) has provided empirical support for using a directed search model in this article. It is common in this literature to abstract from credit constraints and the financial heterogeneity of buyers and sellers (i.e., Díaz and Jerez, 2013; Albrecht, Gautier, and Vroman, 2016; and Head, Lloyd-Ellis, and Sun, 2014), and this limits the ability to explore the connection among housing illiquidity, foreclosures, and endogenous credit supply. The majority of these papers explore the housing market in isolation, ignoring the impact of house price movements for the broad economy.
- ⁴ The appendix contains detailed information on the construction of these variables and different measures of robustness on the variation during the sample period 2005-12.
- ⁵ Months' supply is the ratio of houses for sale to houses sold. This statistic provides an indication of the size of the for-sale inventory in relation to the number of houses currently for sale. Months' supply indicates how long the current for-sale inventory would last given the current sales rate if no additional new houses were built.
- ⁶ All results presented in this article have been calculated using both TOM and months' supply and are very similar. For ease of presentation, we present the results using TOM because TOM is easy to understand.

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Health and Economic Development from Cross-Country Perspectives

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In this article, we provide a comprehensive overview of the role that health plays in economic development. We study cross-country differences in income and health and examine the underused value-of-life and life-year gain measures. In particular, we compare two value-of-life measures, one based on life expectancy and lifetime utility, and the other based on adult mortality and life insurance data. We find that the perception and receptiveness of life insurance are likely better in countries at more advanced stages of economic development. The value-of-life measure based on life insurance data is thus biased upward and downward for developed and developing countries, respectively. We then summarize the strand of theoretical literature and provide several modeling ingredients potentially useful for establishing an integrated analytic structure for understanding the role that health plays in the process of economic development. (JEL I15, O11, O15)

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1 INTRODUCTION

Over the past several decades, we have observed large and persistent disparities in per capita real income across countries. For example, based on our data sample of 80 countries, documented in the next section, the top 10 percent of countries had, on average, relative real income per worker about 85 percent of the U.S. level in 1960, whereas the bottom 10 percent of countries had an average of about 4.0 percent; the comparable figures became 95 percent and 2.5 percent, respectively, in 2010. That is, the ratio of the top 10 percent to the bottom 10 percent of relative income widened from 21 to 38 over 50 years. Such disparities have generated a sizable literature of development accounting, attempting to disentangle the underlying sources causing the income gaps. While the literature has offered extensive studies on potential drivers—particularly factors affecting physical, knowledge, and research capital accumulation—the roles played by health capital have been largely ignored.

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In this article, we provide a comprehensive overview of such roles based on individual decisionmaking. We begin by providing in Section 2 an overview of some well-known cross-country disparities in incomes and education-based measures of human capital. We then construct in Section 3 various measures that illustrate health disparities during 1960-2010. Specifically, we study cross-country differences in the following two most commonly used health measures: life expectancy at birth and adult mortality. We further examine the underused value-of-life and life-year gain measures. While some measures have been analyzed previously, the purpose of our article is to offer a deeper look using a unified framework with a broader set of cross-country data. In particular, to produce more robust findings, we group countries by their stage and speed of development because it is likely that some within-group disparities may exhibit distinct patterns.

Our data analysis enables us to establish several stylized facts. During 1960-2010, the disparity in relative real income per worker widened across countries. A higher income level made it more possible to have a better education and better health in 2010 than in 1960. Despite the overall improvement in health as measured by life expectancy, the adult mortality rate did not experience steady improvement in 1990-2000, most plausibly due to the spread of HIV. In our preferred wealth-based measure of value of life, the United States experienced a 2.5-fold increase in the value of life over the 1960-2010 50-year interval. We also find that the relative position of countries with low growth rates is deteriorating in both the relative income (falling from 32 percent to 20 percent) and relative value of life (falling from 28 percent to 20 percent), where those slow-growing countries experience a modest increase in life expectancy.

With these stylized facts in mind, we would like to call attention to the fact that, in this research area, it is “theory behind empirics.” In Section 4, we thus summarize the strand of theoretical literature and provide several modeling ingredients potentially useful for establishing an integrated analytic structure for understanding the role health plays in the process of economic development. To be more clear, our discussion is organized around the following two fundamental relationships: health production and health evolution. In Section 5, we examine the role of health in economic development from various perspectives, including morbidity and productivity, health investment incentives, quality of life, the contribution of health to growth, and barriers to better health.

We acknowledge there are several dimensions of difficulty in constructing a unified framework that may suit all countries at different development stages. Thus, the reader should view our article as a “first-step organizing framework” toward analyzing the issue concerning health and economic development from cross-country perspectives—one that goes over several useful stylized facts based on cross-country data.

2 CROSS-COUNTRY INCOME AND EDUCATION DISPARITIES

To facilitate cross-country analysis, we adopt income- and year-of-schooling-based human capital data from the Penn World Table 9.0 and health data from the World Development Indicators (WDI) database. To compute relative income measures, we use the United States as the benchmark. That is, relative income of country i is the ratio of its output-based

Table 1**Difference of Life Expectancy at Birth by Country Group**

Year	Classification by initial development stage				Classification by development speed			
	Low	Middle-low	Middle-high	High	Low	Stable	High	Rapid
1960	-25.409	-19.426	-10.062	-2.136	-19.804	-15.472	-8.522	-10.121
1970	-21.386	-16.355	-6.861	-1.336	-17.122	-12.322	-6.037	-5.981
1980	-19.704	-14.461	-5.928	-1.450	-15.402	-11.72	-5.351	-4.786
1990	-18.609	-12.296	-4.258	-0.673	-13.942	-10.828	-3.805	-2.955
2000	-17.816	-11.099	-3.426	0.057	-13.743	-9.819	-2.420	-1.967
2010	-14.106	-9.035	-2.863	0.434	-11.432	-7.697	-1.668	-0.806

SOURCE: PWT 9.0, WDI, and authors' calculations.

real GDP per worker to the comparable figure of the United States. In total, we have 80 countries with data since 1960.¹

We classify countries based on both their initial development stage measured by relative income in 1960 and their development speed measured by the growth of relative income during 1960-2014. For each classification, we categorize countries into four subgroups. For the first classification, we categorize countries as initially low income if their relative income in 1960 is below 0.1; middle-low income if their relative income in 1960 is between 0.1 and 0.2; middle-high income if their relative income in 1960 is between 0.2 and 0.5; and high income if their relative income in 1960 is above 0.5. For the second classification, we categorize countries as low growth if their relative income growth is below -1 percent; stable growth if their relative income growth is between -1 percent and 0.5 percent; high growth if their relative income growth is between 0.5 percent and 2 percent; and rapid growth if their relative income growth is above 2 percent.

We then compute the mean relative income of each subgroup and report in Table 1 the number of countries in each classification. Results based on initial development stage and development speed classifications are shown in Figures 1A and 1B, respectively. We can observe from Figure 1A that the initially middle-high-income group was distinctive in narrowing its income gap between the initially high-income group. From Figure 1B, other than observing the fast increase in income of the rapid-growth group, one cannot seemingly ignore the pattern of large and widening income disparities across countries during 1960-2010.

To contrast with health capital, we also look at knowledge-based human capital using a year-of-schooling measure. We compute education disparity using the ratio of average (knowledge-based) human capital in each subgroup relative to that of the United States for every 10 years starting in 1960. The results are summarized in Figures 2A and 2B. We can observe from Figure 2A that the middle-low group improved its human capital the most during 1960-2010. We can also observe from Figure 2B that the rapid-growth group has overtaken other groups in educational attainment since 1990.

Figure 1**Relative Real GDP per Worker****A. Subgroup by initial development stages** **B. Subgroup by development speed**

SOURCE: Penn World Table (PWT) 9.0 and authors' calculations.

Figure 2**Relative Human Capital Across Country Groups****A. Subgroup by initial development stages** **B. Subgroup by development speed**

SOURCE: PWT 9.0 and authors' calculations.

Figure 3**Relative Human Capital vs. Real GDP per Worker****A. Relative human capital and income in 1960**

Relative human capital in 1960 (U.S. = 1)

B. Relative human capital and income in 2010

Relative human capital in 2010 (U.S. = 1)

SOURCE: PWT 9.0 and authors' calculations.

To see the relationship between income and education, we provide a scatter plot of each country's relative income (horizontal) and relative human capital (vertical), both in the initial year of 1960 and in 2010 (Figures 3A and 3B, respectively). In comparison with the case in 1960, the positive relationship between relative income and relative human capital is tighter in 2010. This suggests that it is likely other factors played an important role, at least in earlier periods.

3 CROSS-COUNTRY HEALTH DISPARITIES

In this section, we will study cross-country disparities of various health outcome measures and the trend in such disparities. Health measures include the more commonly used life expectancy-at-birth and adult-mortality measures, as well as the underused value-of-life measure.

3.1 Life Expectancy

Using WDI data, we observe that in 1960 life expectancy disparities were severe: While life expectancy in advanced countries such as Iceland, the Netherlands, and Norway was 73 years, that in poor countries such as Mali was below 30 years. Moreover, despite a worldwide increase in life expectancy, there still existed large disparities in 2010, ranging from only 50 years in poor countries such as Côte d'Ivoire and Nigeria to more than 82 years in advanced countries such as Japan and Sweden.

Figure 4**Life Expectancy Difference vs. Real GDP per Worker****A. Life expectancy difference and relative income in 1960** **B. Life expectancy difference and relative income in 2010**

SOURCE: PWT 9.0, WDI, and authors' calculations.

To gain better insight, we compute the relative life expectancy, defined as the difference in life expectancy between those in each country and those in the United States for every 10 years starting in 1960. We then calculate the mean of each subgroup in the two classifications. The results are reported in Table 1. It is noticeable that life expectancies and, hence, health conditions of all subgroups improved greatly over the 50-year interval, but at a diminishing rate, with low-income and middle-low-income groups (columns 2 and 3) and low- and stable-growth groups (columns 6 and 7) fast improving. Such improvement suggests that health capital plays a crucial role, particularly during earlier stages of economic development.

The relationship between income and life expectancy is depicted by scatter plots of each country's relative income (horizontal) and relative life expectancy (vertical) in 1960 and 2010 (Figures 4A and 4B, respectively). As we have mentioned, life expectancy around the world improved enormously during 1960-2010. Similar to that for human capital, there is also a notable phenomenon that longer life expectancies and higher relative income levels tend to connect more closely in 2010 than they do in 1960.

3.2 Mortality

In the literature, adult mortality rate, defined as the probability of a 15-year-old dying before reaching age 60 (per 1,000 adults), is considered a good measure of health during working years and the most relevant health indicator for the level of output per worker. We

Table 2**Adult Mortality Rate Difference by Country Group**

Year	Classification by initial development stage				Classification by development speed			
	Low	Middle-low	Middle-high	High	Low	Stable	High	Rapid
A. Adult mortality rate difference, per 1,000 adult males								
1960	186	136	38	-17	136	96	27	52
1970	128	93	6.3	-26	96	69	-4	0.2
1980	127	96	32	-10	98	81	20	9.3
1990	146	97	26	-16	104	96	11	2.3
2000	185	107	38	-12	137	118	10	13
2010	134	80	26	-22	108	81	-4	-5
B. Adult mortality rate difference, per 1,000 adult females								
1960	237	186	78	15	185	136	71	79
1970	185	143	45	1.4	149	105	39	32
1980	163	124	40	5.9	131	100	33	22
1990	160	107	26	1.5	120	102	18	7.8
2000	185	99	25	-6	138	111	6.3	1.5
2010	132	65	17	-13	102	76	-5	-9.4

SOURCE: PWT 9.0, WDI, and authors' calculations.

therefore take male and female adult mortality rate data from WDI, compute the mortality difference between those in each country and those in the United States, and then calculate the mean mortality rate for each subgroup for every 10 years starting in 1960. We summarize the results for males and females in Tables 2A and 2B, respectively. Different from the steadily improving pattern observed in life expectancy for low-income, middle-low-income, low-growth, and stable-growth groups, the declining trend in adult mortality was interrupted during 1990-2000, most plausibly due to the spread of HIV and AIDS-related deaths.

The relationships between income and male and female mortality rates are depicted by scatter plots of each country's relative income (horizontal) and mortality difference (vertical) in 1960 and 2010 (Figures 5A and 5B, respectively). It can be observed that the decrease in female mortality is much more prominent than that for male mortality: During the 50-year interval, the average adult female mortality is reduced by 60.42 percent, whereas the average adult male mortality is reduced by 35.68 percent. Still, the same pattern exists: The relationship between higher income and better health becomes stronger over time.

3.3 Value of Life

Value of life has been more systematically discussed since the pivotal contributions by Rosen (1988) and Ehrlich and Chuma (1990), more recently explored by Murphy and Topel (2006); Hall and Jones (2007); Jones (2016); and Chen, Wang, and Yao (2017).

Figure 5**Adult Mortality Rate Difference vs. Real GDP per Worker****A. Adult mortality rate differences, male**

Adult mortality rate difference in 1960: Male

Adult mortality rate difference in 2010: Male

B. Adult mortality rate differences, female

Adult mortality rate difference in 1960: Female

Adult mortality rate difference in 2010: Female

SOURCE: PWT 9.0, WDI, and authors' calculations.

The conventional empirical measure is the value of a statistical life (VSL), which is the willingness to pay for saving a life. Such figures in the United States range from about \$2 million (CPI adjusted to 2009 constant U.S. dollars) estimated by Ashenfelter and Greenstone (2004) to almost \$7 million estimated by Costa and Kahn (2004). Viscusi and Aldy (2003) provide a detailed review on the VSL for the United States as well as Canada, the United Kingdom, Japan, and six additional countries, showing that the figures vary greatly across studies for any single country. As there is no systematic and consistent cross-country measure on the value of life, with reasonable simplifying assumptions we propose two cross-country measures on the value of life below. The first measure is based on a standard perpetual youth model. The second measure is based on available life insurance data. We will refer to the first measure as a model-based value of life, and the second measure as a life insurance-based value of life.

3.3.1 Model-Based Value of Life. Consider a standard continuous-time lifetime utility of an average individual with a simple flow indirect utility taking a constant intertemporal elasticity of substitution form, given by

$$(1) \quad v(y) = \frac{y^{1-1/\sigma} - 1}{1 - 1/\sigma},$$

where y is per capita real income and σ is the intertemporal elasticity of substitution. Under the concept of permanent income, y is constant, measured by the average over a relevant time period.

Should mortality be chosen as the health outcome measure, one may compute a flow mortality rate μ and, given a constant time preference rate of $\rho > 0$, obtain lifetime utility under a commonly used value of $\sigma = 0.5$ as

$$(2) \quad V = \int_0^{\infty} \frac{y^{1-1/\sigma}}{1 - 1/\sigma} e^{-(\rho+\mu)t} dt = \frac{-y^{-1}}{\rho + \mu},$$

where t is time index and where we have omitted the -1 term because it only adds a constant when we integrate the flow indirect utility and so would not affect the result.

When life expectancy is chosen as the health outcome measure, we can no longer set $\sigma = 0.5$. This is because with negative flow indirect utility, life expectancy becomes an inferior good—the longer it is, the lower lifetime utility will be (see the discussion by Murphy and Topel, 2006). There are two ways to fix the problem: The first way is to assume the flow utility takes a natural log form (i.e., $\sigma = 1$); the second way is to consider a wealth-based value-of-life measure by assuming the flow utility takes a linear form (i.e., $\sigma = \infty$). If assuming a natural log flow utility function, one must ensure that the utility flow is positive either by adjusting the unit a la Murphy and Topel (2006) and Chen, Wang, and Yao (2017), or by adding a constant—say, one—to the log function a la Hall and Jones (2007) and Jones (2016). In the former case, $v(y) = \ln y$, where y is required to exceed the subsistence level of one. In the latter case, $v(y) = \ln(1+y)$, but such a constant distorts the relative disparity across countries: The flow utility value in poor countries is upward biased and that in rich countries is downward biased.

Table 3**Model-Based Value of Life and Gain from One Additional Life-Year for the U.S.**

	Thousands of 2011 U.S. dollars					
	1960	1970	1980	1990	2000	2010
Value of life	1715.058	2189.127	2512.401	2900.608	3667.607	4273.283
Gain from one additional life-year	11.184	13.888	14.812	16.406	20.002	22.205

SOURCE: Authors' calculations.

Nonetheless, the lifetime utility in both cases is curved downward due to the property of the natural log function. We thus choose the wealth-based value-of-life measure, and the lifetime utility given life expectancy T becomes

$$(3) \quad V = \int_0^T y \cdot e^{-\rho t} dt = \frac{y}{\rho} [1 - e^{-\rho T}].$$

Now we are prepared to define the final measure. Notice that one must convert the adult mortality rate at advanced ages to the flow mortality rate measure μ . In a cross-country study with a wide range of life expectancy outcomes, such conversion is likely sensitive to the age at which mortality is measured. The life expectancy-based measure given by equation (3) is, on the contrary, more robust for a cross-country comparison, which is why we chose it as the value-of-life measure in this study. Accordingly, gain from one additional life-year is given by

$$(4) \quad \Delta V = \frac{y}{\rho} [e^{-\rho T} - e^{-\rho(T+1)}],$$

while relative value of life in country j measured against that in the United States becomes

$$(5) \quad \frac{V_j}{V_{US}} = \frac{y_j}{y_{US}} \frac{1 - e^{-\rho T_j}}{1 - e^{-\rho T_{US}}}.$$

In our 80-country sample of income data at 10-year intervals from 1960-2010, the lowest real GDP per worker is \$1,093 (2011 U.S. dollars) in Mozambique in 1960. We thus choose to express y in terms of thousands of 2011 U.S. dollars. Following the literature, the annual time preference rate ρ is set at 0.02. We first compute and report in Table 3 the value of life and gain from one additional life-year for the United States at 10-year intervals from 1960-2010. Our computed value of life for the United States ranges from \$1.72 million in 1960 to \$4.27 million in 2010, falling into the range of the existing computed value of life for the United States, and the value of a life-year gain is more than \$20,000 since 2000. Over the 50-year interval, the value of life and the value of a life-year gain increased the most during 1960-70 and 1990-2000, mainly due to the fast increase in income levels.

To reveal cross-country health disparities, we compute the mean value of life, the mean gain from an additional life-year, and the mean relative value of life for each subgroup in the

Table 4**Model-Based Value of Life by Country Group**

Thousands of 2011 U.S. dollars								
Year	Classification by initial development stage				Classification by development speed			
	Low	Middle-low	Middle-high	High	Low	Stable	High	Rapid
1960	83.309	228.380	494.682	1136.661	482.053	584.591	520.038	206.387
1970	134.468	346.274	805.317	1530.893	619.524	801.374	840.278	431.553
1980	213.126	455.670	1077.642	1873.848	684.960	999.900	1143.189	802.844
1990	273.836	505.487	1227.043	2034.931	625.341	1094.681	1375.646	1099.705
2000	401.778	710.074	1630.365	2586.140	680.036	1368.325	1940.069	1680.754
2010	571.276	982.961	2049.406	2975.411	848.182	1597.444	2379.360	2290.207

SOURCE: Authors' calculations.

Table 5**Model-Based Gain from Additional Life-Year by Country Group**

Thousands of 2011 U.S. dollars								
Year	Classification by initial development stage				Classification by development speed			
	Low	Middle-low	Middle-high	High	Low	Stable	High	Rapid
1960	1.157	2.618	4.263	8.157	4.694	4.539	3.869	1.604
1970	1.465	3.312	6.014	10.210	5.250	5.726	5.814	2.955
1980	1.837	3.577	7.132	11.534	5.176	6.539	7.115	4.966
1990	2.086	3.495	7.285	11.567	4.179	6.551	8.002	6.332
2000	2.716	4.432	9.076	13.824	4.236	7.719	10.582	9.143
2010	3.516	5.675	10.947	15.049	5.066	8.650	12.277	11.638

SOURCE: Authors' calculations.

two classifications at 10-year intervals from 1960-2010 and report the results in Tables 4, 5, and 6, respectively. We can see from Tables 4 and 6 that the initially low-income group increases the most in its value of life because of a big improvement in life expectancy in these countries. On the contrary, the low-growth group increases the least and lags behind other groups in their value of life. As for the gain from an additional life-year, of particular notice are the fluctuations and setback experienced by only the low-growth group: The stable- and high-growth groups increase steadily in their life-year gains, and the rapid-growth group even experienced a fast increase and overtook the stable-growth group during 1990-2000.

We also illustrate in scatter plots the relationship between income and the difference in gain from an additional life-year for each country relative to that of the United States for

Table 6**Model-Based Relative Value of Life by Country Group (U.S. = 1)**

Year	Classification by initial development stage				Classification by development speed			
	Low	Middle-low	Middle-high	High	Low	Stable	High	Rapid
1960	0.049	0.133	0.288	0.663	0.281	0.341	0.303	0.120
1970	0.061	0.158	0.368	0.699	0.283	0.366	0.384	0.197
1980	0.085	0.181	0.429	0.746	0.273	0.398	0.455	0.320
1990	0.094	0.174	0.423	0.702	0.216	0.377	0.474	0.379
2000	0.110	0.193	0.445	0.705	0.185	0.373	0.529	0.458
2010	0.134	0.230	0.480	0.696	0.198	0.374	0.557	0.536

SOURCE: Authors' calculations.

Figure 6**Difference in Value of an Additional Life-Year from the U.S. vs. Real GDP per Worker****A. Life-year gain difference and relative income in 1960**

Life-year gain difference from the U.S. in 1960 (1K 2011 U.S.\$)

B. Life-year gain difference and relative income in 2010

Life-year gain difference from the U.S. in 2010 (1K 2011 U.S.\$)

SOURCE: PWT 9.0 and authors' calculations.

both 1960 and 2010 (Figures 6A and 6B, respectively). A notable difference in the life-year gain can be observed for 1960-2010, as the slope becomes steeper.

3.3.2 Life Insurance-Based Value of Life. Life insurance data contain information about the willingness to pay for the loss of life. However, the data are not “clean” in the sense that they do contain other information. Life insurance data consist of cost structures of insurance companies, reflect the tightness of loanable funds markets, and mirror the development of financial markets and people’s attitudes toward and acceptance of life insurance. Despite all these features, we can still gauge the value of life from these data with reasonable assumptions.

Assume actuarial fairness of the insurance market and zero markups for insurance companies. Further assume that all countries are in the same stages of economic and financial development and that people’s degree of acceptance for life insurance is the same across countries. The value of life can be computed as

$$\text{Value of life} = \frac{\text{Per-person life insurance premiums}}{\text{Probability of death}}.$$

To compute the life insurance-based value of life, we take the adult mortality rates reported in Section 3.2 as the probability of death. For the data on per person life insurance premiums, we take the density data, defined as the ratio of total premiums of life insurance to total population, from the Organisation for Economic Co-operation and Development (OECD).Stat. In total, the OECD.Stat provides life insurance density data for 62 countries for 2007-17, although there are many countries with incomplete data. For better comparison with previous results, we choose to examine year 2010 and set the United States as the benchmark economy. The life insurance-based value of life per capita in the United States is \$22,613 in 2010 (2010 U.S. dollars), which amounts to only 1.16 percent and 0.53 percent of the per capita and per worker model-based values of life, respectively.² This says that the “blurred” data on the willingness to pay life insurance severely underestimate the value of life.

3.3.3 Comparing the Two Measures. To compare the cross-country health disparities using the two value-of-life measures, we plot in Figure 7A the per worker model-based and the per capita life insurance-based *relative* values of life against those in the United States in 2010 for 30 countries in our 1960-2010 sample.³ In Figure 7B, for the 39 countries with available data, we plot the per worker model-based and the per capita life insurance-based relative values of life against those in the United States in 2010.

One can observe that while the two measures are positively related with a fairly high correlation coefficient of 0.6955, the life insurance-based relative value of life mostly lies below the model-based relative value of life. Combining the U.S. numbers mentioned above and the information here, we learn that measuring the value of life using life insurance data not only biases the value of life downward but also underestimates the cross-country variation. Figure 7C further contrasts the per worker and per capita model-based relative values of life to those in the United States in 2010. One can observe that the two series are highly correlated with a correlation coefficient of 0.9565, showing that per worker and per capita model-based relative values of life yield similar results when examining cross-country health disparities.

Figure 7

Relative Value of Life in 2010: Life Insurance Based vs. Model Based (U.S. = 1)

A. Relative value of life:
Insurance based vs. per worker model based,
our 1960-2010 sample with available data

B. Relative value of life:
Insurance based vs. per worker model based,
all available data

C. Model-based relative value of life:
Per worker vs. per capita

NOTE: The dashed blue line is the 45-degree line.

SOURCE: Authors' calculations

As mentioned before, life insurance data not only reflect people's willingness to pay, but also contain other information. We note that the greater a country's lag in financial market development and the greater the markups incurred by life insurance companies are, the higher the life insurance premium would be for the same value of life. Thus, the life insurance-based measure may be potentially biased upward in those countries. On the contrary, when people in a country have negative perceptions about and less receptiveness to life insurance (e.g., superstitions about possible bad luck in purchasing life insurance), life insurance premiums would be forced to stay low (i.e., have markdowns in exchange for bigger sales). In this scenario, the life insurance-based measure may be potentially biased downward. Should the latter effect be dominated by the former two effects, one would expect a natural downward bias when using the life insurance-based measure. Our next task is to identify the dominant effect in the context of a cross-country analysis. To proceed, we use the ratio of the life insurance-based relative value of life to the per worker model-based value of life. We then compute the correlations of this ratio with the relative real GDP per worker (relative to the United States), as well as with the per worker model-based value of life. We obtain a correlation of 0.6187 and 0.6242, respectively. The results indicate that the perception and receptiveness of life insurance are likely better in countries at more advanced stages of economic development.

Although the OECD.Stat dataset is, to our knowledge, the best internationally comparable dataset, the limited country selection misses most of the developing countries of interest, such as those in poverty traps and those rapidly growing. In short, even if a broader-based life insurance dataset were available, one must be cautious about the validity of the measure from cross-country perspectives, particularly when many less-developed countries are included in the analysis.

4 HEALTH PRODUCTION AND HEALTH CAPITAL ACCUMULATION

We now turn to the production side of health. In particular, we are interested in individual and social inputs into health production and factors affecting the process of health capital accumulation.

4.1 Health Production

Since the pivotal contribution by Grossman (1972), an individual's health expenditures z have been viewed as key inputs into one's health output x . It consists of both preventive spending, including nutrition and gym costs, and medical spending, including treatment and insurance costs. In addition to pecuniary input, time input τ is important as well, particularly exercise time. However, considering the nature of many infectious diseases, there are obvious externalities in which a society's health status should affect an individual's health production. This can be captured by the social level of health expenditures, denoted by $\bar{z}$. Moreover, public health facilities f , including clean water, a clean environment, geographic location, and medical facilities, also play critical roles, especially in developing countries. In sum, we can write the health production function as

$$(6) \quad x = x(z, \tau; \bar{z}, f),$$

where we separate the two individual inputs from the two social inputs.

Depending on the issue examined, the pecuniary inputs of health z and time input τ can be further differentiated into inputs by oneself and inputs by parents. As the social levels of health expenditures $\bar{z}$ and public health facilities f vary greatly across countries and across income levels, the functional forms of x shall be country-specific.

4.2 Evolution of Health Capital

Given the health production function specification, we can now construct the health evolution process. Specifically, future health capital h' can be viewed as depending on current health capital h , health production that helps improve health, and health deterioration due to aging. Health deterioration can be specified as the multiple of the health deterioration rate $\delta(t)$ and current health capital. As emphasized by Chen, Wang, and Yao (2017), the health deterioration rate rises with age; that is, $\delta(t)$ is an increasing function of t over one's life cycle $[0, T]$. Moreover, any health shocks such as diseases would rise $\delta(t)$. Accordingly, the evolution of health capital is captured by

$$(7) \quad h' = x(z, \tau; \bar{z}, f) + (1 - \delta(t))h.$$

Realistically, after reaching adulthood, an individual's health capital naturally reduces over time. That is, it is reasonable to expect $x(z, \tau; \bar{z}, f) < \delta(t)h$ regardless of how many individual inputs (z, τ) have been devoted. An individual's lifetime is thus endogenized and he dies as his health capital reaches a threshold level $\underline{h}$.

Another approach of endogenizing the lifetime is to introduce the survival rate to utility function *a la* Murphy and Topel (2006), Hall and Jones (2007), and Jones (2016). The expected lifetime utility, taking the mortality rate into account, is

$$U = \int_0^{\infty} e^{-\rho t} u(c_t) M_t dt,$$

where c_t is consumption, and $M_t = e^{-\int_0^t \delta(x,s) ds}$ is the probability that an agent born at date 0 survives to date t . So far the literature has been focused more on the role of z in health formation, while the discussion about time input τ is relatively small and worthy of exploration.

5 THE ROLE OF HEALTH IN ECONOMIC DEVELOPMENT

We are now prepared to examine the role of health in economic development. We begin by linking health to productivity, investment incentives, and quality of life. We then discuss quantitatively the role that health plays in economic development, followed by a remark about health barriers that may be crucial for countries in the poverty trap.

5.1 Health and Productivity

Grossman (1972) stresses that in addition to education-based human capital, health capital also affects one's labor productivity. Unhealthy individuals are found to have more sick days and exert less effort at work. As a result, they have lower labor productivity and earn lower wages. This explains why an individual's earnings profile is hump-shaped over the life course: Though one's skill and experience rise, his or her health deteriorates. In short, on a per capita basis, income rises not only in physical and human capital, k and s , but also in health capital h :

$$(8) \quad y = y(k, s, h).$$

5.2 Health and Investment Incentives

As noted by Grossman (1972), it is widely accepted that better health leads to longer life expectancy and hence promotes saving and capital accumulation. Lorentzen, McMillan, and Wacziarg (2008) find that higher adult mortality invites more risky behavior, less saving, and less investment. Jayachandran and Lleras-Muney (2009) further point out that the improvement in health also promotes education. So education-based human capital is expected to rise with health capital. We may thus rewrite (8) as

$$(9) \quad y(h) = y(k(h), s(h), h),$$

which under proper assumption of monotonicity enables us to write current health capital as a function of current income:

$$(10) \quad h = h(y).$$

5.3 Health and Quality of Life

In the simple flow indirect utility function discussed above, we have ignored for the sake of simplicity the value of good health. As elaborated by Ehrlich and Chuma (1990); Murphy and Topel (2006); Hall and Jones (2007); and Chen, Wang, and Yao (2017), better health leads to better quality of life. Accordingly, one may modify the lifetime utility expression in (3) to

$$V = \int_0^T [\ln(y) + \beta \ln(h(y))] \cdot e^{-\rho t} dt,$$

where $\beta > 0$. As pointed out by Chen, Wang, and Yao (2017), health has an additional effect on life expectancy and is hence a luxury good. To compute this generalized value of life is nontrivial, however. On the one hand, one must calibrate the parameter β , which is a challenge because it requires joint calibration with other model parameters using multiple targets, including expenditure shares and life expectancy. On the other hand, the health-income relationship must be derived from optimizing behavior, whose forms may involve parameters that are country-specific.

5.4 Theory Behind Empirics

To this end, we would like to point out several dimensions of difficulty in constructing a unified framework that may suit countries at very different development stages. This can be best understood by recognizing that different countries naturally have different primitives in preferences and technology. To be brief, we will list a few of greater importance.

First, preferences toward better health are likely country-specific, depending on cultural and social norms, and on public hazard that may inevitably harm private health. Second, earnings profiles over the life cycle are obviously different across countries. Third, labor income shares and elasticity of capital-labor substitutions also vary by country. Finally, the degree of complementarity between health- and education-based human capital may depend on job requirements and school/workplace peer factors, which are country-specific as well.

In summary, all such differences in primitives mentioned above have posed great challenges in calibrating a unified structural model to fit data from countries at different development stages. Such difficulties are exactly why scholars in this field tend to use reduced form-based “accounting” models for development accounting, rather than a deep structural model as proposed in this article.

5.5 Growth and Development Accounting

Weil (2007), Caselli (2005), and Wang (2012) find that health is important in understanding cross-country income differences, in addition to physical capital and education-based human capital. Typically, growth and development accounting is used to quantify the following relationship between income per worker y , efficiency A , factor inputs such as physical capital k , and human capital per worker:

$$y = Ak^\alpha H^{1-\alpha}.$$

Considering $H = hm$, where h is health capital relevant to production and m is education-related human capital computed from Mincerian regression, Weil (2007) uses microestimates of the effects of adult height, adult survival rate, and age of menarche on individual incomes to construct macroeconomic estimates of h . He finds that eliminating health differences among countries would reduce the variance of log GDP per worker by 9.9 percent. Using adult survival rate and birthweight, Caselli (2005) confirms Weil’s result. On the contrary, with a structural model linking survival probability to health investment, Wang (2012) considers $H = h^\beta m^{1-\beta}$ and finds that health differences explain roughly 8 percent to 9 percent of the variance of log GDP per worker. As health affects income levels both directly through improvement in labor productivity and indirectly through the incentives of saving, education acquirement, and pure enjoyment of good health, the aforementioned results are most likely underestimating the effect of health because only the direct channel of health is measured.

As mentioned previously, there are obvious externalities, such as a natural adverse health environment, inefficiencies in the health sector, and a malfunctioning health system, in which society can affect an individual’s health production. Such externalities, usually deeply rooted in a country’s institutions, may create barriers for a country on its road to prosperity. In the

next section we discuss how such types of institutional barriers are important in determining an economy's fate.

5.6 Barriers to Health

So far we have documented the relationship between health measures—human capital and relative income—and the contribution of health to economic development. We show that such a relationship is not as tight in earlier periods and that the contribution from development accounting is relatively modest. One may then inquire whether it is possible to tighten such a relationship and improve the contribution of health capital. Our earlier work provides a plausible answer to this inquiry.

Specifically, Wang and Wang (2016) show that health barriers are crucial for a developing country to take off successfully. Health-related institutional barriers in an economy can be so great that individuals have few opportunities to invest in their offspring, which then leads to a vicious cycle of poor health, low investment, and bad institutions. To rescue countries from such a poverty trap, Wang and Wang (2016) point out that correcting the institutions to ensure appropriate incentives is the first priority. Pulling a country out of poverty does not call for a complete or even substantial eradication of the institutional barriers: As long as the country overcomes the threshold institutional barriers, the country will be on the right track toward advancement and a better future.

6 CONCLUSION

Focusing on the role of health, we provide in this article an overview of cross-country differences in both the data and literature. We find that despite the overall improvement in income levels and health across countries over a recent 50-year interval, higher income levels and better health tend to connect more closely as time goes by. We also construct a wealth-based measure of the VSL that can be easily applied to cross-country studies. We find that the value of life in the United States increased 2.5-fold during 1960-2010 and that the relative position of countries with low growth rates deteriorated in both relative income and relative value of life.

As pointed out by Caselli (2005), there is still room for us to explore the role of health in cross-country income variations. Health problems facing rich and poor countries are different, and hence the way these health problems affect countries at dissimilar development stages may be very different as well. Therefore, to improve the current literature, researchers need to keep these differences in mind when examining how health affects an individual's choices and how the externalities arising from health influence society as a whole. As such, the reader should view our article as opening the door for valuable research in this fruitful area, rather than as closing the door with a complete quantitative analysis by calibrating a unified model to fit cross-country data. ■

NOTES

- ¹ There are two exceptions: Israel has data for life expectancy at birth available only up to year 1961, and Germany does not have adult mortality data in 1960, 1970, or 1980.
- ² The model-based per capita and per worker values of life in 2010 were \$1,949,245 and \$4,273,283 in 2011 U.S. dollars, respectively.
- ³ We dropped Luxembourg throughout as it is an outlier. Luxembourg's life insurance density was \$51,162 in 2010, compared with Ireland's, the country with the second-highest life insurance density, which was \$7,883 in 2010.

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