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1 INTRODUCTION

Most central banks describe their price stability goals in terms of the behavior of an all-items price index. For example, each January since 2012, the U.S. Federal Reserve’s Federal Open Market Committee (FOMC) has reaffirmed its judgment that “inflation at the rate of 2 percent, as measured by the annual change in the price index for personal consumption expenditures [PCE], is most consistent over the longer run with the Federal Reserve’s statutory mandate.” Nevertheless, “core” inflation measures often play a prominent role in the forecasting frameworks used by policymakers, as well as in their narrative accounts of realized inflation outcomes. The economic projections published four times per year by the FOMC, for example, include policymakers’ projections both for all-items PCE inflation and for PCE inflation excluding food and energy (ex-food-and-energy PCE inflation). Monetary policy statements by the Reserve Banks of New Zealand and Australia often make explicit reference to measures of core inflation, and the Bank of Canada monitors core inflation measures as an “operational guide to help the Bank achieve the total CPI [consumer price index] target” (Bank of Canada, 2018).

Broadly, the motivation for monitoring a core inflation measure is that headline inflation is subject to large transitory shocks unrelated to changes in cyclical inflation pressures or the

Trimmed-mean personal consumption expenditure (PCE) inflation does not clearly dominate PCE inflation excluding food and energy in real-time forecasting of headline PCE inflation. However, trimmed-mean inflation is the superior communications and policy tool because it has been a less-biased real-time estimator of headline inflation and because it more successfully filters out headline inflation’s transitory variation, leaving only cyclical and trend components. (JEL E31, E37, E52)
public’s confidence in the central bank’s commitment to long-run price stability. This transitory variation potentially complicates both inflation forecasting and policymaking.

As regards forecasting, stripping statistical noise from the left-hand side of an equation prior to its estimation yields more-precise coefficient estimates, increasing the chances that the fitted equation will produce superior forecasts. In the current context, there is an advantage to forecasting headline inflation using an equation estimated with core inflation on its left-hand side, to the extent that the difference between headline and core inflation can’t be forecasted.

As regards policymaking, there are both theoretical and practical reasons for thinking that central banks should react more strongly to that portion of headline inflation that is core inflation than to that portion of headline inflation that is not core inflation. According to theory, policy should stabilize “sticky” prices. To the extent that deviations of headline inflation from core are driven by volatile, flexible-price components of the headline index, therefore, those deviations should receive reduced weight in the policy reaction function. Practically, monetary policy affects inflation with a substantial lag, so a strong policy response to transitory inflation movements risks having policy provide stimulus when underlying cyclical inflation pressures are waxing or having policy apply restraint when underlying cyclical pressures are waning.

Policymakers also sometimes draw inferences about slack from the behavior of inflation. If inflation remains low or fails to increase despite historically low unemployment, it is tempting to infer that the natural rate of unemployment must have declined. Such inferences are reliable, however, only to the extent that there is a tight empirical link between inflation and labor-market slack. As discussed above, in a forecasting context, one will more accurately identify any such link if one strips idiosyncratic noise from headline inflation before estimation.

In this article, we compare two alternative measures of core PCE inflation: ex-food-and-energy PCE inflation and trimmed-mean PCE inflation. Given the trimmed mean’s relatively late introduction (in 2005), it is only recently that we have a sufficiently long history to perform a real-time comparison between the two core measures.

We start with a brief history of core inflation. Then, we examine whether either ex-food-and-energy PCE inflation or trimmed-mean PCE inflation is useful in real-time forecasting of headline inflation and whether either core measure has a reliably tight empirical link to slack. We discover that both trimmed-mean and ex-food-and-energy PCE inflation are useful in real-time forecasting of headline PCE inflation and that neither core measure has a strong, consistent forecasting advantage over the other. However, the trimmed-mean measure has exhibited less real-time bias than the ex-food-and-energy measure and is more tightly linked to labor-market slack than is either headline inflation or the conventional core measure. For those reasons, trimmed-mean should arguably receive greater weight than headline and ex-food-and-energy PCE inflation in policy discussion and Federal Reserve communications.

2 A SHORT HISTORY OF CORE INFLATION

The earliest core inflation measures were exclusion based—that is, of the form “inflation excluding [items X, Y, and Z],” as in the U.S. CPI excluding food and energy or ex-food-and-energy PCE inflation.
energy PCE inflation. Beginning with the work of Stephen Cecchetti, Michael Bryan, and others in the 1990s (Bryan and Pike, 1991; Bryan and Cecchetti, 1994; and Bryan, Cecchetti, and Wiggins, 1997), core inflation measures based on robust estimators of the central tendency—medians and trimmed means—gained greater currency. The trimmed-mean PCE inflation rate produced by the Federal Reserve Bank of Dallas is a member of this family.

Core measures of this form do not exclude a priori any particular item or class of items, but rather exclude fixed proportions of mass from the lower and upper tails of the distribution of disaggregated price changes in each period of observation (typically a month). Notable examples for the United States, in addition to the Dallas Fed measure, include the weighted-median CPI inflation rate and the 16 percent trimmed-mean CPI inflation rate published by the Federal Reserve Bank of Cleveland. Abroad, the Reserve Bank of Australia, Bank of Canada, and Reserve Bank of New Zealand all make reference to median or trimmed-mean measures of inflation in their official monetary policy statements; monetary policy statements of the Reserve Bank of Australia, in particular, refer to these measures as measures of underlying inflation.

Earlier studies have noted some advantages of trimmed-mean core inflation measures over exclusion-based measures. Brischetto and Richards (2006) examine data for Australia, the United States, Japan, and the euro area and find that trimmed-mean CPIs outperform headline and exclusion measures on a range of different criteria, including smoothness, ability to track movements in trend headline inflation, and predictive power for near-term headline inflation. Meyer and Venkatu (2014) focus specifically on forecasting ability and find that the median and 16 percent trimmed CPI inflation rates provide better out-of-sample forecasts of headline CPI inflation, over horizons of 6 to 36 months, than either headline CPI or CPI excluding food and energy. More recently, Ball and Mazumder (2019) compare ex-food-and-energy PCE inflation with weighted-median PCE inflation, which they find to be relatively less volatile and more strongly (and stably) linked with unemployment in Phillips curve regressions.

The intuitive argument for trimmed means over exclusion-based measures of core inflation typically notes that for standard exclusion sets—such as food and energy items—it is often the case that there are items outside the exclusion set that display price changes at least as volatile as those of the excluded items. Not all food and energy items are equally volatile, nor are all of the most volatile items exclusively food and energy. This is also one argument, among several, that Bullard (2011) makes against the use of the ex-food-and-energy measure in monetary policymaking.

The more formal, statistical case for trimming draws on insights from robust statistics (Hogg, 1974, and Prescott and Hogg, 1977). If the distributions of monthly price changes are heavy tailed, then the sample mean is unlikely to be an efficient estimator of the distribution’s location or central tendency. Compared with a normal distribution, for example, samples from heavy-tailed distributions are more likely to contain extreme realizations far from the distribution’s central tendency. Since the sample mean is sensitive to these realizations—and since extreme realizations in one direction are, in any given month, unlikely to be matched exactly by extreme realizations in the other direction—the sample mean is apt to be a noisy
estimator of the distribution’s location. Bryan, Cecchetti, and Wiggins (1997) make this argument formally and through Monte Carlo simulations in an analysis of inflation in the CPI and producer price index. Dolmas (2005) makes a similar argument in the case of PCE inflation and provides evidence of excess kurtosis in the distributions of monthly price changes in the PCE basket.

The underlying data for the trimmed-mean PCE are 178 disaggregated price and quantity series; in nominal spending terms, these disaggregated series add up to roughly 100 percent of total personal consumption expenditures. The quantity data are necessary to aggregate the price changes. As described in Dolmas (2005), the form of the aggregation weights is derived from a linear approximation to chain aggregation; in practice, they are close to Tornqvist weights.

The particular disaggregation of PCE used in the construction of the trimmed mean is available consistently from January 1977; the trimmed-mean PCE inflation rate is thus available from February 1977. Monthly real-time vintages of the data, beginning in 2005, are available in the archival ALFRED database of the Federal Reserve Bank of St. Louis.

The construction of the Dallas Fed trimmed-mean PCE inflation rate differs from other trimmed-mean inflation measures—such as the Cleveland Fed’s trimmed-mean CPI—in a few important respects. Notably, the trimming proportions for the trimmed-mean PCE are asymmetric: Since 2009, its calculation trims out 24 percent of the mass (using expenditure-share weights) from the lower tail and 31 percent from the upper tail. The trimming proportions were chosen to minimize the expected distance (in a root-mean-square sense) between the annualized monthly trimmed-mean inflation rate series and three proxies for unobserved “true” core inflation: a centered 36-month moving average of monthly all-items inflation following Bryan, Cecchetti, and Wiggins (1997), a forward-looking 24-month moving average, and a band-pass filtered trend that isolates movements in all-items inflation with a period below 36 months.

Another important difference, relative to CPI-based measures, is the potential for revision. The trimmed-mean PCE series is revised as the underlying data from the Bureau of Economic Analysis (BEA) are revised, with a rhythm typical to National Income and Produce Accounts (NIPA) releases—that is, minor revisions to the most recent month’s data over the subsequent couple months and a major revision, extending back several years, annually (with the release of data for June). The parameters governing the construction of trimmed-mean PCE inflation have been revised once, following the 2009 comprehensive NIPA revision.

### 3 EVALUATION

#### 3.1 Bias

For core inflation to usefully serve as an indicator of trend headline inflation in policy deliberations and Federal Reserve communications, it is important that it neither systematically overstate nor systematically understate headline inflation. When inflation data are subject to revision, what matters are systematic deviations of first-release core inflation from
Table 1

A. Mean Core PCE Inflation Compared with Mean Headline PCE Inflation

<table>
<thead>
<tr>
<th></th>
<th>Mean core inflation</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Ex F&amp;E †</td>
<td>Trimmed mean †</td>
</tr>
<tr>
<td>2005:Q2–2018:Q2</td>
<td>1.61</td>
<td>1.78</td>
</tr>
<tr>
<td>1996:Q1–2018:Q2</td>
<td>1.60</td>
<td>1.90††</td>
</tr>
</tbody>
</table>

B. Median Core Inflation Compared with Median Headline Inflation

<table>
<thead>
<tr>
<th></th>
<th>Median core inflation</th>
<th>Median</th>
<th>Ex F&amp;E †</th>
<th>Trimmed mean †</th>
<th>Headline ‡</th>
</tr>
</thead>
<tbody>
<tr>
<td>2005:Q2–2018:Q2</td>
<td>1.52*</td>
<td>1.79</td>
<td>1.95</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1996:Q1–2018:Q2</td>
<td>1.60**</td>
<td>1.95††</td>
<td>1.96</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

NOTE: Ex F&E, excluding fuel and energy. †Data are first release or as close as possible to first release. ‡Data are September 11, 2018, vintage. */*Difference with headline PCE inflation is statistically significant at the 10/5 percent level. ††/†††Difference with ex-food-and-energy PCE inflation is statistically significant at the 10/1 percent level.

SOURCE: BEA, Federal Reserve Bank of St. Louis ALFRED® database, and authors’ calculations.

Figure 1

Trimmed-Mean and Headline PCE Inflation Share a Common Longer-Run Trend

SOURCE: BEA, Federal Reserve Bank of St. Louis ALFRED® database, and authors’ calculations.
latest-vintage headline inflation. It is, after all, first-release core inflation data that policymakers and the public will be watching and reacting to in real time, while it is the latest-vintage headline numbers that are relevant to an ex-post assessment of inflation-control performance.\textsuperscript{13} Data for real-time trimmed-mean PCE inflation start in 2005:Q2 and for real-time ex-food-and-energy PCE inflation start in 1996:Q1. Table 1A shows mean core and headline inflation rates over sample periods that begin on those dates, while Table 1B shows the corresponding median core and headline inflation rates. (There is little difference between mean and median core inflation, but skew in headline inflation is significant at the 1 percent level.) Additionally, Figure 1 shows plots of rolling 10-year mean core inflation and rolling 10-year mean and median headline inflation. By averaging over long periods, the tables and the figure filter out high frequency and cyclical variation in inflation, highlighting longer-run trends.

The first main lesson from Table 1 and Figure 1 is that trimmed-mean inflation runs higher than ex-food-and-energy inflation: The choice between the two core inflation measures matters. Both the difference between the means of the two core inflation rates and the difference between their medians is highly statistically significant over the sample period that begins in 1996. In addition, the difference between median core inflation rates is significant at the 10 percent level over the sample period that begins in 2005.

Given that trimmed-mean and ex-food-and-energy core inflation tell very different stories, which story is more accurate? The second main lesson from Table 1 is that trimmed-mean inflation has been the better real-time approximation to headline inflation: Ex-food-and-energy inflation is downwardly biased by 16 to 21 basis points, depending on the sample period, whereas trimmed-mean inflation has stayed within 10 basis points of headline inflation, on average. Similarly, median ex-food-and-energy inflation is 43 to 46 basis points below median headline inflation—a much larger shortfall than the 1- to 16-basis-point gap between median headline and median trimmed-mean inflation. While none of the mean inflation gaps is statistically significant at conventional levels, the shortfall in median ex-food-and-energy inflation is statistically significant at the 5 percent level over the sample beginning in 1996 and at the 10 percent level over the sample beginning in 2005.\textsuperscript{14} If you want a sense of whether trend headline inflation is at, above, or below the FOMC’s 2 percent longer-run target, Table 1 suggests you should probably pay more attention to trimmed-mean inflation releases than to ex-food-and-energy inflation releases.

\subsection*{3.2 Links to Slack}

Analysts and policymakers sometimes use inflation data to draw inferences about slack. For example, the Congressional Budget Office (CBO) historically has made revisions to its estimates of the natural rate of unemployment based on the behavior of inflation. The strength and robustness of the relationship between early-release estimates of an inflation measure and latest-vintage estimates of slack determines the usefulness of that inflation measure as a real-time indicator of resource utilization.\textsuperscript{15} Accordingly, we regress early-release estimates of inflation, detrended using the Survey of Professional Forecasters (SPF) measure of long-run inflation expectations, on a constant and latest-vintage CBO estimates of the unemploy-
Table 2

Which Inflation Measure Is Most Closely, and Reliably, Related to Slack?

<table>
<thead>
<tr>
<th>Inflation measure†</th>
<th>Constant (S.E.)</th>
<th>$U - U^*$ (S.E.)</th>
<th>Adj. $R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>2005:Q2–2018:Q2</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Headline</td>
<td>$-0.146$ (0.316)</td>
<td>$-0.124$ (0.103)</td>
<td>0.034</td>
</tr>
<tr>
<td>Ex F&amp;E</td>
<td>$-0.241$ (0.070)</td>
<td>$-0.136$ (0.031)</td>
<td>0.488</td>
</tr>
<tr>
<td>Trimmed mean</td>
<td>0.035 (0.079)</td>
<td>$-0.197$ (0.039)</td>
<td>0.651</td>
</tr>
<tr>
<td>1996:Q1–2018:Q2</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Headline</td>
<td>$-0.367$ (0.170)</td>
<td>$-0.048$ (0.067)</td>
<td>$-0.001$</td>
</tr>
<tr>
<td>Ex F&amp;E</td>
<td>$-0.531$ (0.073)</td>
<td>$-0.049$ (0.031)</td>
<td>0.051</td>
</tr>
<tr>
<td>Trimmed mean</td>
<td>$-0.120$ (0.065)</td>
<td>$-0.152$ (0.033)</td>
<td>0.432</td>
</tr>
<tr>
<td>Headline</td>
<td>$-0.200$ (0.166)</td>
<td>$-0.052$ (0.075)</td>
<td>0.000</td>
</tr>
<tr>
<td>Ex F&amp;E</td>
<td>$-0.166$ (0.138)</td>
<td>$-0.074$ (0.061)</td>
<td>0.023</td>
</tr>
<tr>
<td>Trimmed mean</td>
<td>$-0.151$ (0.059)</td>
<td>$-0.203$ (0.040)</td>
<td>0.458</td>
</tr>
</tbody>
</table>

NOTE: †Inflation measures used in the regressions are deviations of inflation rates from Survey of Professional Forecasters 10-year inflation expectations. S.E., standard error. Ex F&E, excluding fuel and energy. First-release inflation data were used whenever possible; when these data were unavailable (before 2005:Q2 for trimmed-mean inflation and before 1996:Q1 for conventional core inflation) the earliest-available vintage was used instead. The unemployment gap is lagged four quarters, but results were qualitatively similar with a one-quarter lag. Standard errors are Newey-West adjusted. Coefficients statistically significant at the 1 percent level are bolded.

SOURCE: BEA; BLS; CBO; Federal Reserve Bank of Philadelphia Survey of Professional Forecasters; Federal Reserve Bank of St. Louis ALFRED® database; authors’ calculations.

Figure 2

SPF-Detrended Headline PCE Inflation Is Only Loosely Related to Labor-Market Slack

SOURCE: BEA; BLS; CBO; Federal Reserve Bank of Philadelphia Survey of Professional Forecasters; Federal Reserve Bank of St. Louis ALFRED® database; authors’ calculations.
ment gap. The results—shown in Table 2 and Figures 2, 3, and 4—indicate that deviations of trimmed-mean inflation from long-run expected inflation are more strongly and more reliably related to labor-market slack than are similar deviations of headline inflation or ex-food-and-energy inflation. The coefficient on the unemployment gap is larger in magnitude in the trimmed-mean regressions than in either the ex-food-and-energy or headline regressions and is highly statistically significant. The constant term is smaller in magnitude than in the ex-food-and-energy or headline regressions and statistically significant in only one instance. There is no evidence that the relationship between trimmed-mean inflation and the unemployment gap has deteriorated over time. The relationship appears to have been robust even to the Financial Crisis (cf. Figure 4).

Recapping, deviations of trimmed-mean inflation from SPF long-run inflation expectations are a better indicator of whether slack remains in the labor market (as gauged, ex post, by the CBO) than are deviations of either headline or ex-food-and-energy inflation. Put another way, trimmed-mean inflation is more successful at filtering out transitory inflation variation than is ex-food-and-energy inflation: The deviation of trimmed-mean inflation from trend (as captured by SPF long-run expectations) better approximates inflation’s cyclical component.
3.3 Forecasting Headline Inflation

Which core inflation measure is most useful for predicting future headline inflation? Answering that question accurately requires careful thought about how best to estimate forecasting equations in real time. Koenig, Dolmas, and Piger (2003) show that if you will be forecasting using first-release data, then you should estimate your forecasting equation with first-release data on its right-hand side. Analysts often, instead, use end-of-sample-vintage real-time data (the most up-to-date vintage available in real time) on the right-hand side of their real-time forecasting equations. For the left-hand-side variable, the obvious choice is end-of-sample data. However, there are potential gains in coefficient precision (hence, forecast accuracy) from stripping unforecastable noise from the left-hand-side variable before estimation. Gains will be most evident in smaller samples. When forecasting inflation, depending on the forecast horizon, stripping out unforecastable noise could mean using trimmed-mean or ex-food-and-energy inflation as the dependent variable, even if it is headline inflation that you are ultimately interested in forecasting (Koenig and Atkinson, 2012). To shed light on the potential usefulness of core inflation in real-time forecasting of headline inflation, we undertake two simple exercises.
Table 3

A. Rule-of-Thumb PCE Inflation Forecasting

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Lagged headline</td>
<td>1.472</td>
<td>1.229</td>
<td>1.411</td>
</tr>
<tr>
<td>Lagged ex. food and energy</td>
<td>1.060</td>
<td>0.998</td>
<td>1.218</td>
</tr>
<tr>
<td>Lagged trimmed mean</td>
<td>1.134</td>
<td>0.985</td>
<td>0.923</td>
</tr>
</tbody>
</table>

B. Rule-of-Thumb PCE Inflation Forecasting (excluding 2009)

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Lagged headline</td>
<td>1.02</td>
<td>0.95</td>
<td>1.27</td>
</tr>
<tr>
<td>Lagged ex. food and energy</td>
<td>0.82</td>
<td>0.87</td>
<td>1.16</td>
</tr>
<tr>
<td>Lagged trimmed mean</td>
<td>0.84</td>
<td>0.81</td>
<td>0.81</td>
</tr>
</tbody>
</table>

NOTE: When the first-release inflation series was unavailable (before 2005:Q2 for trimmed-mean inflation and before 1996:Q1 for conventional-core inflation), the earliest-available vintage was used instead.

SOURCE: BEA, Federal Reserve Bank of St. Louis ALFRED® database, and authors’ calculations.

Rule-of-Thumb Forecasting. A simple rule of thumb is to set your forecast of inflation over the next four quarters equal to observed inflation over the most recent four-quarter period. The relevant “observed inflation” is first release, while the variable to be forecasted is latest-vintage headline inflation. Results are shown in Table 3A for three sample periods: (i) the period over which we have real-time trimmed-mean inflation, (ii) the period over which we have real-time ex-food-and-energy inflation, and (iii) an extended sample. In every case, lagged core inflation is a substantially better rule-of-thumb forecaster than is lagged headline inflation. Differences in forecast performance across the two core inflation measures are relatively small over those samples where real-time, first-release data are available.

Table 3A results may be distorted by the aftermath of the Financial Crisis, which brought about a sharp decline in inflation during 2009. Most analysts would not have relied on a rule-of-thumb inflation forecast during that period. As it turns out, though, excluding the immediate aftermath of the Financial Crisis from the analysis does not alter any of our main conclusions (Table 3B). It remains the case that rule-of-thumb forecasts based on lagged core inflation do notably better than those based on headline inflation and that differences in forecast performance across the two core inflation measures are relatively small over samples where real-time, first-release data are available.

Recursive Real-Time Forecasts of Headline Inflation. We also recursively estimate an inflation-forecasting equation of the form

\[
\pi(t) = \beta_0 + \beta_1 \pi(t-4) + \beta_2 \pi^c(t-4) + \beta_3 \pi^e(t-4) + \gamma u(t-4) + \varepsilon(t),
\]
where $u$ is the unemployment rate, $\pi$ is four-quarter headline inflation, $\pi^c$ is either ex-food-and-energy or trimmed-mean inflation, $\pi^e$ is SPF long-run inflation expectations, and $\epsilon(t)$ is an error term.\textsuperscript{12} End-of-sample vintage data are used on the equation’s left-hand side and first-release data (or as close to first release as possible) are used on the right-hand side. The first forecast is for 2006:Q2, using first-release data for 2005:Q2. The final forecast is for 2018:Q2, using first-release data for 2017:Q2. We use two different sample starting points: 1996:Q1 and 1982:Q4. The real-time forecasts are compared with latest-vintage headline PCE inflation. The four-quarter period immediately following the Financial Crisis (2009:Q1–2009:Q4) is excluded from both the estimation and forecast evaluation. As shown in Table 4A, forecast performance is slightly better using the trimmed-mean measure of core inflation when the sample period used for estimation is short. That advantage disappears (and forecast performance improves) when the sample period is extended back to the 1980s.

As previously noted, more-precise coefficient estimates (and, so, better forecasts) can sometimes be obtained by stripping noise from the dependent variable, suggesting that there might be an advantage to replacing $\pi(t)$ on the left-hand side of equation (1) with $\pi^c(t)$. Again, left-hand-side data are end-of-sample vintage, and forecasts are compared with latest-vintage headline PCE inflation data. Results are displayed in Table 4B. Forecasting performance with a short sample is much improved when core inflation is used as the left-hand-side variable during estimation, regardless of which core inflation measure is used. (Compare the first columns of Tables 4A and 4B.) However, there is no improvement when the estimation period is extended back to the 1980s. (Compare the second columns of Tables 4A and 4B.) Independent of the sample start date, ex-food-and-energy and trimmed-

<table>
<thead>
<tr>
<th>Table 4</th>
</tr>
</thead>
</table>

<table>
<thead>
<tr>
<th>Estimated recursively over sample period starting…</th>
<th>1996:Q1</th>
<th>1982:Q4</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\pi^c = \text{Ex. food and energy}$</td>
<td>1.21</td>
<td>0.87</td>
</tr>
<tr>
<td>$\pi^c = \text{Trimmed mean}$</td>
<td>1.12</td>
<td>0.89</td>
</tr>
</tbody>
</table>

| **B. Root Mean-Square Forecast Errors from Equation (1) with $\pi^c$ Replacing $\pi$ on the Left-Hand Side, 2006:Q2–2018:Q2 (excluding 2009)** |

<table>
<thead>
<tr>
<th>Estimated recursively over sample period starting…</th>
<th>1996:Q1</th>
<th>1982:Q4</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\pi^c = \text{Ex. food and energy}$</td>
<td>0.87</td>
<td>0.89</td>
</tr>
<tr>
<td>$\pi^c = \text{Trimmed mean}$</td>
<td>0.84</td>
<td>0.89</td>
</tr>
</tbody>
</table>

SOURCE: BEA; Federal Reserve Bank of Dallas; BLS; Federal Reserve Bank of Philadelphia Survey of Professional Forecasters; Federal Reserve Bank of St. Louis ALFRED® database; and authors’ calculations.
mean core inflation measures are about equally useful for forecasting headline inflation. Interestingly, the root-mean-square forecast errors reported in Table 4B are no better than those obtained from simple rule-of-thumb forecasting based on lagged core inflation. (Compare the root-mean-square errors reported in Table 4B with the left-column entries in Table 3B.)

At a four-quarter horizon, evidently, real-time forecasts of core inflation usefully serve, also, as forecasts of headline inflation. It makes little difference whether the core measure is ex-food-and-energy inflation or trimmed-mean inflation.

4 SUMMARY AND CONCLUSIONS

Trimmed-mean PCE inflation is more strongly and reliably related to labor-market slack than are either headline PCE inflation or ex-food-and-energy PCE inflation, and it is more predictable than either of these alternative inflation measures. Real-time trimmed-mean inflation forecasts also serve well as forecasts of headline inflation, sometimes outperforming models that try to forecast headline inflation directly. First-release trimmed-mean inflation rates, averaged over samples that span the business cycle, match up well with latest-vintage mean and median headline inflation rates calculated over the same samples.

We conclude that trimmed-mean inflation shares a long-run trend with headline inflation, but filters out the short-term variation in headline inflation that obscures the relationship between headline inflation and labor-market slack. These features make trimmed-mean inflation useful for forecasting headline inflation, drawing inferences about slack, and explaining Federal Reserve policy decisions.

Ex-food-and-energy PCE inflation appears to be less successful than trimmed-mean PCE inflation at filtering the short-term, noncyclical elements from headline PCE inflation and has substantially understated headline inflation over sample periods that span the business cycle. Consequently, it is less informative about headline inflation trends and about slack and less useful as a communications tool. However, over sample periods that include the recent downturn and ongoing expansion, ex-food-and-energy inflation has been every bit as useful a forecasting tool as trimmed-mean inflation.
NOTES


2. An alternative solution to the delayed-impact issue is to have policy respond to forecasted headline inflation. As we’ve just discussed, however, superior forecasts of headline inflation may come from a model of core inflation.

3. The trimmed-mean inflation rate, discussed in more detail later in the article, is constructed by excluding, or “trimming,” the most extreme component price changes each month. Which components get trimmed thus varies from month to month, and no particular component—whether food, energy, or otherwise—is necessarily included or excluded.

4. The earliest reference to an exclusion-based measure of inflation that we know of is to CPI excluding food, which appeared in the Bureau of Labor Statistics (BLS) detailed CPI reports in 1957 and was subsequently referenced in The Economic Report of the President in 1958. See the 1957 CPI reports archived in FRASER® of the Federal Reserve Bank of St. Louis: https://fraser.stlouisfed.org/title/58.

5. See recent monetary policy statements by these central banks: Reserve Bank of New Zealand (2018), Reserve Bank of Australia (2018), and Bank of Canada (2018).

6. Importantly, the Ball-Mazumder analysis is limited to latest-vintage data, whereas we use real-time vintage data to the extent possible.

7. For example, in data from 1993 to the present, more-processed food items, such as cereals, bakery products, and alcoholic beverages, all have standard deviations of their monthly price changes that are less than the median standard deviation across nonfood, nonenergy components. Electricity services, the least volatile energy component, has a standard deviation only slightly above the nonfood, nonenergy median. And conversely, 44 nonfood, nonenergy items have standard deviations above the median standard deviation among food and energy items.

8. The sources of these data are the Bureau of Economic Analysis’s (BEA’s) Underlying Detail Tables 2.4.4U and 2.4.5U. Note that because their potential sign changes confound the cumulation of expenditure weights, net foreign travel and net expenditures abroad are excluded from the calculation of the trimmed mean. The weight of these two categories has averaged –0.15 percent over the period for which the trimmed mean is calculated.


10. From its introduction in 2005 to the BEA’s comprehensive revision of the National Income and Product Accounts (NIPA) in 2009, the lower and upper trimming proportions had been 19.4 percent and 25.4 percent, respectively.

11. This pass band was chosen to maximize the correlation between the resulting trend estimate and the effective federal funds rate. As discussed in Dolmas (2005), the rationale for this third proxy is to treat true core inflation as the inflation to which policymakers seem to have responded.

12. As part of the 2009 revision, the BEA reorganized its underlying data on component-level PCE prices and quantities, combining some series, disaggregating others and, importantly, separating out the activity of the nonprofit sector from that of the household sector.

13. Except as noted, results were unchanged when we compared first-release core inflation with headline inflation as it appeared after one annual revision.

14. The latter result is not robust to a comparison of first-release ex-food-and-energy inflation with first-annual-revision headline inflation.

15. Alternatively, the analyst armed with a real-time slack measure in which she has confidence might hope to use the behavior of inflation to draw inferences about longer-run inflation expectations. Then it will be useful for early releases of the inflation measure to be strongly and robustly related to longer-run expectations, without having to control for a wide range of influences other than slack.

16. Depending on the data-revision process, it might also mean using early-release data on the left-hand side of the forecasting equation. See, again, Koenig, Dolmas, and Piger (2003).

17. The rule-of-thumb forecasting model is the special case of equation (1) where either β₁ = 1 and all other coefficients are restricted to equal zero or β₂ = 1 and all other coefficients are restricted to equal zero. Equation (1) can be thought of as the reduced form of a three-equation system in trend inflation, cyclical inflation, and transitory
inflation: \(\pi^*(t) = (1 - \delta_1 - \delta_2 - \delta_3)\pi^* + \delta_1\pi(t - 4) + \delta_2\pi'(t - 4) + \delta_3\pi''(t - 4) + \varepsilon_i(t); \pi^*(t) - \pi^*(t - 4) = \alpha_1[\pi^*(t - 4) - \pi^*(t - 4)] + \varepsilon_1(t - 4) - \varepsilon_1(t). \)

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We revisit the Kaldor growth facts for the United States and the United Kingdom during the post-war period. We find that while overall the original Kaldor facts continue to hold, deviations occurred along several dimensions: Instead of staying constant, the growth rates of real GDP per worker and of real capital per worker have slowed down in the United States and the United Kingdom since the 1970s, the capital-to-output ratio has increased in the United Kingdom, and the share of income paid to labor has decreased in the United States since 1990. We discuss how to calculate the Kaldor facts in multi-sector growth models and establish that a slowdown in GDP-per-worker growth naturally results from secular changes in relative prices. (JEL O41, O47)


1 INTRODUCTION

The process of building economic models benefits from the existence of stylized facts that discipline the modeling choices. In the theory of economic growth, these stylized facts were first stated by Kaldor (1961) and are called the Kaldor growth facts (or sometimes for short the Kaldor facts or the growth facts). These facts are that the growth rates of real GDP per worker and real capital per worker exhibit no trend and that the gross return on capital, the capital-to-output ratio, and the GDP share of the payments to capital exhibit no trend growth. Although the field of economic growth has rapidly developed since Kaldor’s article, it is fair to say that being consistent with the original Kaldor facts is still viewed as the minimum requirement for a credible model of economic growth.¹

In this article, we have two primary goals. The first one is to empirically revisit the Kaldor facts more than half a century after Kaldor wrote his article. The second goal is to discuss how to address the Kaldor facts in multi-sector versions of the growth model.
Given the long-standing and seemingly well-established position of the Kaldor facts in the literature, revisiting them may seem a frivolous task to undertake. There are three good reasons for nonetheless doing this. First, and somewhat ironically, the Kaldor (1961) paper that is cited for laying out the Kaldor facts does not actually contain any presentation of facts. Rather, Kaldor reported what he saw as the key patterns to be distilled after looking at various and disparate pieces of information that had been documented by other authors. Second, Kaldor described the experiences of the pre-1950 world. In contrast, many current macroeconomic studies focus on the post-1950 world, making it relevant to assess the state of the Kaldor facts for this period. Third, revisiting the Kaldor facts highlights a number of measurement issues that one needs to take a stand on. Although they are not usually discussed in detail, they can be subtle and are particularly relevant in multi-sector growth models.\(^2\)

We find that overall the Kaldor facts continue to hold, in that constant trends provide a reasonable first-order description to most of the data. But there are sizeable short- and medium-term fluctuations around the trend. In particular, we find evidence of deviations from the Kaldor facts along several dimensions: Instead of staying constant, the growth rates of real GDP per worker and of real capital per worker have slowed down in the United States and the United Kingdom since the 1970s, the capital-to-output ratio has increased in the United Kingdom, and the share of income paid to labor has decreased in the United States since 1990.

Establishing the existence of a balanced growth path in the one-sector growth model and connecting its properties to the Kaldor facts is a standard exercise for first-year Ph.D. students. In recent years, the profession has gone beyond that and studied multi-sector versions of the growth models that capture the effects of secular changes in relative prices and the sectoral composition of the economy (“structural change”). It is therefore natural to ask (i) under what conditions a standard multi-sector model has a balanced growth path along which the updated Kaldor facts hold and (ii) what this multi-sector model has to say about the deviations from the original Kaldor facts. This is the second goal of our article.

One of our key points is that, with the one-sector growth model, it is immediate to go from model-based measures to empirical measures; this is not the case for multi-sector growth models. The reason for this is that the one-sector model has no changes in relative prices, implying that many statistics are effectively unit free. This is not the case for multi-sector growth models, which were constructed precisely to capture the effects of secular changes in relative prices. As a result, the issue of which units should be used to measure the statistics behind the Kaldor facts takes center stage in multi-sector models.

A basic principle of connecting models with data requires measuring objects in the data and the model in the same way. It turns out that this principle has important implications for connecting multi-sector models to the Kaldor facts, in particular with regard to quantities such as gross domestic product (GDP). We report and discuss a recent result by Duernecker, Herrendorf, and Valentinyi (2017a), who showed that if GDP per worker is measured in the model as it is in the data by chaining the Fisher quantity index, then the multi-sector model can naturally generate the first deviation from the original Kaldor facts: GDP-per-worker growth slows down over time, instead of remaining constant.
The rest of the article is organized as follows. Section 2 first presents the original Kaldor facts and then restates them in the context of modern growth theory. Section 3 revisits the Kaldor facts in the context of post-WWII data from the United States and the United Kingdom, paying special attention to how to define the relevant objects in the data. Section 4 introduces a simple two-sector growth model and revisits balanced growth and the Kaldor facts in this setting, paying particular attention to the conditions under which a growth slowdown arises. Section 5 concludes.

2 THE ORIGINAL KALDOR FACTS

2.1 Kaldor’s Statement of the Growth Facts

The seminal article by Kaldor (1961, pp. 178-79) states the following:

As regards the process of economic change and development in capitalist societies, I suggest the following "stylized facts" as a starting point for the construction of theoretical models:

1. The continued growth in the aggregate volume of production and in the productivity of labour at a steady rate; no recorded tendency of a falling rate of growth of productivity.
2. A continued increase in the amount of capital per worker. ...
3. A steady rate of profit on capital, at least in the ‘developed’ capitalist societies. ...
4. Steady capital-to-output ratios over long periods; at least there are no clear long-term trends, either rising or falling, if differences in the degree of utilization of capital are allowed for. ...
5. A high correlation between the share of profits in income and the share of investment in output; a steady share of profits (and of wages) in societies and/or in periods in which the investment coefficient (the share of investment in output) is constant. ...
6. Finally, there are appreciable differences in the rate of growth of labour productivity and of total output in different societies, the range of variation (in the fast-growing economies) being of the order of 2-5 percent. These are associated with corresponding variations in the investment coefficient, and in the profit share, but the above proposition concerning the constancy of relative shares and of the capital-to-output ratio are applicable to countries with differing rates of growth.

The first five facts have become known as the Kaldor growth facts, or, for short, the Kaldor facts or the growth facts. The sixth fact usually receives less attention and is dropped by many authors.

2.2 The Kaldor Facts in the One-Sector Growth Model

The one-sector, closed-economy growth model is a benchmark model for aggregate analysis of economic growth because it generates the Kaldor growth facts in a rather robust and tractable fashion. In what follows, we briefly describe the one-sector model and explain how it generates the Kaldor growth facts.

There is a representative household of size \( N_t \) at time \( t \), with preferences over streams of consumption \( \{C_t\} \) described by
\[
\sum_{t=0}^{\infty} \beta^t N_t \left( \frac{C_t}{N_t} \right)^{1-1/\sigma} - 1
\]

where \( \beta \in (0,1) \) is the discount factor and \( \sigma > 0 \) is the household’s elasticity of substitution between consumption per member at different dates. The household does not value leisure, and the time available for work for each household member is normalized to 1. The total time available for work then equals \( N_t \).

There is an aggregate production function of the Cobb-Douglas form

\[
Y_t = A_t K_t^\theta L_t^{1-\theta},
\]

where \( A_t \) captures exogenous technological progress, \( \theta \) is the capital-share parameter, \( K_t \) is the capital stock at time \( t \), and \( L_t \) is labor input at time \( t \).

The feasibility constraint and the capital-accumulation equation are

\[
Y_t = C_t + X_t,
\]

\[
K_{t+1} = (1 - \delta) K_t + X_t,
\]

where \( X_t \) is investment and \( \delta \in [0,1] \) is the depreciation rate.

The one-sector growth model is completed by assuming that the population and technological progress grow at constant rates \( \eta \) and \( \gamma \), respectively:

\[
N_{t+1} = (1 + \eta) N_t,
\]

\[
A_{t+1} = (1 + \gamma) A_t.
\]

Since the growth facts involve prices, it is natural to focus on a competitive equilibrium of the one-sector growth model. Let \( p_t \) denote the price of output in period \( t \) in current dollars and \( w_t \) and \( r_t \) denote the prices of labor and capital, respectively, in period \( t \) in terms of units of output. As is standard in the literature, we focus on a balanced-growth-path equilibrium (or balanced growth path for short), along which all variables grow at constant rates including zero (that is, they may be constant). Such a balanced-growth-path equilibrium is of interest for two reasons. First, from a theoretical perspective, having a balanced-growth-path equilibrium anchors the asymptotic behavior of the model, which helps in analyzing and solving the model. Second, from an empirical perspective, establishing the existence of a balanced-growth-path equilibrium turns out to be tantamount to establishing consistency with the Kaldor facts. In what follows, we provide a brief summary of the arguments involved in doing this.

The relevant textbook result in our context is that the above economy possesses a balanced-growth-path equilibrium. It is straightforward to show that the balanced-growth-path equilibrium generates the Kaldor growth facts. Specifically, along the balanced-growth-path equilibrium, \( w_t \) grows at the constant rate \( \gamma \) and \( r_t \) is constant. The values of aggregate output, consumption, investment, and the capital stock all grow at the same constant rate.
The per-worker values of output, consumption, investment, and the capital stock grow at the same constant rate $\gamma$. Note that per-worker values equal per capita values in the one-sector growth model. Total labor input grows at the rate $\eta$, and labor input per worker is constant. It immediately follows that all of the Kaldor facts hold along this balanced-growth-path equilibrium:

(i) The growth rate of real GDP per worker is constant: $\%\Delta Y_t/N_t = \gamma$.

(ii) The growth rate of real capital per worker is constant: $\%\Delta K_t/N_t = \gamma$.

(iii) The gross return on capital is constant: $r_t$ constant.

(iv) The capital-to-output ratio is constant: $K_t/Y_t$ constant.

(v) The share of capital income in GDP is constant: $r_tK_t/Y_t$ constant.

Note that (i) to (v) are not a minimal set of facts, because any two of (iii) to (v) imply the remaining third one.

The requirement that population and technology grow at constant rates is stringent and unlikely to hold in the data. However, this is a nonissue because the Kaldor facts do not state that certain growth rates are literally constant, but rather that trend growth rates do not vary. As a practical matter, the key property is that if the paths for population and technology exhibit fluctuations around unchanging trends, then the economy’s equilibrium will basically fluctuate around the balanced growth path.

### 3 REVISITING THE KALDOR FACTS

In this section, we revisit the Kaldor facts. As noted in the introduction, there are three reasons for doing this. First, by today’s standards the paper by Kaldor (1961) did not present any systematic evidence. Second, Kaldor was describing the pre-1950 world. And third, revisiting the Kaldor facts allows us to highlight a number of measurement issues that one needs to take a stand on. This becomes particularly relevant in multi-sector versions of the growth model.

#### 3.1 Revisiting the Kaldor Facts in the Data

Given that the one-sector growth model possesses a balanced-growth-path equilibrium with the properties noted above, we ask, How would one proceed to confirm these implied patterns in the data? An important, general principle to adopt when comparing model-based outcomes with the data is to apply the same measurement practices in both the model and data. Unfortunately, this principle is essentially vacuous in the one-sector growth model. The reason for this is that the one-sector model has just a single homogeneous good in each period, whereas in reality many goods and relative prices exhibit potentially large secular changes. Having multiple goods with changing relative prices gives rise to several questions. First, while measuring the growth rate of real output is straightforward in the model, how should we do it in the data? In the model, capital and output are the same thing and they have a relative price of unity, so $K_t/Y_t$ is both a real ratio and a nominal ratio. But which of these ratios
should we focus on in the data? In the model, the rate of return on capital is unambiguous, given that there is a single good, but in a world with many goods, one could express the return on capital in terms of different numeraires. Which one should we focus on?

Best-practice methods for many measurement issues have evolved over time. For example, not that long ago the standard practice for measuring real quantities was to use base-year prices, which were then updated at regular intervals. But the growth rates of real variables so constructed depended on the choice of the base year. Current best practice addresses this problem by computing real quantities using chained Fisher indexes that eliminate the dependence of growth rates on the base-year prices; see Whelan (2003) and Duernecker, Herrendorf, and Valentinyi (2017a) for discussion of calculating GDP with the chained Fisher index. We follow this best practice in reporting the facts for aggregate output and capital per worker.

Contemporaneous ratios may be measured as ratios of nominal or real variables. Using nominal values has the advantage that the resulting ratios are unit free, are unaffected by the choice of numeraire or base year, and are based on the same current prices that people face when they make their choices (Caselli and Freyer, 2007). In contrast, ratios of real variables tend to have undesirable properties and are often hard to interpret. For example, if the real variables are calculated in fixed prices of a base year, then their ratios depend on the choice of the base year. And if the real variables are calculated with the chained Fisher index, then it is not clear what they mean conceptually, because the chained Fisher index does not preserve additivity.

We measure the return to capital as the nominal payments to capital divided by the nominal value of the capital stock. Doing this avoids the pitfalls around using the real variables described in the previous paragraph. It also avoids the issue of having to choose a numeraire in which to calculate rates of return over time.

Summarizing the above discussion, we calculate the Kaldor statistics as follows:

(i) Real output per worker: GDP calculated with the chained Fisher index divided by persons engaged
(ii) Real capital per worker: capital calculated with the chained Fisher index divided by persons engaged
(iii) Return to capital: payments to capital in current dollars divided by the capital stock in current dollars
(iv) Capital-output ratio: capital in current dollars divided by GDP in current dollars
(v) Capital’s share of income: payments to capital in current dollars divided by GDP in current dollars

Note that the statistics for (iii) to (v) are unit free because we calculated them with nominal, not real, variables. While capital and output are naturally in the same units in the one-sector model and the capital-to-output ratio is unit free, this is not necessarily true in the data or in multi-sector growth models.
3.2 The Updated Kaldor Facts for the United States and United Kingdom

We are now ready to present the analogues to the Kaldor facts for both the United States and the United Kingdom over the post-WWII period. We think that it is of interest to extend the analysis to other countries as data permit, but note that it seems wise to separately consider countries that experienced prolonged transition periods, either because of significant destruction during a war or because the balanced growth path shifted after a large-scale change in the institutional environment. We think that both the United States and United Kingdom avoided prolonged transitions, and so they are good candidates for learning about the relevance of balanced growth as an empirical phenomenon. Other potential candidates that share this feature include Australia, Canada, and New Zealand. In contrast, the large economies of continental Europe (e.g., France, Germany, and Italy) and East Asia (e.g., Japan) seem less promising in this regard given their prolonged transitions with strong catch-up growth after WWII.

Figure 1 displays the Kaldor facts for the United States. Several comments are in order. First, the graphs support facts (i) to (iv): Although there are indeed sizeable short- and medium-term fluctuations around trend, constant trends provide a reasonable description of the data. Second, as is well known by now, the constancy of the labor share does not provide a good description of the U.S. economy in the period since 1990. Prior to 1990 there were significant medium-run departures, but the data are still well described as being without trend.

Figure 2 displays the Kaldor facts for the United Kingdom. Once again, there are substantial medium-term departures from each of the trend lines shown, but with the exception of the series for \( \frac{K}{Y} \), the series seem consistent with the Kaldor facts. The \( \frac{K}{Y} \) series first trended upward, then stabilized, and then has trended upwards again since 1990. The main reason for the upward trend is the large increase in the price of dwellings in the United Kingdom since 1990. We also note that the behavior of the labor share in the United Kingdom differed from what we found for the United States: In the United Kingdom, the labor share declined in the 1970s and 1980s but has since bounced back to its long-run average value of two-thirds.

The main message that we take away from these pictures is that the Kaldor facts are indeed first-order features of the post-WWII evolution of both the U.S. and the U.K. economies. That notwithstanding, there are some departures worth noting as well as some interesting low-frequency fluctuations. For example, we do observe substantial differences in growth rates of GDP per worker and capital per worker across subperiods. To make this observation more precise, Table 1 shows the values of the GDP-per-worker growth rates for the postwar period 1947-2017 and four subperiods. The first three subperiods span 20 years each, starting in 1947 and lasting until 1967, 1987, and 2007. The last subperiod spans the 10 years 2007-17 that we treat separately because of the Great Recession. Clearly, the average growth rates were considerably stronger during 1947-67 than in the following three subperiods. This, of course, is a restatement of the well-documented fact that since the 1970s there has been a productivity growth slowdown. An additional observation is that in the last subperiod the average growth rates were particularly low, which is expected given that it includes the Great Recession.

One of the hotly debated questions of the moment is whether the growth slowdown is a temporary or a permanent phenomenon. Fernald and Jones (2014) pointed out that engines
Figure 1
The Kaldor Facts for the Postwar United States

A. GDP Per Worker, 1947 = 1
Log Scale

B. Capital Stock Per Worker, 1947 = 1
Log Scale

C. Gross Return on Capital
Percent

D. Capital-to-GDP Ratio

E. Labor Share
Percent

NOTE: The capital share of the corporate sector was used in the calculations.
SOURCE: BEA NIPA, BEA NIPA Fixed Asset Tables.

SOURCE: BEA NIPA, BEA NIPA Fixed Asset Tables.

NOTE: The graph displays the labor share of the corporate sector.
SOURCE: BEA NIPA.
Figure 2
The Kaldor Facts for the Postwar United Kingdom

A. GDP Per Worker, 1950 = 1

B. Capital Stock Per Worker, 1950 = 1

C. Gross Return on Capital

D. Capital-to-GDP Ratio

E. Labor Share


NOTE: Structures are excluded from the capital stock.

SOURCE: A Millennium of Macroeconomic Data for the U.K. Version 3.1

NOTE: Self-employed labor income has been imputed in the capital share calculation.

SOURCE: BEA NIPA.

NOTE: Self-employed labor income has been imputed in the labor share calculation.

SOURCE: BEA NIPA.
of economic growth such as education or research and development require the input of time that cannot be increased ad infinitum. This suggests that there is a natural limit to growth and that the slowdown might well be permanent. Gordon (2016) reached the same conclusion, arguing that we picked the “low-hanging fruit” (e.g., railroads, cars, and airplanes) during the “special century 1870-1970” and that more-recent innovations pale in comparison. Duernecker, Herrendorf, and Valentinyi (2017b) studied the extent to which structural change contributed to the growth slowdown. They found that although the effect of structural change on productivity was sizeable in the past, in the future it is likely to be considerably smaller.

In this article, our approach is somewhat more modest than those in the above papers. We just want to understand under what conditions the growth slowdown may occur in the growth model and which model features are in principle responsible for it. The material that follows answers these questions, drawing heavily on and Duernecker, Herrendorf, and Valentinyi (2017a).

4 THE KALDOR FACTS AND THE GROWTH SLOWDOWN

4.1 The Growth Slowdown in the One-Sector Growth Model

We previously argued that, subject to a few restrictions, one can find a balanced-growth-path equilibrium in the one-sector version of the growth model if the rate of technological change is constant. Along this balanced-growth-path equilibrium, GDP-per-worker growth is constant and a growth slowdown cannot occur by construction. However, a growth slowdown could still occur if a balanced growth path with high growth was unexpectedly replaced by a balanced growth path with low growth. Although the growth of GDP per worker is not constant overall, there would be two regimes with constant growth rates within each regime. The fact that one observes different growth rates for two subperiods would simply mean that the economy is shifting to the new balanced growth path.\textsuperscript{13}

While this interpretation is a natural starting point to account for the growth slowdown, it relies on exogenous, unexpected, and permanent changes in the balanced growth path. Such changes are hard to detect and usually become identifiable only with hindsight long after they happened. It is therefore of interest to present an alternative interpretation of the
4.2 A Two-Sector Growth Model

There are two main contexts in which economists have built multi-sector growth models to capture that changing relative prices are a quantitatively important empirical phenomenon. The first focuses on consumption versus investment, or more specifically, on nondurable consumption versus equipment; see Greenwood, Hercowitz, and Krusell (1997) for an early analysis of this in the context of a growth model. The second focuses on how the composition of GDP changes as the economy develops (“structural change”); see Baumol (1967) for an early analysis, which emphasized the implications of changing relative prices of goods and services, and Herrendorf, Rogerson, and Valentinyi (2014) for a recent review.

In what follows, we use a simple two-sector growth model with consumption and investment to study how a growth slowdown may endogenously arise. We can think of this two-sector model as representing the consumption-investment dynamics that result from a richer multi-sector model with several consumption goods and one investment good, in which structural change reallocates production from consumption goods with strong productivity growth to consumption services with weak productivity growth. For the sake of space, we present only the two-sector model, referring the reader to Duennecker, Herrendorf, and Valentinyi (2017a) for an analysis of the multi-sector model.

There is a representative household with preferences given by

\[ \sum_{t=0}^{\infty} \beta^t \log C_t. \]

Note two simplifications compared with the one-sector model: The population size is constant and normalized to 1, and the period utility is log. Whereas the first simplification is merely for convenience, the second is crucial for deriving a balanced growth path of the multi-sector model; see Ngai and Pissarides (2007).

There are two sectors, which produce consumption and investment. The production functions are assumed to be Cobb-Douglas. They have the same capital intensity but potentially different total factor productivities (TFPs), which captures technological progress:

\[ C_t = A_{ct} k_{ct}^{\theta} l_{ct}^{1-\theta}, \]
\[ X_t = A_{xt} k_{xt}^{\theta} l_{xt}^{1-\theta}. \]

TFP grows at rates \( \gamma_{ct} \) and \( \gamma_{xt} \):

\[ A_{ct+1} = (1 + \gamma_{ct}) A_{ct}, \]
\[ A_{xt+1} = (1 + \gamma_{xt}) A_{xt}. \]
The capital-accumulation equation is as usual:

\[ K_{t+1} = (1 - \delta) K_t + X_t. \]

### 4.3 Balanced Growth in the Two-Sector Model

Just as studies based on the one-sector growth model typically focus on properties of a balanced growth equilibrium, it is common for analyses of multi-sector versions of the growth model to look for and examine equilibrium paths that possess a similar constant growth property.

To proceed with the analysis of equilibrium, we normalize the price of investment in each period to be unity and let \( w_t, r_t, \) and \( p_{ct} \) denote the period-\( t \) prices for labor, capital, and consumption, respectively. We note that the price of consumption relative to investment is given by the inverse of the sector TFPs:

\[ p_{ct} = \frac{A_{xt}}{A_{zt}}. \]

Hence, differential rates of TFP growth imply changing relative prices. Moreover, to replicate the secular increase in the relative price of consumption, TFP growth must be stronger in investment than in consumption. In what follows, we restrict \( \gamma_{xt} \) to be constant because that is required for the existence of a balanced growth path. We also let \( \gamma_{ct} \) change over time because that is required for matching the data feature that \( p_{ct} \) displays an increasing growth rate.

A natural first step in assessing the ability of the two-sector model to account for the Kaldor facts is to mimic what we did above and look for something analogous to the balanced-growth-path equilibrium in the one-sector model. One immediately realizes that it is no longer entirely clear how to extend the notion of a balanced-growth-path equilibrium to the two-sector model. For example, if one thought that a key feature of a balanced growth path in the one-sector model is that output grows at a constant rate, then one could not export this notion to the current setting without deciding how to measure output. As we discuss below, this choice can affect whether a balanced-growth-path equilibrium exists. Another feature of the balanced-growth-path equilibrium in the one-sector model is that the real rental rate of capital is constant, or equivalently, that the marginal product of capital is constant. But again, in an economy with multiple goods and multiple prices, it is not immediately obvious which prices should be used when obtaining these variables.

We describe next how the literature has typically looked for the analogue of the balanced-growth-path equilibrium found in the one-sector growth model. First, consistent with the assumption made in the one-sector model, it is assumed that technological progress of investment grows at a constant rate, but, importantly, it is not assumed that technological progress of consumption grows at a constant rate. The literature has typically looked for an equilibrium path in which the marginal value product of capital in the investment sector is constant when the investment good is the numeraire. In equilibrium, the marginal value product of capital is equalized across sectors, so the marginal value product of capital in all sectors will be constant when expressed in units of the investment good. This is a generalization of the condition
that holds along a balanced-growth-path equilibrium in the one-sector model, since in that model both the physical marginal product and the marginal value product of capital are equal to each other and are constant.

It turns out that such an equilibrium path exists and has the following properties; see Duernecker, Herrendorf, and Valentinyi (2017a) for the proofs. If we define aggregate real output in current units of the numeraire investment as 
\[ Y_t = p_tC_t + X_t, \]
then along this equilibrium path, \( Y_t \) will grow at the constant rate \( \gamma_x \). The physical capital stock and investment will also grow at rate \( \gamma_x \), and given that the investment good is the numeraire, this is also the growth rate of the physical capital stock when measured in units of the numeraire. Lastly, consumption expenditure \( p_oC_t \) in units of the numeraire will grow at rate \( \gamma_x \) as well. Because all production functions are Cobb Douglas with the same capital intensity, it trivially follows that in the competitive equilibrium the labor share of output will be constant.

We call this path an aggregate balanced growth path. The reason for the modifier “aggregate” is that whereas in the one-sector model all equilibrium variables grow at constant (though possibly different) rates, it is not necessarily the case here that the relative price of consumption and the real quantity of consumption grow at constant rates. In fact, as shown below, both of them must not grow at constant rates if the model is to generate the slowdown in the growth of GDP per worker.\(^{14}\)

### 4.4 The Kaldor Facts and the Growth Slowdown in the Two-Sector Model

Our goal in this subsection is to highlight that the connection between the two-sector model and the data is not as simple or straightforward as is sometimes suggested. Given that along the aggregate-balanced-growth equilibrium path, \( Y_t \) and \( K_t \) grow at the same constant rate and that the rental rate of capital is constant, one might be tempted to conclude that the results from the one-sector model directly extend to the two-sector model and the two-sector model matches all of the Kaldor facts. However, as we shall see below, this conclusion is incorrect for the growth of aggregate quantities such as GDP.

Let us begin with the capital-to-output ratio. Our empirical measure was the nominal value of the capital stock relative to nominal GDP. In the one-sector model, this is equivalent to \( K_t/Y_t \) since both quantities have the same price. In our two-sector model with the price of investment normalized to unity, it turns out that the relevant object for the Kaldor facts is again \( K_t/Y_t \), where \( K_t \) is the current capital stock measured in units of investment and \( Y_t \) is current output measured in units of investment. While in this regard the result from the one-sector model directly extends to the two-sector model, it only does so when investment is the numeraire. If instead one chose consumption as the numeraire, then one would have to include the price of capital relative to consumption, \( p_{Ki} \), in the numerator of this expression, leading to \( (p_{Ki}K_t)/Y_t \).

A similar result holds regarding the return on capital. Our empirical measure was the nominal payments to capital divided by the nominal value of the capital stock. In the one-sector model, this is simply the rental rate of capital, since the numerator is \( r_tK_t \) and the denominator is \( K_t \). Choosing investment as the numeraire once again leads to a generalization from the one-sector model to the two-sector model in which the relevant object is the rental
rate of capital. If, instead, we had chosen a different numeraire, then the relevant object from the model would have been \( r_t K_t / p_t K_t = r_t / p_t \) instead of \( r_t \). Moreover, note that if we had multiple capital goods, then the close parallel to the one-sector model would necessarily fail.

Lastly, we consider the model’s implications for the behavior of the growth of GDP per worker along the aggregate balanced growth path. The model-based quantity \( Y_t \) was defined above as current output measured in units of the numeraire investment. We stress that, if the relative price of consumption to investment changes over time, then this model-based quantity will not correspond to the chained Fisher index of GDP per worker that is reported in the National Income and Product Accounts (NIPA) from the Bureau of Economic Analysis (BEA); see and Duernecker, Herrendorf, and Valentinyi (2017a) for the details. This fact implies that constant growth of GDP per worker in the model will not in general correspond to constant growth of GDP per worker in the data. Differently from the one-sector model, the general principle of consistency put forth earlier has bite in the two-sector model: To connect the model with the data in a consistent fashion, one must use the same procedure for measuring GDP per worker in both the model and data.

There are two ways to satisfy the general principle of consistency: We could measure GDP per worker both in the model and the data with either the numeraire investment or the Fisher quantity index. Duernecker, Herrendorf, and Valentinyi (2017a) compare the two possibilities and come down strongly in favor of using the Fisher index. Their main argument is that in the current two-sector model, changes in GDP per worker measured with the Fisher index turn out to approximate to first-order approximate changes in a natural welfare measure. We follow their lead and focus on measuring GDP per worker in the model with the Fisher index as is done in the NIPA. In concrete terms, this means that we proceed in two steps: First, construct an aggregate balanced growth path with the numeraire investment, as outlined above; second, calculate GDP per worker by applying the Fisher quantity index to the model quantities generated from the aggregate balanced growth path. Having done this, Duernecker, Herrendorf, and Valentinyi (2017a) show the following key result:

*If \( %\Delta p_{ct} \) is increasing, then the growth of GDP per worker measured with the Fisher index slows down along the aggregate balanced growth path constructed with the numeraire investment.*

To provide intuition for this result, it is useful to ask under which conditions \( %\Delta p_{ct} \) is increasing. Since \( %\Delta A_{ct} \) is constant and in equilibrium \( p_{ct} = A_{ct} / A_{ct} \), we have that \( %\Delta p_{ct} \) is increasing over time if and only if \( %\Delta A_{ct} \) is decreasing over time. Put differently, while TFP in investment grows at an unchanged rate, TFP in consumption must grow at a decreasing rate. If one uses the numeraire investment to measure GDP-per-worker growth, one nonetheless ends up with constant GDP-per-worker growth. The reason for this is that along the aggregate balanced growth path constructed above, the expenditure share of consumption, \( p_{ct} C_t / Y_t \), is constant, and so the decreasing growth rate of \( C_t \) is exactly offset by the increasing growth rate of \( p_{ct} \). This property will cease to hold when prices from periods other than the current one are used to evaluate the contribution of consumption expenditure to GDP. An example is the chained Fisher index, which combines current-period and last-period prices and thus picks up that \( %\Delta C_t \) slows down when \( %\Delta p_{ct} \) speeds up. For these reasons, the chained
Fisher index records a growth slowdown of GDP per worker; although measured in the numeraire investment, the growth of GDP per worker is constant.

In sum, applying the general principle of consistency to the current situation makes us change our conclusion dramatically. If we measure GDP growth consistently with the Fisher index, then it is no longer constant in the model but slows down as in the data. While this implies that the two-sector model is consistent with the dynamics in the data, it also implies that, measured with the Fisher index, an aggregate balanced growth path with constant GDP-per-worker growth no longer exists in the two-sector model.

Structural change is a natural microfoundation for the increase in $\%\Delta p_c^t$; see Baumol (1967) for the original idea. Duernecker, Herrendorf, and Valentinyi (2017a) establish this by studying a model in which structural change within consumption reallocates production from goods, which have higher-than-average productivity growth, to services, which have lower-than-average productivity growth. They show that structural change implies that $\%\Delta p_c^t$ speeds up while $\%\Delta C^t$ slows down.

We end this section by pointing to three related papers. Ngai and Pissarides (2007) mentioned that structural change can lead to a slowdown of GDP growth when GDP is calculated with constant relative prices. However, they nonetheless framed their analysis in terms of constant GDP growth measured in a current numeraire. Moro (2015) provided a model in which structural change reduces GDP growth measured with the Fisher index, but his analysis focused on the role of differences in the sectoral intermediate-input shares. Leon-Ledesma and Moro (2017) also asked to what extent structural change may lead to violations of the Kaldor growth facts. Simulating a model with multiple consumption goods, they found that structural change leads to a growth slowdown of GDP per worker measured with the Fisher index. However, they did not provide analytical characterizations of the conditions under which a growth slowdown occurs in the standard two-sector model studied here.

5 CONCLUSION

We have revisited the Kaldor growth facts for the United States and the United Kingdom during the postwar period. We have presented evidence of deviations from the original Kaldor facts along several dimensions: Instead of staying constant, the growth rates of real GDP per worker and real capital per worker have slowed down in the United States and the United Kingdom since the 1970s, the capital-to-output ratio has increased in the United Kingdom, and the share of income paid to labor has decreased in the United States since 1990. We have discussed how to calculate the Kaldor facts in multi-sector growth models and have established that the first deviation naturally results from secular changes in relative prices once model GDP is measured by a chained Fisher index in the same way as it is in the NIPA.

We have remained quiet about the other deviations of the evidence from the original Kaldor facts. With regard to the growth slowdown of capital per worker, we did not wish to disaggregate capital into its components—equipment, structures, and intellectual property products. We conjecture that if we did this, then similar arguments as those put forth regarding the GDP growth slowdown would explain the capital growth slowdown. In particular, a
sizeable part of the capital stock—structures—has experienced an accelerating relative price. Following the logic underlying the growth slowdown of GDP per worker outlined above, this acceleration is likely to reduce the model growth rate of capital per worker if it is measured with the chained Fisher index as it is in the NIPA. Be that as it may, the fact that dwellings have experienced a strong increase in their relative price explains why in the United Kingdom the capital-to-output ratio has shown a pronounced upward trend. An interesting question is why the relative price of dwellings has increased so much in the United Kingdom, but not in the United States. We conjecture that stringent regulation of building permits plays a central role in the United Kingdom.

With regard to the decline of the labor share, the standard multi-sector growth model has nothing to say because by construction the labor share is constant if all production functions are Cobb-Douglas with equal labor-share parameters. Without feeling overly apologetic for this, we refer the reader to the growing literature about the decline of the labor share. For example, Elsby, Hobijn, and Şahin (2013) discuss various reasons for why the labor share decreased. Other contributions to this literature include Karabarbounis and Neiman (2014), Bridgman (2018), Glover and Short (2018), and Koh, Santaeulàlia-Llopis, and Zheng (forthcoming).

NOTES

1. See Jones and Romer (2010) and Jones (2016) for summaries of a broader set of growth facts.
2. An exception is Kongsamut, Rebelo, and Xie (2001), who go into some detail to update the Kaldor facts.
3. While imposing the Cobb-Douglas functional form is convenient, it is not necessary for constructing a balanced growth path in the one-sector model. All arguments would go through for a general production function \( Y_t = F(K_t, A_t L_t) \) as long as it had constant returns to scale and technological change was labor augmenting.
4. See, for example, Barro and Sala-i-Martin (2003). Conditional on there being constant growth rates for population and technology, the three core assumptions that guarantee the existence of such a balanced-growth-path equilibrium are that the utility function is of the CRRA (constant relative risk aversion) variety, the production function has constant returns to scale, and technological change augments only labor.
5. There is also a second-order term, \( \gamma \eta \), which we ignore for simplicity.
6. When Kaldor wrote his study, capital data included only equipment and structures. The Bureau of Economic Analysis (BEA) now includes also intellectual property products in their investment and capital series. All statistics we report include intellectual property products in investment and capital. None of the conclusions would change if we left intellectual property products out.
7. To be specific, if each of the real components of a total is calculated with the chained Fisher index, then they do not add up to the real value of the total except in the reference year (Whelan, 2002).
8. Persons engaged are full-time equivalent workers plus the self-employed.
9. This differs from Leon-Ledesma and Moro (2017), who do not impose that ratios are unit free when they study how they change in the face of structural transformation from goods to services.
10. Note that the series for capital per worker excludes structures, because we do not have their real values for the United Kingdom.
11. We are not the first to discover that the labor share behaved differently in the United States and the United Kingdom. For previous evidence, see, for example, Annex B of the International Labour Organisation and Organisation for Economic Co-operation and Development (2015).
Note that for the United Kingdom, Table 1 does not report the growth rates of capital per worker. The reason for this is that the U.K. data that we have for the real capital stocks exclude structures.

Andolfatto and MacDonald (1998) elaborated on this idea. They modeled technological progress as resulting from irregular Schumpeterian innovations of different sizes. They showed that a slowdown in the growth of GDP per worker may occur in such an environment.

The concept of aggregate balanced growth was introduced by Ngai and Pissarides (2007). It has since been used widely, including by Duerneccker, Herrendorf, and Valentinyi (2017a) and Herrendorf, Rogerson, and Valentinyi (2018).

For a generalization with structural change in both consumption and investment, see Herrendorf, Rogerson, and Valentinyi (2018).

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1 INTRODUCTION

The large dispersion in real wages across countries suggests a potentially huge global misallocation of human capital. Thus, reallocating human capital could substantially increase global output and drastically change the world income distribution. To be sure, reallocating humans across countries is a much more complex endeavor than reallocating physical capital. Migrant workers, and not machines, leave behind friends, families, and other attachments...
and may face cultural and anti-immigrant resistance. Moreover, the impact—real or perceived—of foreign workers on the local population has been used as a political banner that has no counterpart with the impact of capital inflows. Yet, despite all those frictions and barriers, workers and their human capital have been continuously reallocated across countries, oftentimes in great measure. As of today, in the United States and in many other countries, such a reallocation is evident not only in high-human-capital-intensive institutions, such as universities, hospitals, and research institutions, but also much more generally in stores, restaurants, and farms, all of which often agglomerate workers from all over the world.

In this article, we assess the potential global efficiency gains and distributional impacts of reallocating human capital across countries. To this end, we face a number of challenges. First, we need to take a stand on which factors are fixed in each country and which factors can be reallocated—if any—including human capital. Second, we need to control for factor intensity differences across countries to avoid confusing them with distortions. Third, we need to measure or infer the marginal valuation of human capital across countries and incorporate some of the distributional constraints that countries may impose for the entry of workers from abroad. We use the recent work by Monge-Naranjo, Santaeulàlia-Llopis, and Sánchez (2019) that provides exactly the data required to address these three issues for a sample of 76 countries and for the years 1970 to 2005. First, aside from pure total factor productivity (TFP), natural resources are ultimately the only fixed inputs of production in each country. Using the measures in Monge-Naranjo, Santaeulàlia-Llopis, and Sánchez (2019), we assess the curvature of the production function of the different countries with respect to all the mobile factors, that is, human and physical capital, and evaluate the gains of reallocating human capital only or human and physical capital simultaneously. Second, we use the measures in Monge-Naranjo, Santaeulàlia-Llopis, and Sánchez (2019) to control factor intensity differences across countries, which they show are not sensitive to policy distortions. Third, we circumvent the lack of direct and reliable measurements of the relative value of human capital across countries and periods, using the model to generate two extreme and opposite bounds for the observed costs of labor across countries.

Our basic efficiency benchmark consists of equating the marginal returns to human capital across countries. Doing so points to large misallocation of human capital during the sample period, in the range of 40 to 50 percent of global output, with an upward trend over time. Our findings resemble those in Klein and Ventura (2009) and Kennan (2013), using different models, countries, and data. This basic benchmark abstracts from the barriers to reallocating human capital (workers) across countries, which can be very stringent. Some of the barriers are natural, such as the emotional cost of reallocating human beings across countries with different languages, cultures, and values. But other barriers are the result of policies and legislation, mainly in the more developed countries. Such barriers are surely motivated to prevent a reduction in the wages of some of the domestic workers. In fact, the large implied global output gains from the basic benchmark come at the cost of drastic reductions in the wage rate (per unit of human capital) in developed countries.

To appraise the potential gains in global output without the negative impact on the domestic workers of developed countries, we construct policy counterfactuals that are constrained
so that the real wages of workers must be kept constant (at the implied levels from the data). By design, if workers were the only factor that could be reallocated across countries, no reallocation would take place and global gains would be zero. However, if both human and physical capital could be reallocated, even under such a conservative exercise, the global gains would be substantially higher than reallocating physical capital alone, around 8 percent to 9 percent of global output in the 1970s and up to 6 percent by the 2000s.1 Interestingly, the reallocation is largely from the richer and poorer countries (first and fourth income quartiles) toward the middle ones (second and third income quartiles.)

Overall, a proper assessment of global misallocation considers both human and physical capital. The complementarity between these two factors plays a role, as they must be directed toward the countries with higher fixed productivity, either because of TFP or natural resources. Observed allocations deviate from such an alignment. More interestingly, if human and physical capital can be reallocated jointly to equalize their marginal returns across countries, the direction of the physical capital flows can be reverted relative to the case when physical capital is the only mobile factor. In fact, the premise that capital should flow from rich to poor countries is unwarranted: When both factors are reallocated, capital and labor would flow from some of the poor and middle-income countries toward some of the richer countries. This simple yet often ignored point could be one of the keys to understanding the consequences of alternative integration schemes with or without labor mobility for countries and regions with different productivities and fixed endowments (e.g., the United States and Puerto Rico and the European Union on one side, with NAFTA on the other).

The article is organized as follows. Section 2 describes the data used. Section 3 presents our organizing model framework. Section 4 describes the behavior of the estimated marginal product of human capital. Section 5 presents the main results in terms of misallocation of human capital. Section 6 studies the effect of migration flows on the changes in misallocation over time. The conclusion follows.

2 DATA

In this section, we describe the available data, the countries for which we have consistent reliable data, and the method used to compute input’s share of output.

2.1 Countries

We use Monge-Naranjo, Santaeulàlia-Llopis, and Sánchez’s (2019) estimates of the factor shares for natural resources, together with data from Penn World Table (PWT) 8.0 for all other variables, that is, output, labor shares, international prices of consumption, and output, and estimates for physical and human capital.2 We have consistent data from 1970 to 2005 for the following 79 countries:

- Africa: Burkina Faso, Côte d’Ivoire, Cameroon, Kenya, Morocco, Mozambique, Niger, Nigeria, Senegal, Tunisia, Tanzania, South Africa, and Zimbabwe
- Asia: Bahrain, China, Hong Kong, Indonesia, India, Iran, Israel, Japan, Jordan, the
Republic of Korea, Kuwait, Sri Lanka, Malaysia, Oman, the Philippines, Qatar, Saudi Arabia, Singapore, Thailand, Turkey, and Taiwan

- Europe: Austria, Belgium, Bulgaria, Switzerland, Cyprus, Germany, Denmark, Spain, Finland, France, the United Kingdom, Greece, Hungary, Iceland, Italy, Luxembourg, Malta, the Netherlands, Norway, Poland, Portugal, and Sweden
- The Americas: Argentina, Barbados, Bolivia, Brazil, Canada, Chile, Colombia, Ecuador, Costa Rica, the Dominican Republic, Guatemala, Honduras, Jamaica, Mexico, Panama, Peru, Paraguay, Trinidad & Tobago, the United States, and Uruguay
- Oceania: Australia and New Zealand

We exclude Burkina Faso, Nigeria, and Oman from our reallocation exercises because these countries do not have data on human capital. This implies a total of 76 countries for our benchmark sample.

In Section 5.2, we expand our analysis to countries for which we can retrieve information on rents of natural resources, factor shares, physical capital, human capital, and output for the year 2005. The improvement on data collection and sources over time and the presence of new countries since the early 1990s (e.g., from Eastern Europe), implies more countries for which the required data are available. This new set of countries includes Armenia, Benin, Botswana, the Central African Republic, Croatia, the Czech Republic, Estonia, Fiji, Gabon, Kazakhstan, Kyrgyzstan, Latvia, Lesotho, Lithuania, Macao, Mauritania, Mauritius, Moldova, Mongolia, Namibia, Romania, Russia, Rwanda, Serbia, Sierra Leone, the Slovak Republic, Slovenia, Swaziland, Tajikistan, Togo, and Ukraine. This yields a total sample of 107 countries for the year 2005.

### 2.2 Input’s Share of Output

We now explain how we incorporate the Monge-Naranjo, Santaeulàlia-Llopis, and Sánchez (2019) estimates of the factor shares for natural resources, $\phi^R_{j,t}$, for the computation of the output shares for capital and labor.

We denote the labor share of output by $\theta_{j,t}$. In this article, we use the PWT variable $labsh$. This measure of the labor share aims to correct for the part of ambiguous income, mainly proprietors’ income (i.e., the self-employed), that needs to be attributed to labor income in order to avoid underestimating the contribution of labor to output. This is a particularly relevant issue in countries in which a significant amount of labor is allocated to family-owned farms and other various forms of self-employment.\(^3\)

For the output share of physical capital, denoted here by $\phi^K_{j,t}$, the standard practice is to equate it to 1 minus the labor share. All nonlabor income must be capital income, an assumption driven by a constant-returns-to-scale production function with only physical and human capital as factors. Instead, as proposed by Caselli and Feyrer (2007), correctly accounting for the income shares of natural capital factors, the physical capital share should be calculated as

\[
\phi^K_{j,t} = 1 - \theta_{j,t} - \phi^R_{j,t},
\]
Thus, we are able to make this adjustment using data on the income shares of natural capital, $\phi^R_{jt}$, from Monge-Naranjo, Santaeulàlia-Llopis, and Sánchez (2019). Note that the output share of natural resources is important for our computations because it determines the returns to scale of mobile factors—human and physical capital—in each of the countries.

3 THE MODEL

In this section, we set out our baseline model and derive the benchmarks used to evaluate the degrees of misallocation of mobile factors across countries.

3.1 The Baseline Environment

Consider a world economy, populated by an arbitrary number $J$ of countries, indexed by $j = 1, 2, \ldots, J$. Given our data, we index the (yearly) time periods by $t = 1970, 1971, \ldots, 2005$. Our baseline model assumes a single tradable good, which can be consumed or invested across all countries. In each country, output is produced using the service flows of the country’s stocks of physical capital, $K_{jt}$; natural resources (land and other natural resources), $T_{jt}$; and human capital-augmented labor, $H_{jt} = h_{jt}L_{jt}$, where $L_{jt}$ indicates the number of workers in country $j$ in period $t$ and $h_{jt}$ their average skills or human capital. Production in the country is also a function of the country’s overall TFP, $A_{jt}$.

Our baseline model stems from the standard one-sector growth model, assuming that production of the good in country $j$ at time $t$ is Cobb-Douglas. Specifically, we consider a production function of $Y_{jt}$ in the form

$$Y_{jt} = A_{jt} \left( K_{jt}^{\gamma_{jt}} T_{jt}^{1-\gamma_{jt}} \right)^{1-\theta_{jt}} \left( H_{jt} \right)^{\theta_{jt}},$$

where $0 < \theta_{jt} < 1$ is the labor share of output. The non-labor share of output, $1 - \theta_{jt}$, is divided between a share $\gamma_{jt} (1 - \theta_{jt})$ for produced capital, $K_{jt}$, and a share $(1 - \gamma_{jt}) (1 - \theta_{jt})$ for natural resources. This specification extends the standard model in two dimensions. First, it introduces non-produced capital (natural resources) $T_{jt}$. Second, it allows for country-time variation in the factor shares as documented in the previous section.

In our framework, the marginal product of one unit of human capital in terms of the quantity of goods (QMPH$_{jt}$) is simply given by

$$QMPH_{jt} = \theta_{jt} \frac{Y_{jt}}{H_{jt}}.$$

Similarly, the marginal product of one unit of physical capital in terms of the quantity of goods (QMPK$_{jt}$) is given by

$$QMPK_{jt} = \phi_{jt} \frac{Y_{jt}}{K_{jt}} = \gamma_{jt} \left( 1 - \theta_{jt} \right) \frac{Y_{jt}}{K_{jt}}.$$
3.2 Efficient Allocations

We focus on the efficiency of the allocation of factors across countries, treating the global supply of human and physical capital as predetermined in any period. Thus, we abstract from the impact of misallocation on the incentives to accumulate those factors. Instead, we explore the potential gains, in every period, from reallocating human capital across countries. For concreteness, we assume that all output is globally mobile. For brevity, we bundle the fixed factors in each country, TFP and natural resources, in the term \( Z_{j,t} \equiv A_{j,t} \gamma_{j,t}(1-\theta_{j,t}) \).

3.2.1 Baseline. The optimal global allocation is defined by the maximization of global output

\[
Y_{W,t}^{K',H'} = \max_{\{K_{j,t},H_{j,t}\}} \sum_{j=1}^{J} Z_{j,t} \left( K_{j,t} \right)^{\gamma_{j,t}(1-\theta_{j,t})} \left( H_{j,t} \right)^{\theta_{j,t}}
\]

subject to

\[
\sum_{j=1}^{J} H_{j,t} \leq H_{W,t} \quad \text{and} \quad \sum_{j=1}^{J} K_{j,t} \leq K_{W,t},
\]

where \( H_{W,t} \equiv \sum_{j=1}^{J} H_{j,t} \) and \( K_{W,t} \equiv \sum_{j=1}^{J} K_{j,t} \) are the observed levels of human and physical capital, respectively. In addition to equalizing the QMPK of all countries to a common world price, \( r_{t}^{K} \), efficiency requires that all QMPH be equalized to a common price

\[
r_{t}^{H} = \theta_{j,t} Z_{j,t} \left( K_{j,t} \right)^{\gamma_{j,t}(1-\theta_{j,t})} \left( H_{j,t} \right)^{\theta_{j,t}-1}.
\]

Thus, the world supply levels \( K_{W,t} \) and \( H_{W,t} \) and the productivities and endowments of natural resources \( Z_{j,t} \) of all countries pin down the equilibrium \( r_{t}^{K} \) and \( r_{t}^{H} \). These prices and the factor shares determine the factor intensity of each country:

\[
\frac{K_{j,t}}{H_{j,t}} = \frac{\gamma_{j,t}(1-\theta_{j,t}) r_{t}^{H}}{\theta_{j,t} r_{t}^{K}}.
\]

The efficient allocation implies that human and physical capital are allocated across countries to complement their TFP and natural resources as allowed by their country-specific returns to scale of mobile factors. There is no closed-form solution except for the case of common (time-varying) factors shares, but the numerical optimization is trivial.

We will also present results for reallocating only human capital. In that case, the allocation of physical capital is taken as given, in the same way that the allocation of natural resources is taken as given in the problem presented above.

3.2.2 Value Benchmark. The previous benchmark presumes that workers are indifferent as to where to work and cross-country differences in output per worker are sustained by policy barriers to worker migration. The global misallocation measure derived from the corresponding counterfactual assesses the global costs of those policy barriers.
The completely opposite view is that instead of policy barriers, wage differences are sustained by compensating differences; i.e., wage differences are sustained by workers demanding different wages to live in different places. Alternatively, we can consider political constraints that prevent as unfeasible any reallocation that lowers the real wages of workers. In any event, to circumvent these concerns, we now consider the simple exercise in which the reallocation of workers and capital is constrained to keep constant the real wages of workers in all countries in terms of consumption goods.

This exercise requires data on wages (per unit of human capital), the price of consumption, and the price of output, to construct the values of \( w^h_{jt}, P^C_{jt}/P^Y_{jt} \) real wages in terms of output, for each country in each period. The PWT has measures for the price of consumption and of output but does not contain direct measurements of wages per unit of human capital in terms of output, \( w^h_{jt} \). Thus, we use our model and infer these wages as \( w_{jt} = \theta_{jt} Y_{jt}/H_{jt} = QMPH_{jt} \). We now explore the misallocation of factors given the constraint that any reallocation must keep the wages of workers in each country at this level. Notice also that if only workers, but no physical capital, are allowed to move, the reallocation would be minimal, due only to the small variation in the data for the relative price \( P^C_{jt}/P^Y_{jt} \). Notice also that by fixing the real wages of all countries at a point in time, this counterfactual is consistent with any decomposition of those wages arising from compensating differentials or barriers to the mobility of workers.

For this efficiency benchmark, we keep the assumption that output is completely mobile across countries. Then, the maximization is the same, but the resource constraints are different. First, the global amount of goods paid for human capital services in each period is equal to the one inferred in the data:

\[
\sum_{j=1}^{J} \frac{P^C_{jt}}{P^Y_{jt}} w^h_{jt} H_{jt} \leq H^N_{W,t},
\]

where \( H^N_{W,t} \equiv \sum_{j=1}^{J} \frac{P^C_{jt} w^h_{jt}}{P^Y_{jt}} H^O_{jt} \) and \( H^O_{jt} \) is the observed data value for country \( j \) in period \( t \). Similarly, we impose the restriction

\[
\sum_{j=1}^{J} \frac{P^K_{jt}}{P^Y_{jt}} K_{jt} \leq K^N_{W,t}.
\]

Finally, as mentioned above, this maximization is also subject to providing the same amount of consumption goods to workers as inferred from the data, before the reallocation.

There is an intuitive interpretation for this exercise. Imagine a firm owner who is able to reallocate resources across countries, and the firm is small enough that it takes prices as given. In terms of wages, imagine this owner is limited by country-specific regulations (unions, minimum wages, and so on) to pay the period-t wage in country \( i \) for any worker that the owner reallocates to country \( i \) in period \( t \). The owner is given the task of reallocating workers across countries to maximize real output subject to keeping the company’s payroll constant. Since we measure wages by QMPH (disregarding \( P^C_{jt}/P^Y_{jt} \) differences), the firm’s owner has no incentives to reallocate workers if capital cannot be reallocated. In this sense, this exercise provides...
a lower bound for the global gains of human capital reallocation. Once capital can also be reallocated, there are potential gains of reallocating workers, even subject to the constraint of keeping wages constant in each country.

The optimality conditions require the equalization across countries of the price-corrected marginal product of physical and human capital; that is,

\[ R^K_t = \frac{P^Y_{j,t}}{P^K_{j,t}} \gamma_{j,t} \left( 1 - \theta_{j,t} \right) A_{j,t} T_{j,t}^{(1 - \gamma_{j,t})} \left( K_{j,t} \right)^{(1 - \theta_{j,t}) - 1} \left( H_{j,t} \right)^{\theta_{j,t}} \]

for physical capital and

\[ R^H_t = \frac{P^Y_{j,t}}{P^C_{j,t} w^C_{j,t}} \theta_{j,t} A_{j,t} T_{j,t}^{(1 - \gamma_{j,t})} \left( K_{j,t} \right)^{(1 - \theta_{j,t})} \left( H_{j,t} \right)^{\theta_{j,t} - 1} \]

for human capital. Note that, given the world’s returns \( R_t \) and \( R^{H}_{t} \), the physical-to-human capital ratio in country \( j \) should be

\[ \frac{K_{j,t}}{H_{j,t}} = \gamma_{j,t} \left( 1 - \theta_{j,t} \right) \frac{P^C_{j,t} w^C_{j,t}}{P^K_{j,t}} \frac{R^H_t}{R^K_t}. \]

Thus, in the efficient allocation, physical capital intensity relative to human capital intensity varies across countries according to their (i) factor shares in production, (ii) relative prices of consumption and capital goods, and (iii) effective costs of labor. While natural resources, \( T_{j,t} \), and pure TFP, \( A_{j,t} \), enhance the amount of human and physical capital a country should receive, the cost in terms of output of both factors, respectively \( P^K_{j,t} / P^Y_{j,t} \) and \( P^C_{j,t} w^C_{j,t} / P^Y_{j,t} \), reduces them. It is trivially true that this maximization dominates the one where only capital can be reallocated. The interesting question is how much and whether the capital flows change in magnitude and direction.

4 THE MARGINAL PRODUCT OF HUMAN CAPITAL

First, we report salient features of the behavior of the cross-country dispersion in the marginal product of human capital (MPH). These results complement the characterization in the behavior of the marginal product of physical capital (MPK) provided by Monge-Naranjo, Santaelulàlia-Llopis, and Sánchez (2019). The dispersion of MPH is large and growing over time, and the accumulation of human capital does not track the behavior of the determinants of MPH. Second, to the extent that differences in MPH are driven by barriers to the mobility of labor across countries, the global gains of reallocating human capital would be an order of magnitude higher than those of reallocating physical capital. Third, the ability to reallocate workers would not only enhance the gains in global output from reallocating physical capital, but, more interestingly, also induce a reversal in the direction of reallocation of capital across countries. Instead of flowing from richer to poorer countries, capital from poorer countries...
would follow some of their workers in the direction of richer countries. This simple result could be useful in understanding the difference between integration agreements with labor mobility (e.g., the European Union) and without it (e.g., the North American Free Trade Agreement [NAFTA]).

We can simply decompose the cross-sectional variance of $\ln QMPH_{j,t}$ in terms of the labor share of output and the output-to-human capital ratios:

$$
\text{var} \left[ \ln QMPH_{j,t} \right] = \text{var} \left[ \ln \theta_{j,t} \right] + \text{var} \left[ \ln \left( Y_{j,t} / H_{j,t} \right) \right] + 2 \text{cov} \left[ \ln \theta_{j,t}, \ln \left( Y_{j,t} / H_{j,t} \right) \right].
$$

Table 1 reports the values of these variances and the covariances for a number of years in the sample period. The right side of the panel also reports a number of covariances of interest with respect to the joint reallocation of human and physical capital across countries.

There is an upward trend in the dispersion in the $\ln QMPH$. From a low value of 0.713 in 1980, the variance in $\ln QMPH$ grows thereafter until reaching its highest value of 0.978 in 2000. Almost all of the variation is driven by the dispersion in $\ln \left( Y_{j,t} / H_{j,t} \right)$. Indeed, the cross-country correlation between $\ln QMPH$ and $\ln \left( Y_{j,t} / H_{j,t} \right)$ is always above 0.95. Cross-country variation in the labor shares of output, $\ln \theta_{j,t}$, accounts for at most 9 percent of the variation in $\ln QMPH$ and tends to remain flat, mildly oscillating around 7 percent to 8 percent, during the sample period. The covariance between $\ln \theta_{j,t}$ and $\ln \left( Y_{j,t} / H_{j,t} \right)$ provides a negligible contribution.

The cross-country covariation between the marginal products of human and physical capital is key for the potential gains of jointly reallocating these factors. We find that this covariation is negative, but its magnitude is weak. The same applies to the other factors shown in the last four columns of Table 1. In the next section, we use the simple efficiency benchmarks derived above to assess the potential global gains of reallocating physical and human capital across countries.

### Table 1

<table>
<thead>
<tr>
<th>Year</th>
<th>$QMPH_{j,t}$</th>
<th>$\theta_{j,t}$</th>
<th>$Y_{j,t} / H_{j,t}$</th>
<th>$\theta_{j,t} Y_{j,t} / H_{j,t}$</th>
<th>$QMPK_{j,t}$</th>
<th>$QMPH_{j,t} P_{j,t}^{n}$</th>
<th>$QMPH_{j,t} Y_{j,t} / H_{j,t}$</th>
<th>$QMPH_{j,t} Y_{j,t} / K_{j,t}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1970</td>
<td>0.756</td>
<td>0.064</td>
<td>0.788</td>
<td>-0.048</td>
<td>-0.082</td>
<td>0.019</td>
<td>0.740</td>
<td>-0.042</td>
</tr>
<tr>
<td>1980</td>
<td>0.713</td>
<td>0.061</td>
<td>0.726</td>
<td>-0.037</td>
<td>-0.169</td>
<td>0.058</td>
<td>0.689</td>
<td>-0.105</td>
</tr>
<tr>
<td>1990</td>
<td>0.748</td>
<td>0.058</td>
<td>0.642</td>
<td>0.024</td>
<td>-0.149</td>
<td>0.111</td>
<td>0.666</td>
<td>-0.107</td>
</tr>
<tr>
<td>2000</td>
<td>0.978</td>
<td>0.059</td>
<td>0.899</td>
<td>0.010</td>
<td>-0.038</td>
<td>0.029</td>
<td>0.909</td>
<td>-0.021</td>
</tr>
</tbody>
</table>

SOURCE: Authors’ calculations based on PWT 8.0.
5 GAINS OF REALLOCATION

We compute the gains of reallocation for two samples. The first one consists of 76 countries with consistent reliable data for the years 1970 to 2005. Then, we extend the sample to 107 countries, considering countries with data available for the year 2005.

5.1 Results for the Years 1970 to 2005

Figure 1 shows the global output gains of reallocating both physical and human capital (Panel A) and human capital only (Panel B). In each panel, the dashed lines represent the gains from the benchmark. The solid lines represent the gains from the value benchmark defined above.

The most salient result is that the global gains of reallocating workers can be very large. The quantity benchmark indicates that, for all the years in the sample, the global gains would be approximately 40 percent of world output (see Panel B of Figure 1). Those gains remain relatively flat over the sample period. Although reallocating human capital per se leads to very large gains in the quantity benchmark counterfactual, they do not account for the total gains of joint reallocation, since the gains of reallocating both physical and human capital are even larger (see Panel A of Figure 1), in the range of 55-60 percent of global output.

The more restricted value benchmark also indicates large gains, but only when reallocating both human and physical capital. Under this benchmark, almost by construction, the gains of reallocating human capital only would be negligible and mostly driven by a handful of countries with dissimilar output and consumption prices. To be sure, the complementarity
between these two factors is an important determinant for the gains of jointly reallocating physical and human capital.

Most interestingly, under both the baseline and the more restrictive benchmark, we find that jointly reallocating physical and human capital across countries can lead to capital flow reversals relative to reallocating physical capital only. This is not a minor point. In cases in which only physical capital can be reallocated, that physical capital would flow from rich to poor countries, as highlighted by Lucas (1990) long ago and explored further by an extensive

**Figure 2**

*Countries’ Physical Capital Observed in 2005 and Counterfactual Reallocation*

A. Reallocating Only K, Baseline Benchmark

B. Reallocating K and H, Baseline Benchmark

C. Reallocating Only K, Value Benchmark

D. Reallocating K and H, Value Benchmark

SOURCE: Authors’ calculations based on PWT 8.0, World Bank, and the Food and Agriculture Organization of the United Nations (FAOSTAT).
ensuing literature. In cases in which both physical capital and human can be reallocated, both may flow toward some of the rich countries, often from poor countries. This simple yet often ignored point could be one of the keys to understanding the consequences of alternative integration schemes with or without labor mobility for countries and regions with different productivities and fixed endowments (e.g., the United States and Puerto Rico and the European Union on one side, with NAFTA on the other).

To illustrate this result, for 2005, the last year in our baseline sample, Figure 2 reproduces the observed physical capital (horizontal axes, in logs) and compares it with the hypothetical level that each country would receive under the different counterfactual exercises (vertical axes, in logs). In Panels A and B, we compare the results from the baseline, real quantities exercise. In Panels C and D, we compare the results from the more restrictive value exercise. In the left panels, A and C, we report the results for reallocating only physical capital. In the right panels, B and D, we report the results for reallocating both physical and human capital.

As anticipated above, Figure 2 shows that the implied reallocation of capital can reverse direction and instead of moving from rich to poor countries, may end up moving from some poor—and some rich—countries to other rich countries. Noticeably, when reallocating only physical capital, the observed levels and the resulting levels are fairly similar; that is, the observations are concentrated near the 45-degree line. This is true regardless of whether we use the baseline or the restricted value benchmark. However, the patterns are very different in the right panels, when reallocating both physical and human capital. In those cases, we see that
quite a few countries with low levels of physical capital would end up having even lower levels after the efficient reallocations. This is evident especially in Panel B, where many countries lie much lower than the 45-degree line. But notice that it is not only that capital would flow from poor to rich countries, but indeed, there would be massive flows from some rich to other rich countries.

To examine these distributional implications further, in Figure 3 we show the hypothetical change in the output of the countries grouped by income quartiles. In Panel A, we show the results of equating both quantity marginal products—$QMP_K$ and $QMP_H$—across all countries. Panel B shows the results for the more restricted counterfactual equating $VMP_K$ and $VMP_H$ across countries, where we impose that the wages of workers across countries must remain constant at the level before the reallocation. Two interesting patterns emerge. First, in the quantity counterfactual, the richer countries (fourth quartile) and sometimes the middle-to-high income countries (third quartile) would expand production, while the poorer countries (first and second quartiles) always contract. Such a reallocation from poor to rich necessarily involves physical capital. Clearly, the required reallocation is exactly the opposite from Lucas (1990). This simple result could prove useful for understanding the resulting capital flows from economic integrations, differentiating between those in which workers can be reallocated (e.g., the European Community and the United States and Puerto Rico) and those in which they cannot (e.g., NAFTA and the Central America-Dominican Republic Free Trade Agreement [CAFTA]). This simple result could also be useful in understanding the allocation of physical and human capital across regions within large countries (e.g., the United States, Brazil, and China).

Second, the quantity and the value counterfactuals lead to very different reallocation patterns. Once we impose the distributional restriction that foreign workers must earn the same income as domestic workers, the direction of global reallocation reverts, from rich to poor countries. Wage restrictions of the form imposed here endogenously make the human capital of countries behave as fixed factors, and reallocations tend to be similar as when physical capital is the only mobile factor. The wages of developed countries are too high, resulting in factor flows to countries in the second and third income quartiles, but not to the poorest ones, because of their lower productivity and larger curvature.

5.2 Results Extending the Sample of Countries

So far, we focused on a sample of 76 countries for which we were able to consistently retrieve information on rents of natural resources, factor shares, physical capital, human capital, and output, from 1970 to 2005. With improvement in data collection with time, as well as the emergence of new countries in the 1990s (for example, after the fall of communism in Eastern Europe), data for more countries are available now than in the past. In this section, we extend our benchmark sample to the set of 107 countries for which we can retrieve all necessary information to perform our analysis for the year 2005. Thus, we explore the robustness of our main results to the increased sample size.

In Table 2, we compare the global output gains from equalizing physical and human capital between our benchmark sample and the extended sample. We find minor differences across samples—if at all; our benchmark sample tends to underestimate the global gains of
reallocation compared with the extended sample. First, equalizing MPH yields similar insights. Second, the joint global reallocation of physical and human capital implies that, in quantity terms, our output gains in the benchmark sample are 55.96 percent, while in the extended sample they are 57.32 percent. That is, our extended sample leads to more global output gains. These underestimations are more apparent in value terms, where the output gains are 5.78 percent in our benchmark sample and 7.74 percent in our extended sample.

For the extended sample, in Figure 4 we use maps to show winners and losers of reallocation. The pattern of reallocation of human capital is quite interesting. The countries receiving migrants (blue in the map) are all developed: the United States, Canada, Western Europe, and Australia. The countries sending the most human capital abroad are China, India, Ukraine, Brazil, and other Eastern European and African countries.
6 ANOTHER REALLOCATION PUZZLE?

The previous results suggest that instead of physical capital, the culprit of misallocation is human capital. Even in our restrictive value benchmark, the ability to reallocate workers across countries would greatly enhance the global output gains of reallocating physical capital. Moreover, there is indication that the allocation of labor has not improved over time, because the gains of joint reallocation are flat over time, while the gains of reallocating physical capital have declined—as shown by Monge-Naranjo, Santaeulàlia-Llopis, and Sánchez (2019). There is already a literature discussing the puzzling direction of physical capital flows (Feldstein and Horioka, 1980; Gourinchas and Jeanne, 2013; Ohanian, Restrepo-Echavarria, and Wright, 2013; and Monge-Naranjo, Santaeulàlia-Llopis, and Sánchez, 2019). In this section, we conduct an analogous analysis of human capital flows.

To examine whether there is a reallocation puzzle for human capital, we regress the change in human capital on several variables and find the following: The measure of initial MPH appears insignificant in accounting for the change in human capital (displayed in Table 3). Changes in TFP and physical capital are insignificant in accounting for changes in human capital. The R-squared values of these regressions are low, indicating that these forces are not that important in driving investment in human capital. These results seem to be in line with Easterly (2001, pp. 72-73), who argues that “The growth response to the dramatic educational...
expansion of the last four decades has been distinctly disappointing...creating skills where there exists no technology to use them is not going to foster economic growth.”

To measure the role of human capital flows more directly, we construct a counterfactual sequence of human capital stock for each country $\tilde{H}_{j,t}$. More precisely, the stock of human capital of country $j$ in year $t$ is

$$\tilde{H}_{j,t} = s_{j,1970} \cdot H_{W,t},$$

where $H_{W,t}$ is the world stock of human capital and $s_{j,1970} = \frac{H_{j,1970}}{H_{W,1970}}$.

We also examine the flows of human capital by analyzing net migration flows to each particular country $\{f_{j,t}^H\}$. Since we do not have information about the human capital of the migrants, we assume that migration changes the number of persons living in a country but not the average human capital index or the share of people employed. For example, that would be the case if the net flows from each country have the same characteristics as the population of that country.

Data on net migration are taken from the World Bank and are available at 5-year intervals starting in 1972; we use linear interpolation to infer missing flows. To construct human capital flows $\hat{f}_{j,t}^H$ from population flow data $f_{j,t}^H$, we make several assumptions. We assume that a share $d_t$ of migrants $f_{j,t}^H$ are employees. This share is equal to the average employment-to-population ratio:
$$d_t = \sum_{j} \frac{L_{j,t}}{P_{j,t}} / N.$$ 

To convert these employment flows $d_{j,t}$ to human capital-augmented labor $\hat{f}_{j,t}$, we assume that migrant human capital is equal to the human capital in the country $h_{j,t}$ into/out of which labor is flowing, so that $\hat{f}_{j,t} = h_{j,t} \cdot \{d_{j,t} \cdot f_{j,t} \}$. Assuming migrant human capital is equal to the global mean yields similar results. As with physical capital, the sum of human capital flows does not add to zero. Adjusting the flows to ensure these flows add to zero does not change our results.

We find that the observed investments in human capital since 1970 made the global allocation of human capital significantly worse (Figure 5). If in 2005 human capital had been distributed according to the shares per country in 1970, the gains of reallocation would have been 30 percent instead of 43 percent. The difference, 13 percent of global output, is a measure of how much worse the allocation of human capital is due to changes that have taken place since 1970. Adding migration flows does not change the picture, so the changes in human capital that worsen the allocation of human capital are internal.

### 7 CONCLUSIONS

We use new data on natural resources shares from Monge-Naranjo, Santaeulália-Llopis, and Sánchez (2019) to uncover the degree of global misallocation of human capital. We find the implied global efficiency losses of the misallocation of human capital are almost 60 percent. If anything, the misallocation of human capital seems to have worsened. Some interesting patterns arise when we explore the joint reallocation of physical and human capital. First, the gains are substantially higher. Second, the direction of reallocation can change and, instead of capital flowing from rich to poor countries, as first explored by Lucas (1990), we find that capital—and workers—should flow from poor to rich countries. This simple point could help in understanding the consequences of alternative integration schemes with or without labor mobility for countries and regions with different productivities and fixed endowments (e.g., the United States and Puerto Rico and the European Community on one side, with NAFTA on the other).
NOTES
1 According to the Monge-Naranjo, Santaeulália-Llopis, and Sánchez (2019) estimate, the gains of just reallocating physical capital for the same countries and years are about 3 percent.
2 We focus on the human capital measure available in PWT 8.0 since our exercise requires a measure that is widely available for many countries, including those at the bottom of the income distribution. Models with imperfect substitutability (e.g., Jones, 2014, and Caselli and Ciccone, 2019) and comparative advantage (e.g., Hsieh et al., forthcoming, and Monge-Naranjo, Mies, and Tapia, 2019) would provide a richer framework to evaluate the gains of reallocating different types of workers across countries but would require much more data and/or estimates across many countries.
4 Modeling and empirically disciplining the workers’ compensating differences for living and working in different countries lies outside the limits of this article. See Klein and Ventura (2009) for interesting quantitative work.
5 See the discussion in Section 1 of Monge-Naranjo, Santaeulália-Llopis, and Sánchez (2019.)
7 These are simple quartiles, that is, unweighted by population or other criteria for size.

REFERENCES


The college income premium is the extra income earned by a family whose head has a college degree over the income earned by an otherwise similar family whose head does not have a college degree. This premium remains positive but has declined for recent graduates. The college wealth premium (extra net worth) has declined more noticeably among all cohorts born after 1940. Among families whose head is White and born in the 1980s, the college wealth premium of a terminal four-year bachelor’s degree is at a historic low; among families whose head is any other race and ethnicity born in that decade, the premium is statistically indistinguishable from zero. Among families whose head is of any race or ethnicity born in the 1980s and holding a postgraduate degree, the wealth premium is also indistinguishable from zero. Our results suggest that college and postgraduate education may be failing some recent graduates as a financial investment. (JEL I26 J15)


Having a four-year college degree is associated with many positive outcomes, including higher income and wealth, better health, a higher likelihood of being a homeowner and of being partnered (married or cohabiting), and a lower risk of becoming delinquent on any obligation (Table 1, Panel A). Among college graduates, families headed by someone who completed a postgraduate degree fare even better on these and other measures than families with a head with only a bachelor’s degree (Table 1, Panel B). The fact that an increasing share of the adult population is completing four years or more of college suggests a widespread belief that college is, indeed, worth it (Figure 1).

Yet signs have emerged that the economic benefits of college may be diminishing. Despite large income and wealth advantages enjoyed on average by families with a head with a bachelor’s degree or higher over families with a head without a postsecondary degree, recent cohorts of college graduates appear to be faring less well than previous generations.¹

¹ William R. Emmons is the lead economist, Ana H. Kent is a policy analyst, and Lowell R. Ricketts is the lead analyst at the Center for Household Financial Stability of the Federal Reserve Bank of St. Louis. William R. Emmons is also an assistant vice president at the Federal Reserve Bank of St. Louis.

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Table 1
Characteristics of Families in the 2016 SCF by Education Level

<table>
<thead>
<tr>
<th>SCF respondent's highest education</th>
<th>Share of all U.S. families (percent)</th>
<th>Median family income (2016 $)</th>
<th>Median family net worth (2016 $)</th>
<th>Share reporting respondent's health as good or excellent (percent)</th>
<th>Share that own primary residence (percent)</th>
<th>Share married or cohabitating (percent)</th>
<th>Share delinquent on loan obligations 60+ days (percent)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A. Families headed by college grads and non-grads</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Less than a four-year college degree</td>
<td>66.0</td>
<td>40,505</td>
<td>53,502</td>
<td>66.3</td>
<td>58.2</td>
<td>53.8</td>
<td>6.9</td>
</tr>
<tr>
<td>At least a four-year college degree</td>
<td>34.0</td>
<td>91,947</td>
<td>290,904</td>
<td>86.3</td>
<td>74.4</td>
<td>62.4</td>
<td>3.7</td>
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<tr>
<td>B. Families headed by four-year degree holders and postgraduate degree holders</td>
<td></td>
<td></td>
<td></td>
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<td></td>
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</tr>
<tr>
<td>At most a four-year college degree</td>
<td>20.9</td>
<td>84,251</td>
<td>228,580</td>
<td>85.0</td>
<td>72.4</td>
<td>59.7</td>
<td>4.2</td>
</tr>
<tr>
<td>A postgraduate degree</td>
<td>13.1</td>
<td>112,200</td>
<td>443,148</td>
<td>88.2</td>
<td>77.7</td>
<td>66.6</td>
<td>2.8</td>
</tr>
</tbody>
</table>

SOURCE: SCF and authors' calculations.
We use the Federal Reserve Board’s Survey of Consumer Finances (SCF), which covers family heads born throughout the twentieth century, to determine whether the economic and financial benefits of obtaining a postsecondary degree have changed over time. Our evidence is mixed but discouraging on balance. The income advantage of recent college graduates remains positive but may have declined for some demographic groups relative to older graduates. Meanwhile, the wealth-building advantage of higher education has declined among recent graduates of all demographic groups. Among all racial and ethnic groups born in the 1980s, only the wealth premium for White four-year college graduates remains statistically significant. Thus, we identify a striking divergence between the income and wealth outcomes of college graduates across birth cohorts.

Our findings highlight the fact that income and wealth measures, while related, are distinct and may provide different insights into college and postgraduate experiences. We suggest three potential explanations, each of which may contribute something to the patterns we identify:

- The luck of when you were born, since beginning to save and accumulate wealth at a time when asset prices (stocks, bonds, and housing) are high makes subsequent rates of return low and vice versa
- Financial liberalization, which may have created more opportunities for people born in the 1980s than in the 1940s, for example, to use (and misuse) credit when they were young, affecting their wealth but not their incomes
- The rising cost of higher education, which would not reduce college graduates’ incomes but would reduce their wealth, at least early in life
The article has four sections. In Section 1, we document the large income and wealth premiums enjoyed on average by the typical family with a head holding a terminal bachelor’s or postgraduate degree over the typical family with a head holding no college degree; this is the conventional wisdom. In Section 2, we show with SCF data that aggregate statistics conceal important differences between income and wealth trends across college graduates from successive birth cohorts. Section 3 outlines some of the features any plausible explanation of our findings must possess; we leave a detailed investigation of these hypotheses to future research. Section 4 concludes.

1 INCOME AND WEALTH PREMIUMS ENJOYED BY THE TYPICAL COLLEGE GRADUATE

The conventional wisdom that bachelor’s and, even more, postgraduate degrees pay off in terms of higher income and wealth are strongly supported in aggregate data (that is, pooled across race, ethnicity, and birth year). We present income and wealth trends for three separate groups—families headed by someone with both a bachelor’s and a postgraduate degree (postgraduate families); families headed by someone whose highest level of education is a bachelor’s degree (bachelor’s degree families); and families headed by someone whose highest level of education is less than a four-year college degree (nongraduate families). Our data source throughout is the SCF.
**Shares of Families with Bachelor’s and Postgraduate Degrees**

The share of U.S. families headed by a college graduate has increased significantly in recent years. (Figure 2). In 1989, about 23 percent of families were headed by someone with a four-year college degree or more; by 2016, the share had reached 34 percent. Families headed by someone with a postgraduate (as well as a four-year college) degree increased from almost 9 percent of all families in 1989 to about 13 percent in 2016. Among White families alone (not shown), the share of families with a four-year degree or more increased from 26 to 38 percent between 1989 and 2016, while among families of all other races and ethnicities, the share increased from 14 to 25 percent.

**Family Income.** The income premium enjoyed by the median bachelor’s degree family over the median nongraduate family (the college income premium) has held steady during the past few decades at roughly 100 percent (Figures 3 and 4). The income premium enjoyed by the median postgraduate family over the median nongraduate family (the postgraduate income premium) has increased, standing in 2016 at about 175 percent. The share of all income earned by families with a head with at least a bachelor’s degree increased from 45 to 63 percent between 1989 and 2016, as both the number of bachelor’s degree and postgraduate families and their average incomes increased faster than those of nongraduate families.

**Family Wealth (Net Worth).** Figure 5 shows that the net worth of both median bachelor’s degree and postgraduate families increased between 1989 and 2016, while that of the median nongraduate family declined during that period. Thus, the wealth premiums enjoyed by bachelor’s degree and postgraduate families over the nongraduate family (the college and postgraduate wealth premiums, respectively) have climbed greatly during the past few decades (Figure 6). The postgraduate wealth premium increased by a large margin, standing in 2016 at over 700 percent (i.e., eight times as large). The share of all wealth owned by families with a head with at least a bachelor’s degree increased even more than was the case for income—from 50 to 74 percent between 1989 and 2016.

**What These Figures Hide.** The median income and net worth figures from aggregate data shown here turn out to be misleading when careful account is taken of key underlying demographic dimensions and family and individual characteristics. Comparing families that are similar in terms of race and ethnicity, decade of birth, and family size, we find that the college income and wealth premiums are quite variable. Moreover, the conclusion that the college wealth premium is larger and increasing faster than the college income premium is reversed when comparing demographically matched groups of families. In fact, we show in Section 2 that the wealth premium has fallen across successive birth cohorts. Among those born in the 1980s, the wealth premiums of bachelor’s degree families and of postgraduate-degree families are statistically indistinguishable from zero for all groups with the single exception of White bachelor’s degree families.
Figure 3
Median Family Income

SOURCE: SCF and authors’ calculations.

Figure 4
Income Premiums of the Median Bachelor’s Degree Family and the Median Postgraduate Family Over the Median Nongraduate Family

SOURCE: SCF and authors’ calculations.
Figure 5
Median Family Net Worth

SOURCE: SCF and authors' calculations.

Figure 6
Net-Worth Premiums of the Median Bachelor’s Degree Family and the Median Postgraduate Family Over the Median Nongraduate Family

SOURCE: SCF and authors’ calculations.
2 COLLEGE INCOME AND WEALTH PREMIUMS AMONG DEMOGRAPHICALLY MATCHED FAMILIES

Large and growing income and wealth premiums associated with college degrees measured in aggregate data mask a diverse range of experiences among bachelor’s degree and post-graduate families when compared with nongraduate families of the same race and ethnicity who were born in the same decade. It turns out that very favorable income and wealth outcomes experienced by mostly White college grads born many decades ago cause aggregate data to overstate the income and wealth advantages experienced by more-recent college grads.

To quantify the changing economic and financial benefits of postsecondary degrees, we estimate the income and wealth premiums earned by bachelor’s degree families and, separately, postgraduate families compared with otherwise demographically similar nongraduate families. The advanced degrees that qualify a family as postgraduate are quite diverse; see Table A1 for a list of those degrees and a description of all variables used in this article.

We focus on college graduates born in one of six decade-long cohorts starting in the 1930s, concluding with those born during the 1980s. In previous research, we found evidence of structural, systemic, or other unobservable barriers to income generation and wealth accumulation by non-White Americans, perhaps due to historical discrimination and exclusion in education, housing, employment, and wealth-building programs. Therefore, we estimate cohort-specific college and postgraduate income and wealth premiums separately for each of the four racial and ethnic groups available in the public release of the SCF. Our estimates of the pure life cycle components of both income generation and wealth accumulation differ substantially across racial and ethnic groups, reinforcing the argument that separate regressions by race and ethnicity are more meaningful than a single, pooled regression.

Income. To measure income for the SCF, the interviewers requested information on the family’s cash income, before taxes, for the full calendar year preceding the survey. The components of income in the SCF are wages; self-employment and business income; taxable and tax-exempt interest; dividends; realized capital gains; food stamps and other related support programs provided by government; pensions and withdrawals from retirement accounts; Social Security; alimony and other support payments; and miscellaneous sources of income for all members of the primary economic unit in the household. All income figures are adjusted for inflation to be comparable with values recorded in 2016.

We adjust for household size as follows:

\[ Y_i = \frac{y_i}{\sqrt{H_i}}, \]

where \( y_i \) is the income of household \( i \) and \( H_i \) is the number of people in that household, excluding individuals that do not usually live there and who are financially independent. The square-root adjustment we use is one of the “equivalence scales” recommended by the Organisation for Economic Co-operation and Development to reflect important economies of scale in household consumption. This also adjusts for households with multiple income earners. For example, a two-earner household with exactly two members earning $2Y$ is considered...
1.414 times as large as a single-person one-earner household earning $Y. Due to likely economies of scale in consumption, the two-earner household effectively has higher disposable income but not twice as much.

To assess secular trends in the returns to higher education, we pool responses for all 10 triennial SCF survey years, the first of which was conducted in 1989 and the most recent in 2016. This yields a sample of 47,776 households. Our full specification is a log-quadratic ordinary least-squares regression of the form

\[
\ln(Y_i) = \beta_0 + \beta_1 A_i + \beta_2 A_i^2 + \beta_3 G_i + \beta_4 P_i + \beta_5 C_{i,1} + \ldots + \beta_{k+1} C_{i,k} + \beta_{k+2} G_i + \ldots + \beta_{2k} P_i + \ldots + \beta_{3k} C_{i,k} + \epsilon.
\]

We apply the natural-log function to size-adjusted income. \(A_i\) is the age of the household respondent, and \(A_i^2, A_i^3\) are the squared and cubic terms capturing the effects of the life cycle, respectively. \(G_i\) and \(P_i\) are binary variables equal to 1 if the respondent earned a terminal four-year college degree or continued on and achieved a postgraduate degree, respectively. Therefore, \(\beta_4\) and \(\beta_5\) represent the income premium attributed to a terminal four-year college degree and postgraduate degree, respectively. The effect on expected earnings associated with the respondent’s birth cohort (defined by decades) is captured by \(k\) binary variables denoted as \(C_{i,1:k}\), with \(k-1\) binaries included in the specification to both avoid perfect multicollinearity and allow control of the reference group. Birth cohorts and education binaries are interacted to capture changes in the college premium over time. For ease of interpretation, we opt to vary the omitted birth cohort and focus on differences in \(\beta_4\) and \(\beta_5\) in order to compare changes in the college premium over time.

For example, when omitting \(C_i\) for the 1980s cohort, \(\beta_4\) and \(\beta_5\) are the respective earnings premiums associated with bachelor’s degree families and postgraduate families with a head born in the 1980s relative to nongraduate families with a head also born in the 1980s. Omitting \(C_i\) for the 1950s cohort would change the reference group to the average family with a non-college head born in the 1950s, and so on.

Estimation was conducted using R statistical software and relied upon the “survey” and “mitools” packages. Source code is available upon request. Nonresponse-adjusted sampling weights were used in the analysis to adjust for the fact that the SCF sample is not an equal-probability design. Given the oversample of wealthy households and the use of both wealth and income as dependent variables, we believe that using weights in the regression analyses is appropriate. Standard errors are bootstrapped with 999 replicates in accordance with the sample design and are adjusted for imputation uncertainty.

There is substantial heterogeneity in both income and wealth across racial and ethnic groups, especially among families with a head with a college degree. Rather than relying on binary variables to adjust for large and persistent racial and ethnic wealth gaps, we partitioned the sample and estimated regressions separately for each of the four racial and ethnic groups.

Regression results for White and African-American or Black (henceforth Black) families are shown in Tables 2 and 3, respectively. Results for Hispanic and other families are in Tables A2 and A3, respectively. The life cycles of both income and wealth are empirically
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<td><strong>Income Regressions: White Families</strong></td>
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Dependent variable: Income  
Racial/ethnic group: White  
Pseudo $R^2$: 0.16  
N: 37,044

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**NOTE:** SE, standard error. Standard errors are bootstrapped with 999 replicates in accordance with the sample design and are adjusted for imputation uncertainty. Nonresponse-adjusted sampling weights were also used.  
**SOURCE:** SCF and authors’ calculations.
### Table 3

**Income Regressions: Black Families**

**Dependent variable:** Income  
**Racial/ethnic group:** Black  
**Pseudo R²:** 0.11  
**N:** 5,186

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<td>0.40</td>
<td>-1.68</td>
<td>0.09</td>
<td>(Omitted)</td>
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</tr>
</tbody>
</table>

**Note:** SE, standard error. See Table 2 note.  
**Source:** SCF and authors’ calculations.
quite different across racial and ethnic groups, as shown by widely varying parameter estimates for the unstandardized age coefficients within our regressions. The relatively small sample sizes for Hispanic and for other non-White college-graduate families greatly diminish the statistical precision of those estimates, as reflected by considerably wider confidence intervals for $\beta_4$ and $\beta_5$. Nonetheless, results for these groups do not alter any of our main conclusions.

**Trends in the Expected Income Premiums for Bachelor’s Degree and Postgraduate Families.** We found that the college income premium over otherwise similar nongraduate families—from the same birth decade and race or ethnicity—declined somewhat among White families, on balance, between the 1930s and the 1980s birth cohorts but remained positive (Figure 7). Among Black families, there was no significant change between the 1940s and the 1980s, with all income premiums significantly above zero (Figure 8). The figures show point estimates and corresponding 95 percent confidence intervals.

The income premium for postgraduate families over nongraduate families was typically higher at the mean relative to that for bachelor’s degree families over nongraduate families (Figures 9 and 10 for Whites and Blacks, respectively, and Figures A3 and A4 for Hispanics and other non-White families, respectively). The income premium for postgraduate White families followed a more pronounced downward trajectory than that for White bachelor’s degree families but remained positive for all cohorts. Among Black postgraduate families, the income premium ranged more widely and was large for all cohorts. In sum, the postgraduate families of all races and ethnicities from all six birth decades that we consider enjoy a clear income advantage over families without at least a bachelor’s degree.

**Household Net Worth.** Household net worth, also adjusted for household size, is our preferred measure of wealth. The SCF is considered the gold standard of balance sheet information precisely because of its detailed accounting of household assets and liabilities. Family net worth is the difference between a family’s assets and its debts at a point in time. Total assets include both financial assets, such as bank accounts, mutual funds, and securities, and tangible assets, including real estate, vehicles, and durable goods. Total debt includes home-secured borrowing (mortgages), other secured borrowing (such as vehicle loans), and unsecured debts (such as credit cards and student loans). Debt incurred in association with a privately owned business or to finance investment in real estate is subtracted from the asset’s value, rather than being included in the family’s debt. All wealth figures also are adjusted for inflation.

We adjust net worth for household size as for income:

$$W_i = \frac{W_i}{H_i}.$$ (3)

Our wealth specification has the same structural form (explanatory variables and their interactions) as that used to estimate the income premium. However, the transformation used for the dependent variable ($W$) is the inverse hyperbolic sine (IHS) transformation rather than the natural log. The transformed dependent variable is given by

$$\sinh^{-1} (\theta W_i) = \ln \left[ \theta W_i + \left( \theta^2 W_i^2 + 1 \right)^{1/2} \right] / \theta,$$ (4)
Figure 7
Expected Income Premium, White Bachelor’s Degree Families, by Cohort

SOURCE: SCF and authors’ calculations.

Figure 8
Expected Income Premium, Black Bachelor’s Degree Families, by Cohort

SOURCE: SCF and authors’ calculations.
Figure 9
Expected Income Premium, White Postgraduate Families, by Cohort

Source: SCF and authors’ calculations.

Figure 10
Expected Income Premium, Black Postgraduate Families, by Cohort

Source: SCF and authors’ calculations.
Figure 11
Expected Wealth Premium, White Bachelor’s Degree Families, by Cohort

SOURCE: SCF and authors’ calculations.

Figure 12
Expected Wealth Premium, Black Bachelor’s Degree Families, by Cohort

SOURCE: SCF and authors’ calculations.
Figure 13
Expected Wealth Premium, White Postgraduate Families, by Cohort

SOURCE: SCF and authors’ calculations.

Figure 14
Expected Wealth Premium, Black Postgraduate Families, by Cohort

SOURCE: SCF and authors’ calculations.
### Table 4

**Wealth Regressions: White Families**

<table>
<thead>
<tr>
<th>Dependent variable: Net worth</th>
<th>Pseudo R²</th>
<th>N</th>
<th>Independent variables</th>
<th>β</th>
<th>SE</th>
<th>t-Stat</th>
<th>p-Value</th>
<th>β</th>
<th>SE</th>
<th>t-Stat</th>
<th>p-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Life cycle</td>
<td>0.30</td>
<td>13,645</td>
<td>Intercept</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>0.00</td>
<td>1,412</td>
<td>Age</td>
<td>1.03</td>
<td>0.01</td>
<td>21.96</td>
<td>0.00</td>
<td>0.76</td>
<td>1.33</td>
<td>0.15</td>
<td></td>
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<tr>
<td>Age × graduate</td>
<td>0.00</td>
<td>1,412</td>
<td>Age × graduate</td>
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<td>0.00</td>
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<td>0.00</td>
<td>0.00</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>Age × postgraduate</td>
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<td>Age × postgraduate</td>
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<td>0.00</td>
<td>0.00</td>
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<td>0.00</td>
<td>0.00</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>Age × born in 1930s</td>
<td>0.00</td>
<td>1,412</td>
<td>Age × born in 1930s</td>
<td>0.00</td>
<td>0.00</td>
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<td>0.00</td>
<td>0.00</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>Age × born in 1940s</td>
<td>0.00</td>
<td>1,412</td>
<td>Age × born in 1940s</td>
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<td>0.00</td>
<td>0.00</td>
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<td>1.00</td>
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<tr>
<td>Age × born in 1950s</td>
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<td>Age × born in 1950s</td>
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<td>0.00</td>
<td>0.00</td>
<td>1.00</td>
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<tr>
<td>Age × born in 1960s</td>
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<td>1,412</td>
<td>Age × born in 1960s</td>
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<td>0.00</td>
<td>0.00</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>Age × born in 1970s</td>
<td>0.00</td>
<td>1,412</td>
<td>Age × born in 1970s</td>
<td>0.00</td>
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<tr>
<td>Age × born in 1980s</td>
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<td>Age × born in 1980s</td>
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<td>0.00</td>
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<td>0.00</td>
<td>0.00</td>
<td>1.00</td>
<td></td>
</tr>
</tbody>
</table>

**NOTE:** SE, standard errors. Standard errors are bootstrapped with 999 replicates in accordance with the sample design and are adjusted for imputation uncertainty. Nonresponse-adjusted sampling weights were also used. Household-size adjusted net worth was transformed with the inverse hyperbolic sine function, with a scaling factor of 0.0001. The Halvorsen-Palmquist transformation provides a similar interpretation of the coefficients on binary variables as that of a log-linear model.

**SOURCE:** SCF and authors’ calculations.
## Table 5

**Wealth Regressions: Black Families**

**Dependent variable**: Net worth

**Racial/ethnic group**: Black

**Pseudo R²**: 0.19

**N**: 5,186

| Independent variables | (1) \(\hat{β}\) | SE | H-P (\(\hat{β}\)) | t-Stat | p-Value | (2) \(\hat{β}\) | SE | H-P (\(\hat{β}\)) | t-Stat | p-Value | (3) \(\hat{β}\) | SE | H-P (\(\hat{β}\)) | t-Stat | p-Value | (4) \(\hat{β}\) | SE | H-P (\(\hat{β}\)) | t-Stat | p-Value | (5) \(\hat{β}\) | SE | H-P (\(\hat{β}\)) | t-Stat | p-Value | (6) \(\hat{β}\) | SE | H-P (\(\hat{β}\)) | t-Stat | p-Value |
|----------------------|----------|----|----------------|--------|---------|----------|----|----------------|--------|---------|----------|----|----------------|--------|---------|----------|----|----------------|--------|---------|----------|----|----------------|--------|---------|
| **Intercept**        | 1.819    | 3.049 | 0.60 | 0.55 | 3.134 | 3.179 | 0.99 | 0.32 | 1.495 | 3.399 | 0.44 | 0.66 | 1.294 | 3.335 | 0.39 | 0.70 | 1.791 | 3.120 | 0.56 | 0.58 | -0.38 | 3.225 | -0.29 | 0.77 |
| **Life cycle**       |          |      |      |      |        |        |      |      |        |        |      |      |        |        |      |      |        |        |      |      |        |        |      |      |        |        |
| Age                  | -0.74    | 2.22 | -0.33 | 0.74 | -0.74 | 2.22 | -0.33 | 0.74 | -0.74 | 2.22 | -0.33 | 0.74 | -0.74 | 2.22 | -0.33 | 0.74 | -0.74 | 2.22 | -0.33 | 0.74 | -0.74 | 2.22 | -0.33 | 0.74 |
| Age²                 | 10.0     | 2.22 | 0.03  |      | 10.0  | 2.22 | 0.03  |      | 10.0  | 2.22 | 0.03  |      | 10.0  | 2.22 | 0.03  |      | 10.0  | 2.22 | 0.03  |      | 10.0  | 2.22 | 0.03  |      |
| Age³                 | 0.0      | 0.00 | -2.69 | 0.01 | 0.0   | 0.00 | -2.69 | 0.01 | 0.0   | 0.00 | -2.69 | 0.01 | 0.0   | 0.00 | -2.69 | 0.01 | 0.0   | 0.00 | -2.69 | 0.01 | 0.0   | 0.00 |
| **Income premium**   |          |      |      |      |        |        |      |      |        |        |      |      |        |        |      |      |        |        |      |      |        |        |
| Terminal four-year graduate (G) | 18.075 | 1.680 | 5.09 | 10.76 | 0.00 | 12.626 | 1.503 | 2.53 | 8.40 | 0.00 | 8.151 | 1.443 | 1.26 | 5.65 | 0.00 | 10.201 | 1.115 | 1.77 | 9.15 | 0.00 | 1.642 | 1.420 | 0.18 | 1.17 | 0.24 |
| Postgraduate (P)     | 16.542   | 3.115 | 4.23 | 5.31 | 0.00 | 18.073 | 1.419 | 5.09 | 12.02 | 0.00 | 16.613 | 2.166 | 3.22 | 8.05 | 0.00 | 16.664 | 2.487 | 0.18 | 0.67 | 0.50 | 1.648 | 2.844 | 0.16 | 0.52 | 0.61 |
| **Birth cohorts**    |          |      |      |      |        |        |      |      |        |        |      |      |        |        |      |      |        |        |      |      |        |        |
| Born before 1930 or after 1989 | -2.312 | 0.900 | -0.21 | -2.57 | 0.01 | -3.326 | 0.875 | -0.30 | -4.45 | 0.00 | -1.987 | 0.899 | -0.18 | -2.31 | 0.02 | -1.796 | 0.865 | -0.16 | -2.07 | 0.01 | -2.286 | 0.878 | -0.20 | -2.60 | 0.01 |
| Born in 1930s        | (Omitted) |      |      |      |        |        |      |      |        |        |      |      |        |        |      |      |        |        |      |      |        |        |
| Born in 1940s        | 1.314 | 0.757 | 0.14 | 1.74 | 0.08 | (Omitted) |      |      |        |        |      |      |        |        |      |      |        |        |      |      |        |        |
| Born in 1950s        | -0.325 | 0.867 | -0.03 | -0.37 | 0.71 | (Omitted) |      |      |        |        |      |      |        |        |      |      |        |        |      |      |        |        |
| Born in 1960s        | -0.525 | 0.844 | -0.05 | -0.62 | 0.53 | (Omitted) |      |      |        |        |      |      |        |        |      |      |        |        |      |      |        |        |
| Born in 1970s        | -2.664 | 0.000 | 0.03 | 0.98 |      | (Omitted) |      |      |        |        |      |      |        |        |      |      |        |        |      |      |        |        |
| Born in 1980s        | -2.747 | 0.915 | -0.24 | -3.00 | 0.00 | (Omitted) |      |      |        |        |      |      |        |        |      |      |        |        |      |      |        |        |
| **Cohort X income premium** |          |      |      |      |        |        |      |      |        |        |      |      |        |        |      |      |        |        |      |      |        |        |
| Born before 1930 or after 1989 + G | -16.834 | 4.133 | -0.81 | -4.07 | 0.00 | -11.375 | 4.062 | -0.68 | -2.80 | 0.01 | -4.697 | 3.934 | -0.50 | -2.26 | 0.02 | -4.950 | 3.961 | -0.59 | -2.26 | 0.02 | -4.122 | 3.934 | -0.04 | -0.10 | 0.92 |
| Born before 1930 or after 1989 + G + | (Omitted) |      |      |      |        |        |      |      |        |        |      |      |        |        |      |      |        |        |      |      |        |        |
| Born before 1930 or after 1989 + P | -9.777 | 6.462 | -0.62 | -1.51 | 0.13 | -11.307 | 6.233 | -0.68 | -1.82 | 0.07 | -7.865 | 6.398 | -0.54 | -1.23 | 0.22 | 5.102 | 6.451 | 0.67 | 0.79 | 0.43 | 5.298 | 6.163 | 0.70 | 0.86 | 0.39 |
| Born before 1930 or after 1989 + P + | (Omitted) |      |      |      |        |        |      |      |        |        |      |      |        |        |      |      |        |        |      |      |        |        |
| **SOURCE**: SCF and authors’ calculations.

**NOTE**: SE, standard error. See Table 4 note.
where \( \theta \) is a scaling parameter, which controls how much of the function’s domain is approximately linear and how much resembles the natural logarithm. The IHS transformation is quite useful when working with wealth outcomes because it can accommodate negative and zero balances (unlike the natural log transformation). The scaling parameter is estimated using maximum likelihood, and we use 0.0001 as is typical in the literature.\(^{22}\)

As shown in Halvorsen and Palmquist (1980), unlike in a log-linear model, the expected change in wealth attributed to a terminal four-year degree and postgraduate degree is not simply \( 100 \times \beta_4 \) and \( 100 \times \beta_5 \). The semi-logarithmic nature of the IHS requires a modified form of the Halvorsen-Palmquist transformation to provide a similar percentage-change interpretation. We use the same form as that used in Gale and Pence (2006): \( e^{\beta \theta} - 1 \).

Similar to the regressions of income, we estimate six variations of our wealth specification, switching the omitted birth cohort for each decade. Again, due to considerably different wealth life cycles and historical context, we estimate regressions separately for the four racial and ethnic groups available within the SCF (Tables 4 and 5 for White and Black families, respectively, and Tables A4 and A5 for Hispanic and other families, respectively).

**Trends in the Estimated Wealth Premiums of College Graduates.** In contrast to relatively stable income premiums across successive birth decades, the wealth premium enjoyed by bachelor’s degree families over otherwise demographically similar nongraduate families declined progressively between the 1930s and 1980s cohorts. Among White bachelor’s degree families, for example, the 1930s cohort owned 247 percent more wealth and the 1940s cohort owned 195 percent more wealth than nongraduate families of the same age, but the 1980s cohort owned only 42 percent more wealth (Figure 11).

Among Black bachelor’s degree families, the wealth premium peaked at 509 percent in the 1930s cohort, fell to 177 percent for the 1960s cohort, and was statistically indistinguishable from zero for both the 1970s and 1980s cohorts (Figure 12). In other words, we cannot reject the null hypothesis that the average Black bachelor’s degree family with a head born between 1970 and 1989 had no more wealth than the average Black nongraduate family with a head born in the same decade.

To be clear, these estimates take into account the fact that the older cohorts have had more time to accumulate wealth than the younger cohorts. Our models explicitly adjust for age by including a flexible life cycle component in each specification. Our estimates of wealth premiums are conditional on the amount of wealth accumulation we would expect at any given age.

The results are even starker among postgraduate families. Among White postgraduate families, the 403 percent wealth premium enjoyed by members of the 1930s cohort had shrunk to only 116 percent and 28 percent for the 1970s and 1980s cohorts, respectively (Figure 13). The drop-off for this 1970s cohort is much steeper than that for White bachelor’s degree families in the same cohort. For the 1980s cohort, the expected wealth premium for White postgraduate families over nongraduate families is statistically indistinguishable from zero at standard confidence levels. The \( t \)-statistic estimated for \( \beta_5 \) falls to 1.95, just below the threshold for rejecting the null hypothesis that \( \beta_5 = 0 \).\(^{23}\)

Among Black postgraduate families, the expected wealth premium ranged from 509 percent for the 1940s cohort to levels slightly above but statistically indistinguishable from zero...
for cohorts born in the 1960s, 1970s, and 1980s (Figure 14). This suggests that, on average, postgraduate Black families with heads born in the 1960s, 1970s, or 1980s have not accumulated more wealth than Black nongraduate families with heads born in the same decades.

In sum, Whites are the only racial or ethnic group born in the 1980s for whom a bachelor’s degree provides a family with a reliable wealth advantage over comparable nongraduate families—albeit one that is much smaller than those enjoyed by earlier cohorts of college graduates. Even more surprisingly, the expected wealth premium among postgraduate families with a head born in the 1980s is indistinguishable from zero at standard confidence levels for all races and ethnicities.24

3 WHY HAS THE COLLEGE INCOME PREMIUM BEEN MORE DURABLE THAN THE WEALTH PREMIUM?

Why has the college wealth premium for college graduates over nongraduates declined in successive cohorts? And why do generational trends in wealth accumulation differ so markedly from those for income? Plausible explanations for a declining college wealth premium across successive birth cohorts—even while the college income premium remains largely intact—must satisfy three criteria:

• The explanation describes factors that affect wealth accumulation differently from how they affect income.
• The explanation is consistent with a decline in the college wealth premium that has been underway for many decades, with a large cumulative effect.
• The explanation is not primarily related to the racial and ethnic mix, the educational attainment, or the average family size of particular cohorts, since our premium estimates explicitly control for these elements.

We offer three categories of explanations that appear plausible in the sense that they satisfy the criteria outlined above. We leave for future research a detailed investigation of these hypotheses.

First Plausible Explanation: Aggregate Wealth Fluctuations. A favorable or unfavorable financial climate may play a role in explaining large differences in wealth accumulation across cohorts. A generation that acquires assets when asset prices or valuations are low has an advantage over a subsequent generation that accumulates assets when they are expensive. Gale and Pence (2006) found that differences in the amount of capital gains received by various birth cohorts were substantial in SCF data through 2001.

The working-paper version of this article includes a simulation of wealth accumulation by cohorts born at different times in the presence of large fluctuations in asset valuations over time.25 That exercise demonstrated that the three oldest cohorts we studied generally have experienced fortuitous asset price fluctuations. This explanation has little to say about the very low wealth premiums we estimate for the 1980s cohort, however, which had little asset accumulation by the end of our sample period.
Second Plausible Explanation: Financial Liberalization. Accumulation of financial knowledge takes time, so young college graduates are potentially vulnerable to making financial mistakes. A highly deregulated financial environment is one in which those who are less financially savvy, including young people, have greater access to credit and consequently greater risk associated with managing more consumer debt.

The explosion of consumer debt beginning in the early 1980s has been remarkable. The long-term increase in debt and debt burden has been particularly large for younger cohorts. Additionally, debt ratios generally are higher among college graduates than nongraduates. The leveraging of college-graduate balance sheets over time is entirely consistent with the progressive weakening of their overall financial positions that we identified—even while the college and postgraduate income premiums remained intact.

Third Plausible Explanation: Rising Cost of College. A secular increase in the cost of attending college checks all of the boxes as a plausible explanation for our findings—it directly affects wealth, not income; it is a long-running story; and it is unrelated to changes in the demographics of college graduates for which we could control.

While the overall level of consumer prices has increased by a factor of four since 1978, the cost of college tuition and fees has increased by a factor of almost 14—more than triple the overall increase in consumer prices. Moreover, the rate of excess tuition increases—the amount by which college-tuition inflation exceeded overall inflation—increased after 2000. If the secular increase in the cost of attending college is part of the explanation of progressively weaker wealth outcomes across cohorts, then an acceleration of college costs might show up as a marked deterioration in wealth for the affected cohorts. This is, in fact, what we find—the 1980s cohort of college graduates, most of whom attended college after 2000, experienced a very sharp decline in wealth outcomes.

4 SUMMARY AND CONCLUSIONS

Using the Federal Reserve’s Survey of Consumer Finances, we showed that large and increasing income and wealth premiums in aggregate data associated with families whose heads have a bachelor’s or higher over families whose heads have no postsecondary degree are misleading. Comparing bachelor’s degree and postgraduate families to nongraduate families of the same race and ethnicity born in the same decade, we confirmed that the income premium generally remains positive for all birth decades between the 1930s and the 1980s. However, the premium may have declined somewhat among the most recent cohort (1980s) of White families.

We found a different pattern for the wealth premium. A high and rising wealth premium enjoyed by the average bachelor’s degree family and the average postgraduate family in aggregate data in fact masks a lower and declining premium across successive birth cohorts. Among families with heads born in the 1980s, the college wealth premium weakens to the point of statistical insignificance with the single exception of White bachelor’s degree families, for which it remains positive but much smaller than that enjoyed by previous cohorts. Results were similar for all races and ethnicities.
Thus, the promise of economic and financial advantages associated with postsecondary degrees remains only partially supported by the most recent data. Careful analysis by birth decade and race and ethnicity is required to identify diverging trends for income and wealth premiums over time.

**APPENDIX A**

**Table A1**

**Variable Descriptions**

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<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Source</th>
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<tr>
<td>Household size-adjusted net worth</td>
<td>Inflation-adjusted net worth divided by the square root of household size.</td>
<td>Networth (Board)</td>
</tr>
<tr>
<td>Household size-adjusted income</td>
<td>Inflation-adjusted income divided by the square root of household size.</td>
<td>Income (Board)</td>
</tr>
<tr>
<td>Household size</td>
<td>Number of people in the household according to the HHL.</td>
<td>X101</td>
</tr>
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<td>Age</td>
<td>Respondent’s age.</td>
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</tr>
<tr>
<td>Age2</td>
<td>Respondent’s age squared.</td>
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</tr>
<tr>
<td>Age3</td>
<td>Respondent’s age cubed.</td>
<td>X14</td>
</tr>
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<td>4-Year college graduate</td>
<td>Maximum educational attainment of household respondent was a 4-year college degree (e.g., BA, AB, BS).</td>
<td>1989-2013: X5901, X5904, X5905; 2016: X5931</td>
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<tr>
<td>Postgraduate</td>
<td>Maximum educational attainment of household respondent was a postgraduate degree. This includes master’s degrees (e.g., MA, MS, MENG, MED, MSW, MBA), professional degrees (e.g., MD, DDS, DVM, LLB, JD), and doctoral degrees (e.g., PhD, EDD).</td>
<td>1989-2013: X5901, X5904, X5905; 2016: X5931</td>
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<tr>
<td>White</td>
<td>Respondent identified the race or ethnicity that best describes them as White.</td>
<td>X6809</td>
</tr>
<tr>
<td>Black</td>
<td>Respondent identified the race or ethnicity that best describes them as Black/African-American.</td>
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</tr>
<tr>
<td>Hispanic</td>
<td>Respondent identified the race or ethnicity that best describes them as Hispanic/Latino.</td>
<td>X6809</td>
</tr>
<tr>
<td>Other</td>
<td>Respondent identified the race or ethnicity that best describes them as Asian or American Indian/Alaska Native or Native Hawaiian/Pacific Islander or Other or identified with multiple races or ethnicities. NOTE: All of these responses are combined by Board staff for confidentiality reasons.</td>
<td>X6809</td>
</tr>
<tr>
<td>Birth cohorts</td>
<td>Six birth cohorts represented by binary variables equal to one if the survey respondent was born within the respective decade. Decades include: 1930s, 1940s, 1950s, 1960s, 1970s, and 1980s. Respondents born prior to 1930 or after 1989 were represented by a “catch-all” binary variable and included in regressions to avoid perfect multicollinearity. Results for this variable were not included in analysis.</td>
<td>Survey year, X14</td>
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</tbody>
</table>

**NOTE:** These variables are available in all survey waves from 1989-2016.
**SOURCE:** SCF and authors’ calculations.
## Table A2

### Income Regressions: Hispanic Families

**Dependent variable:** Income  
**Racial/ethnic group:** Hispanic, any Race  
**Pseudo R²:** 0.10  
**N:** 3,553

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<td>t-Stat</td>
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<td></td>
</tr>
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**SOURCE:** SCF and authors’ calculations.

**Note:** SE, standard error. See Table 2 note.
### Table A3

**Income Regressions: Families of Other Races**

**Dependent variable:** Income

**Racial/ethnic group:** Other Races

**Pseudo R²:** 0.20

**N:** 1,993

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**Note:** SE, standard error. See Table 2 note.

**Source:** SCF and authors’ calculations.
### Table A4

**Wealth Regressions: Hispanic Families**

Dependent variable: Net worth  
Racial/ethnic group: Hispanic, any Race  
Pseudo R²: 0.17  
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</tr>
<tr>
<td>Born in 1960 (Omitted)</td>
<td>2.372</td>
<td>4.714</td>
<td>0.27</td>
<td>0.50</td>
<td>0.61</td>
<td>3.687</td>
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<tr>
<td>Born in 1970 (Omitted)</td>
<td>-8.684</td>
<td>4.505</td>
<td>-0.08</td>
<td>-0.20</td>
<td>0.84</td>
<td>-9.532</td>
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<tr>
<td>Born in 1980 (Omitted)</td>
<td>-8.872</td>
<td>4.360</td>
<td>-0.25</td>
<td>-0.66</td>
<td>0.51</td>
<td>-4.876</td>
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<tr>
<td>Born before 1940 or after 1989</td>
<td>6.520</td>
<td>10.339</td>
<td>0.92</td>
<td>0.63</td>
<td>0.53</td>
<td>-0.625</td>
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<tr>
<td>Born in 1930 (Omitted)</td>
<td>-11.146</td>
<td>5.499</td>
<td>-0.67</td>
<td>-2.03</td>
<td>0.04</td>
<td>-8.573</td>
</tr>
<tr>
<td>Born in 1940 (Omitted)</td>
<td>11.146</td>
<td>5.499</td>
<td>0.25</td>
<td>0.63</td>
<td>0.04</td>
<td>2.573</td>
</tr>
<tr>
<td>Born in 1950 (Omitted)</td>
<td>5.283</td>
<td>4.742</td>
<td>0.70</td>
<td>1.11</td>
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<td>5.028</td>
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<td>Born in 1960 (Omitted)</td>
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<td>0.61</td>
<td>-14.024</td>
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<tr>
<td>Born in 1970 (Omitted)</td>
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<td>5.476</td>
<td>-0.07</td>
<td>-2.02</td>
<td>0.04</td>
<td>-2.218</td>
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</tbody>
</table>

**Note:** SE, standard errors. See Table 4 note.  
**Source:** SCF and authors' calculations.
## Table A5

### Wealth Regressions: Families of Other Races

**Dependent variable:** Net worth

**Racial/ethnic group:** Other Races

**Pseudo R²:** 0.27

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<th>(3)</th>
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<td>Intercept</td>
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<td>Age</td>
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<tr>
<td>Age²</td>
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<td>Income premium</td>
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<td>Birth cohorts</td>
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<td>Cohort Income premium</td>
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<td></td>
</tr>
<tr>
<td>Note: SE, standard error. See Table 4 note.</td>
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<td></td>
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</tr>
</tbody>
</table>

**Source:** SCF and authors' calculations.
Figure A1

Expected Income Premium, Hispanic Bachelor’s Degree Families, by Cohort

SOURCE: SCF and authors’ calculations.

Figure A2

Expected Income Premium, Other Bachelor’s Degree Families, by Cohort

SOURCE: SCF and authors’ calculations.
**Figure A3**

Expected Income Premium, Hispanic Postgraduate Families, by Cohort

SOURCE: SCF and authors' calculations.

---

**Figure A4**

Expected Income Premium, Other Postgraduate Families, by Cohort

SOURCE: SCF and authors' calculations.
**Figure A5**

**Expected Wealth Premium, Hispanic Bachelor’s Degree Families, by Cohort**

SOURCE: SCF and authors’ calculations.

**Figure A6**

**Expected Wealth Premium, Other Bachelor’s Degree Families, by Cohort**

SOURCE: SCF and authors’ calculations.
Figure A7
Expected Wealth Premium, Hispanic Postgraduate Families, by Cohort

SOURCE: SCF and authors’ calculations.

Figure A8
Expected Wealth Premium, Other Postgraduate Families, by Cohort

SOURCE: SCF and authors’ calculations.
NOTES

1. For evidence that college graduates enjoy large income and wealth advantages over noncollege graduates on average, see Emmons, Kent, and Ricketts (2018a). For evidence that recent cohorts (including noncollege graduates and graduates alike) have fallen behind the wealth-accumulation trajectories of earlier generations, see Emmons, Kent, and Ricketts (2018b).

2. A terminal degree implies that the household head has not achieved any higher level of educational attainment than that degree. The differentiation is important because most, if not all, postgraduate degree holders also have a bachelor’s degree.

3. See Bricker et al. (2017) for a description of the methodology and some results from recent waves of the SCF. See Emmons, Kent, and Ricketts (2018a) for income and wealth trends across education levels.

4. Families are grouped by the survey respondent’s primary racial/ethnic identification choice.

5. See Emmons, Kent, and Ricketts (2018c).


7. SCF family respondents born before 1930 or after 1989 are included in all regressions but are not highlighted in any of the tables or figures displayed due to low sample sizes, complex and possibly time-varying rates of household formation among the youngest adults, and education-related survivorship biases among the oldest cohorts.


9. The groups are White, African-American or Black, Hispanic, and other races and ethnicities. This latter group includes respondents that identify as Asian, American Indian/Alaska Native, Native Hawaiian/Pacific Islander, another race, or multiple races or ethnicities. In order to protect the identities of respondents, Board staff combine results for all of the “other” groups.

10. For robustness, we also estimated regressions of income and wealth including all races and ethnicities; our key results were qualitatively similar but much more difficult to interpret. We allowed for and found significant interactions between race or ethnicity, birth decade, and education level. Disentangling these effects was very difficult. See Emmons and Ricketts (2017) for an interpretation of large, relatively unchanging racial and ethnic wealth gaps as the result primarily of structural, systemic, or other unobservable factors rather than differences in individual effort or choice. Also see Darity et al. (2018) for a discussion of structural and systemic determinants of racial wealth gaps.

11. In addition to recording a household’s actual income in the previous year, respondents are asked, “Is this income unusually high or low compared to what you would expect in a “normal” year, or is it normal?” We also ran regressions with “usual” rather than actual income and found very similar results.


13. The nonlinear age terms are grounded in the theoretical “hump-shaped” life cycle of income and wealth with additional curvature at older ages. This complex shape has empirical support within the SCF (see Emmons and Noeth, 2015, pp. 12-14). To check the robustness of our results, we estimated the same income and wealth regression models for White and Black households while omitting $A_2$ and $A_3$. Our results were unchanged with the exception of the wealth premium for White postgraduate families with a head born in the 1980s, for whom we found a statistically significant, but still small, premium.

14. R Core Team (2017), Lumley (2017), and Lumley (2004). Publicly available scripts written by Anthony Damico (n.d.) were particularly helpful for working with SCF data in R.

15. See the 2016 SCF codebook for more information regarding analysis weights.

16. For more on the unique dual-frame sample design of the SCF, see Kennickell (1998). For a thoughtful discussion of whether to incorporate weights into regression analysis, see Solon, Haider, and Woolridge (2013). Pence (2006) makes the case that in median regressions with wealth as the dependent variable using SCF data, sample weights should be used. Otherwise, the identifying assumption doesn’t hold ($med(\epsilon|X \neq 0)$. Holt, Smith, and Winter (1980) provide a similar recommendation to avoid the same issue in the context of least squares regression ($E(\epsilon|X \neq 0)$.

17. See Kennickell (2000) for information on the construction of these replicates.
Except for a few early cohorts in which confidence bands were very wide, the same conclusion applies to Hispanic and other bachelor's degree families (Figures A1 and A2).

The confidence interval for the 1980s cohort was widest by a considerable margin. The premium for this group was much higher in regressions using usual income, along with a much tighter confidence interval around the mean. There were only 20 SCF families in which the respondent was Black, held a post-graduate degree, and was born in the 1980s. Of these 20 families, two had actual income different from usual income. In these cases, actual income was much lower than usual income. This introduced a notable outlier where actual income was $0 versus a usual income of $55,936. This likely introduced considerable variation around the premium estimate given the small sample size.

Johnson (1949) pioneered the use of the IHS transformation. Burbidge, Magee, and Robb (1988) provide an excellent overview of the transformation. See Pence (2006) for an informative application of IHS in the context of working with SCF data.

Note that this result is dependent on the inclusion of $A^2$ in the model.

Figures A5 through A8 show that these conclusions hold also for Hispanic families and those of all other races and ethnicities.

For the working paper, see https://www.stlouisfed.org/household-financial-stability/events/past-events/is-college-still-worth-it.

See Agarwal et al. (2009).

See Emmons, Kent, and Ricketts (2018b).

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