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Wages, Skills, and Skill-Biased Technical Change: The Canonical Model Revisited

Abstract

The canonical supply-demand model of the wage returns to skill has been extremely influential; however, it has faced several important challenges. Several studies show that the standard approach sometimes produces theoretically wrong-signed elasticities of substitution, yields counterintuitive paths for skill-biased technical change (SBTC), and does not account for the observed deviations in college premia for younger vs. older workers. This paper shows that these failings can be explained by mis-measurement of relative skill prices and supplies (based on standard demographic composition-adjustments) and by inadequate ad hoc functional form assumptions about the path for SBTC. Improved estimates of skill prices and supplies that account for variation in skill across cohorts within narrowly defined groups help explain the observed deviation in the college premium for younger vs. older workers, even with perfect substitutability across age. Re-estimating the model with these prices and supplies produces a good fit with better out-of-sample prediction and robustly yields positive elasticities of substitution between high and low skill workers. The estimates suggest greater substitutability across skill and a more modest role for SBTC. We implement two new approaches to modelling SBTC. First, we study the extent to which recessions induce jumps or trend-adjustments in skill bias and find evidence that both features are important (but differ across recessions). Second, we link SBTC to direct measures of information technology investment expenditures and show that these measures explain the evolution of skill bias quite well. Together, these approaches suggest that the ad hoc assumptions for SBTC previously employed in the literature are too crude to fit the data well, leading to the incorrect conclusion that SBTC slowed during the early-1990s and under-estimates of the elasticity of substitution between high and low skill workers.

JEL-Codes: E240, J240, J310, O330.

Keywords: skills, human capital, college, skill-biased technical change, wage premium.

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1 Introduction

A simple supply–demand framework has formed the basis of a large body of research on the determinants of wage returns to skill in the post-war US economy. The basic framework, introduced in Katz and Murphy (1992) and termed the "canonical model" in Acemoglu and Autor (2011), considers two broad types of skills — low and high skill (typically associated with high school and college, respectively) — whose relative prices and supplies are determined in equilibrium. The primary aim of this literature has been to understand the extent to which supply and demand factors, especially technological changes, have influenced the evolution of the skilled (i.e., college) wage premium, motivated in large part by the dramatic rise in wages among college-educated relative to high school-educated workers over a sustained period of growth in the supply of college-educated labor.[1]

Two features of aggregate productivity play leading roles in the canonical supply–demand framework: (1) the productivity of high-skilled relative to low-skilled workers and (2) the substitutability between high- and low- skilled labor inputs. The literature on skill-biased technological change (SBTC) emphasizes the evolution of relative productivity levels (Katz and Murphy 1992, Heckman, Lochner and Taber 1998, Katz and Autor 1999, Goldin and Katz 2008, Autor, Katz and Kearney 2008, Acemoglu and Autor 2011), while the literature studying the general equilibrium effects of government policy relies heavily on the elasticity of substitution (Heckman, Lochner and Taber 1998a, 1998b, Lee and Wolpin 2006, Abbott, *et al* 2019).

Estimates of the canonical model using standard composition-adjusted wages and aggregate skill supplies (assumed to be exogenously determined by demographic factors) and a linear time trend representing SBTC fit the evolution of the college wage premium in the US remarkably well over the 1963–1987 period studied by Katz and Murphy (1992). These estimates suggest a significant role for SBTC and a low elasticity of substitution between high school- and college-educated labor, σ, that ranges from 1.4 to 1.8.[2]

Unfortunately, recent studies have highlighted several problems that arise when extending the Katz and Murphy (1992) analysis over a longer time horizon. For example, estimates of the canonical

[1]While most of this literature has focused on the US (Katz and Murphy 1992, Heckman, Lochner and Taber 1998, Katz and Autor 1999, Card and Lemieux 2001, Beaudry and Green 2005, Ciccone and Peri 2005, Autor, Katz and Kearney 2008, Goldin and Katz 2008, Acemoglu and Autor 2011, Autor, Goldin, and Katz 2020), Crivellano (2016) studies the effects of relative supply shifts on returns to education across Europe from 1994-2009.

[2]Estimates from this literature suggest a major role for SBTC when estimated directly as linear trend changes in production function parameters following the approach of Katz and Murphy (1992) or indirectly through capital-skill complementarity coupled with increases in capital (Krusell, *et al* 2000).

model based on Katz and Murphy's time period (1963–1987) provide poor out-of-sample prediction for the college wage premium after 1987 (Acemoglu and Autor 2011). More troubling, estimates of σ based on later time periods (assuming a linear time trend for SBTC as in Katz and Murphy (1992)) typically have the wrong sign (Beaudry and Green 2005, Acemoglu and Autor 2011). Using an extended time period (1963–2008) and allowing for more flexible time trends for SBTC (e.g., cubic polynomial in time or a single break in trend in the early 1990s) improves the fit for relative wages over time and implies an elasticity of substitution similar to that estimated by Katz and Murphy; however, the implied path for SBTC is inconsistent with other direct evidence from, for example, expansions in computer use (Card and DiNardo 2002, Beaudry and Green 2005, Acemoglu and Autor 2011).[3] Finally, Card and Lemieux (2001) show that the rapid rise in the college wage premium from 1975 to 1995 was largely confined to younger workers, inconsistent with the assumptions underlying standard estimates of the canonical model.[4]

This paper makes two key methodological contributions. First, we build on the approach of Heckman, Lochner and Taber (1998) and Bowlus and Robinson (2012), henceforth BR, to better measure the evolution of relative skill prices and inputs when the skill levels of workers (within narrowly defined groups) are changing across cohorts. These improved measures are then used to re-estimate the canonical model, providing new estimates of SBTC and the elasticity of substitution between high school- and college-educated workers. Second, we develop two new approaches to modeling and identifying SBTC when using the canonical model to study the evolution of relative wages over a period that spans several decades. Together, these methodological improvements help to resolve many of the aforementioned concerns raised about the canonical model and its predictions, lending greater legitimacy to the simple supply–demand framework favored by much of the literature. Our findings lead to subtantially different conclusions about the elasticity of substitution between high school- and college-educated workers and about the importance of SBTC for long-term relative wage growth in comparison with previous estimates in the literature.

Estimates of SBTC and the substitutability of high school- and college-educated workers from the canonical model depend critically on the underlying measures of relative skill prices and aggregate

[3]Based on these inconsistencies, Beaudry and Green (2005) argue for an entirely new model of transformational technological change, while Acemoglu and Autor (2011) argue for a task-based approach to wage determination.

[4]They address this problem by disaggregating high school and college labor inputs by age and allowing for imperfect substitutability across these age and education groups. While successful, this resolution detracts from the simplicity of the original canonical framework.

skill supplies used in estimation. The standard measurement approach employs a relatively simple and straightforward composition adjustment to account for demographic changes in the composition of each broad skill type (high school- vs. college-educated) based on observable characteristics such as years of educational attainment, age or experience, and gender. It does not account for changes in the productivity of workers within narrowly defined categories. That is, it assumes that a 30–35 year-old male college graduate in 2000 provides the same effective high-skilled labor input as his counterpart from the 1960s (or even as far back as the early-1900s in Autor, Goldin, and Katz (2020)), effectively ignoring any cohort differences in the selection of individuals into college or in the lifecycle accumulation of human capital. Several recent studies call this assumption into question (Carneiro and Lee 2011, BR, Hendricks and Schoellman 2014), suggesting that trends in composition-adjusted relative wages and skill supplies are likely to suffer from systematic mis-measurement. While studies estimating the canonical model often acknowledge the possibility of changing within-group skill levels across cohorts, few have attempted to directly address this concern within the context of the basic supply–demand framework (Heckman, Lochner and Taber 1998, Carneiero and Lee 2011). The composition-adjustment approach, first employed by Katz and Murphy (1992), remains standard in the literature.

This paper, instead, follows the approach of BR and Heckman, Lochner and Taber (1998) to measure the evolution of relative skill prices and aggregate supplies over time. By exploiting changes in the wages of older workers, this approach directly identifies skill price changes unconfounded by variation in on-the-job skill investments common among younger workers (Becker 1964, Ben-Porath 1967). Most importantly, this approach accurately measures the evolution of relative skill prices and supplies when the skill levels of workers are changing across cohorts. As noted previously by BR, the observed differences in time patterns for the college wage premium by age can be easily explained by lifecycle differences in the relative skill levels of college- and high school-educated workers across cohorts, suggesting little need to differentiate skill types further by age as in Card and Lemieux (2001).

Using these improved relative price and skill supply measures to re-estimate the canonical model eliminates the problem of wrong-signed estimates of the elasticity of substitution for later time periods. Indeed, estimates of this elasticity are notably higher than previous estimates, suggesting that equilibrium price changes in response to policy shifts are likely to be weaker than previously thought. At the same time, the new estimates of technological change suggest a reduced role for

SBTC compared to previous studies. Instead, much of the increase in the college wage premium is explained by an increase in the skills of college-educated workers relative to those with a high school degree or less.

Although we find that using the BR price and skill measures reduces the role of SBTC, our estimates still imply a slowdown in SBTC during the 1990s when assuming that SBTC evolves according to a smooth, low-order polynomial in time (or is characterized by a single trend-break in the early-1990s). To better understand the evolution of SBTC over the 55 years we study, we break from the traditional *ad hoc* specifications for SBTC by considering two alternative approaches.

Our first approach is motivated by economic theories suggesting that technological change is more likely to occur during recessions. One line of theoretical work emphasizes the importance of learning, adapting, and implementing new technologies, which can lead to temporary slowdowns until workers are able to fully take advantage of new methods or machines (e.g. Hornstein and Krusell 1996, Klenow 1998). Galor and Moav (2000) argue that, because high-skilled workers adapt more quickly to new technologies, the wages of these workers are likely to rise (relative to the wages of low-skilled workers) throughout this process. Greenwood and Yorokoglu (1997) argue that major technological innovations require shifts in the workforce composition towards skilled labor (e.g. engineers, technicians, computer programmers) to install and implement new technologies, which can lead to both SBTC and short-term reductions in aggregate output. A second line of theoretical research develops the idea that recessions are a good (i.e. inexpensive) time to re-tool factories and implement new technologies (e.g. Cooper and Haltiwanger 1993, Cooper, Haltiwanger, and Power 1999).

The idea that SBTC may accelerate during (and following) recessions is broadly consistent with the relatively weaker employment declines of more skilled workers over several US recessions, as documented by Hoynes, Miller, and Schaller (2012) and Forsythe (2016). Using data on internet job postings, Hershbein and Kahn (2018) further show that both the demand for skilled workers and capital investments increased more in metropolitan areas hit harder by the Great Recession. By contrast, Beaudry, Green, and Sand (2016) argue that a long-run positive trend in SBTC was reversed following the 2000–01 "Dot-Com" Bust.[5] Altogether, these studies suggest that SBTC can

[5]Two other lines of empirical research are also relevant. First, studies of plant-level data establish several patterns on investment behavior (e.g., Doms and Dunne 1998, Doms, Dunne, and Troske 1997): (i) plant investments are lumpy with major investments followed by lengthy periods with little investment, (ii) major investment periods are correlated with aggregate investment and do not average out across plants, (iii) plants using more new technologies employ more

change sharply (accelerating or decelerating) during recessions.

To account for the potential importance of recessions, as well as the apparent reversal in demand for skill circa 2000–01, we estimate a flexible model of SBTC that allows for jumps and trend changes in SBTC during recessions. The elasticity of substitution between high school- and college-educated workers is then identified from relative price and supply movements between recessions. The resulting estimates suggest greater substitution between these skill types than previous studies and show a relatively modest long-run rate of SBTC with no slowdown in the 1990s. Consistent with Beaudry, Green, and Sand (2016), SBTC exhibits a slowdown after the 2001 recession, but this lasts for less than a decade before returning to its previous long-run trend after the Great Recession.

Our second approach takes the opposite tack by modeling SBTC as a function of direct measures of technology investment. Building on the work by Beaudry, Green, and Sand (2016), we model SBTC as a function of private fixed investment in information processing and equipment as a percent of GDP (*IPES*) or two of its main technology-focused subcomponents. This produces remarkably similar results to our more flexible specification that accounts for technology shifts and trend changes during recessions. Combining the two approaches by allowing for long-run trends to be explained by changes in *IPES* (or its subcomponents) and temporary jumps in SBTC during recessions provides an even closer correspondence. Importantly, these specifications do not show a slowdown in SBTC in the 1990s, which suggests that the 'puzzling' SBTC slowdown in the 1990s estimated by previous studies is a consequence of restrictive functional forms used to capture SBTC.

The rest of this paper is structured as follows. Section 2 summarizes the canonical model and introduces the distinction between relative prices and composition-adjusted relative wages. We introduce the data used to estimate the canonical model in Section 3, documenting relative composition-adjusted wages, skill prices, and skill supplies. This section also shows that imperfect substitution by age or experience is not needed to explain the different paths of relative wages by age or experience. Section 4 presents estimates of the canonical model based on standard assumptions about SBTC, considering both the 1963–2008 period studied in Acemoglu and Autor (2011) and extending this to 1963–2017 to include the Great Recession. This section contrasts estimates of the canoni-

high-skilled workers and pay higher wages, and (iv) plants that increase investment more in computing equipment (but not other forms of investment) experience larger increases in non-production labor. Second, a large literature uses structural vector autoregressions or dynamic stochastic general equilibrium models to estimate the extent to which technology shocks can explain business cycles; yet, little consensus has been reached (see Ramey (2016) for a detailed survey). The only study within this literature to explicitly estimate the role of skill-biased technology shocks finds that they produce strong declines in aggregate work hours (Balleer and van Rens 2013).

cal model based on relative skill prices and supplies that adjust for unobserved differences across cohorts with estimates based on relative wages and skill supplies obtained using the traditional composition-adjustment approach. We consider two new approaches for modeling SBTC in Section 5, first incorporating insights from research on technological change and recessions, and second, modeling SBTC as a function of direct measures of aggregate investments in information technology (IT). Section 6 provides concluding thoughts, including new avenues for future research.

2 Prices and Supplies in the Canonical Model

In this section, we formally describe the canonical model and the well-known skill premium equation, pointing out the important roles played by SBTC and the elasticity of substitution between skill types. We also discuss the distinction between observed wages and actual skill prices, and the concomitant challenges in measuring the latter, as well as aggregate skill supplies, when worker skill levels are changing within narrowly defined groups. Finally, we explore the implications of these challenges for estimation of the canonical model.

2.1 The Standard Two Skill Type Model

The canonical model assumes competitive labor markets with two imperfectly substitutable skill types: low and high.[6] The total supplies of aggregate low- and high-skilled inputs to production in period t are, respectively:

$$L_t = \int_{i \in \mathcal{L}} l_{it} n_{it} \, di \qquad \text{and} \qquad H_t = \int_{i \in \mathcal{H}} h_{it} n_{it} \, di,$$

where l_{it} (h_{it}) reflect the efficiency units of low (high) skill supplied each hour and n_{it} reflects total hours worked for worker i in skill set $\mathcal{L}$ ($\mathcal{H}$). The aggregate production function is of the CES form:

$$Y_t = \left[(A_{Lt} L_t)^{\frac{\sigma-1}{\sigma}} + (A_{Ht} H_t)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}, \tag{1}$$

where A_{Lt} and A_{Ht} reflect technology constants that determine the productivity of low- and high-skilled labor inputs, respectively, and $\sigma > 0$ reflects the elasticity of substitution between the two skill types. Factor-augmenting technical change is captured by changes over time in A_{Lt} and A_{Ht}.

[6] The literature generally associates low- and high-skill types with high school- (or non-college-) and college-educated workers, respectively. We follow this convention in our empirical analysis below, discussing the model in more general terms in this section.

The competitive labor market assumption implies that firms set the value of the marginal products of L and H equal to the price per efficiency unit of each type of skill:

$$\frac{\partial Y}{\partial L} = A_{Lt}^{\frac{\sigma-1}{\sigma}} \left[(A_{Lt}L_t)^{\frac{\sigma-1}{\sigma}} + (A_{Ht}H_t)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{1}{\sigma-1}} L_t^{\frac{-1}{\sigma}} = \pi_{Lt} \tag{2}$$

$$\frac{\partial Y}{\partial H} = A_{Ht}^{\frac{\sigma-1}{\sigma}} \left[(A_{Lt}L_t)^{\frac{\sigma-1}{\sigma}} + (A_{Ht}H_t)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{1}{\sigma-1}} H_t^{\frac{-1}{\sigma}} = \pi_{Ht}. \tag{3}$$

As discussed further below, it is important to recognize that these skill prices, π_{Lt} and π_{Ht}, differ from the corresponding hourly wages received by low- and high-skilled workers given by $\pi_{Lt}l_{it}$ and $\pi_{Ht}h_{it}$, respectively. Observed wages depend on both the price of skill and the amount of skill workers bring to the market.

Combining equations (2) and (3) and taking logs yields the relative demand function:

$$ln(H_t/L_t) = (\sigma - 1)ln(A_{Ht}/A_{Lt}) - \sigma \ \ln(\pi_{Ht}/\pi_{Lt}). \tag{4}$$

Relative demand depends on a technology component $(\sigma - 1)ln(A_{Ht}/A_{Lt})$, which may evolve over time due to SBTC, and relative skill prices. The elasticity of substitution determines both the slope of the demand function, $-\sigma$, with respect to relative prices, as well as the importance of changes in technology.

Defining relative skill prices $\pi_t \equiv \pi_{Ht}/\pi_{Lt}$, equation (4) may be re-arranged to yield the canonical skill premium equation:

$$\ln(\pi_t) = \left(\frac{\sigma - 1}{\sigma}\right) \ln(A_{Ht}/A_{Lt}) - \left(\frac{1}{\sigma}\right) \ln(H_t/L_t). \tag{5}$$

This equation clearly shows that, even in an era of secular increases in the supply of high-skilled labor (i.e. increases in H_t/L_t), the skill premium can increase if relative demand shifts at a faster pace. This is often characterized as a race between education (supply shifts) and technology (demand shifts).[7] As emphasized in Goldin and Katz (2008) and evident from equation (5), the elasticity of substitution plays a critical role in this race. The larger is σ; the greater is the impact of changes in technology (A_{Ht}/A_{Lt}) on the skill premium relative to changes in relative skill supplies (H_t/L_t). Intuitively, as high- and low-skilled workers become closer substitutes, the skill premium becomes less sensitive to any change in relative supplies and more responsive to any SBTC-induced demand shifts.

[7]See, for example, Acemoglu and Autor (2011) and Goldin and Katz (2008) who attribute the first use of the phrase to Tinbergen (1974).

Identifying the relative importance of demand and supply shifts in determining the path of the skill premium is complicated by the fact that technology parameters related to SBTC, $\ln(A_{Ht}/A_{Lt})$, cannot be measured directly. The most common approach in the literature assumes an *ad hoc* parametric time trend for $\ln(A_{Ht}/A_{Lt})$ (e.g., a low-order polynomial in time) and estimates both SBTC and σ using data on composition-adjusted relative wages and skill supplies.[8] A second approach for measuring SBTC assumes only that relative wages and skill supplies are on the demand curve and uses a constant "reasonable" value of σ obtained from the literature, together with measures of relative skill prices and supplies, to back out the implied SBTC from equation (5) using various sub-periods of the data.[9] Finally, Krusell *et al* (2000) explore a capital–skill complementarity hypothesis and use measures of aggregate capital over time to study shifts in the demand for skill. We investigate alternative approaches to modeling SBTC below in Section 5; however, we first consider a different measurement challenge that has largely escaped attention in the literature.

2.2 Relative Prices, Relative Wages and Composition Adjustments

The canonical model, encapsulated in equation (5), applies directly to relative skill prices, π_{Ht}/π_{Lt}, and aggregate relative skill supplies, H_t/L_t. However, neither of these are directly observed by researchers. When there is on-the-job investment of the form discussed in Becker (1964) and Ben-Porath (1967), it is particularly difficult to separate the price of skill from the individual supply of skill for two reasons. First, when workers make on-the-job investments in their future skills, the amount of skill they supply to the market is less than their current skill level (e.g. workers may spend only a fraction of their time producing, spending the remaining time investing in new skills). Second, both skills and skill prices may change over time.

To address this fundamental measurement problem, the previous literature has typically employed a composition-adjustment approach.[10] Let $\bar{l}_{jt}$ ($\bar{h}_{jt}$) be the (hours-weighted) average level of low- (high-) skill supplied to the market for workers $i \in \mathcal{L}_j$ ($i \in \mathcal{H}_j$) in period t, where $\mathcal{L}_j$ ($\mathcal{H}_j$) reflect different subsets, or cells, of workers defined by age, gender, and educational attainment. Then,

[8] This approach also (implicitly) assumes that deviations in relative supplies from assumed smooth time trends are exogenous. See Acemoglu and Autor (2011) for a survey or most of the studies listed in footnote 1.

[9] For example, see Katz and Murphy (1992), Autor, Katz, and Krueger (1998), Goldin and Katz (2008) and Autor, Levy, and Murnane (2003).

[10] See Katz and Murphy (1992), Katz and Autor (1999), Card and Lemieux (2001), Autor, Katz and Kearney (2008), and Acemoglu and Autor (2011) for applications of the composition-adjustment approach. Heckman, Lochner, and Taber (1998) is a notable exception, taking an approach similar to that of this paper.

aggregate supplies of low- and-high skilled labor are given by:

$$L_t = \sum_{j \in \mathcal{J}_L} n_{jt} \bar{l}_{jt} \qquad \text{and} \qquad H_t = \sum_{j \in \mathcal{J}_H} n_{jt} \bar{h}_{jt}, \tag{6}$$

where n_{jt} is the total number of person-hours worked in cell j at time t, while $\mathcal{J}_L$ and $\mathcal{J}_H$ reflect the set of all low- and high-skill subgroups, respectively.[11]

The standard composition-adjustment approach assumes that $\bar{l}_{jt} = \bar{l}_j$ and $\bar{h}_{jt} = \bar{h}_j$ are constant over time (or that changes 'average out' across groups over time). Then, the composition-adjusted aggregate supplies of low- and high-skilled labor are, respectively, given by:

$$L_t^c = \sum_{j \in \mathcal{J}_L} n_{jt} \bar{l}_j \qquad \text{and} \qquad H_t^c = \sum_{j \in \mathcal{J}_H} n_{jt} \bar{h}_j. \tag{7}$$

This approach explicitly accounts for changes over time in the composition of the workforce across observable groups (e.g. groups defined by age, gender, and educational attainment) through changes in n_{jt}. However, it does not account for changes in average skills (supplied to the market) *within* cells (i.e. variation in $\bar{l}_{jt}$ and $\bar{h}_{jt}$ over time).

Once supplies have been determined, composition-adjusted wages can be obtained by dividing the total wage bills for workers of each skill type (W_{Lt} and W_{Ht}) by the composition-adjusted supplies yielding $w_{Lt}^c \equiv W_{Lt}/L_t^c$ and $w_{Ht}^c \equiv W_{Ht}/H_t^c$ for low- and high-skilled workers, respectively.[12] As discussed further below, these average wage measures do not generally vary one-for-one with skill prices (π_{Lt}, π_{Ht}) when the skill levels of workers within narrowly defined groups are changing.

While convenient, the assumption that average skill levels within groups have not changed over time is a strong assumption for an analysis covering several decades. There are, at least, three important reasons that skills supplied to the market may have changed substantially since the early 1960s, even within narrowly defined observable groups. First, there have been dramatic changes in educational attainment and labor supply, raising concerns about changing selection into various skill groups. The systematic increase in college attendance rates over time suggests that recent college graduates may possess different natural talents and skill levels compared to those of earlier cohorts when fewer completed college (Carneiro and Lee 2011, Hendricks and Schoellman 2014). Bowlus and Robinson (2020) show that the dramatic increases in female labor force participation

[11] For example, $\bar{l}_{jt} \equiv (\int_{i \in \mathcal{L}_j} n_{it} l_{it} \, di)/n_{jt}$, where $n_{jt} \equiv \int_{i \in \mathcal{L}_j} n_{it} \, di$.

[12] One could also calculate composition-adjusted wages by taking hours-weighted averages of observed wages within broad high- and low-skill types, $\mathcal{H}$ and $\mathcal{L}$.

and occupational shifts (conditional on education and age) have impacted the within-group skill levels of women working today relative to those working in the 1960s. Notably, the skills of college-educated women have risen relative to those of non-college-educated women. Second, changes in the education system and learning/training in the workplace are also likely to have led to changes in worker skill levels, even within education and experience groups. After all, we have observed major innovations in the production of capital through the advent of computers and information technology. It would be surprising if these innovations had left the production of human capital unaltered. At the same time, the increase in career opportunities for college-educated women appears to have led to a decline in the average quality of teachers (Lakdawalla 2006, Bacolod 2007). Consistent with these findings, Hanushek and Zhang (2009) estimate that the quality of primary and secondary schooling has declined in the US, while the quality of post-secondary education appears to have increased. Third, changes in on-the-job training and other forms of costly investments in worker skills can produce changes in the amount of skill workers supply to the market even if the skills possessed by workers adjust very little (in the short-term). As highlighted in Heckman, Lochner, and Taber (1998), changes in current and future skill prices (π_{Lt}, π_{Ht}) lead to adjustments in lifecycle skill investments and, by extension, the amount of skill supplied to the market. Altogether, these studies suggest that the assumption of time invariant skill levels within narrowly defined groups is unlikey to be true for an analysis covering the past several decades.

These studies also highlight the challenge in measuring the evolution of relative skill prices and supplies over time, which arises because changes in wages not only reflect changes in prices but also in skill levels. The presence of on-the-job skill investments, especially among younger workers, further exacerbates this problem. Recognizing that human capital investments decline to zero and skills stop evolving near the end of workers' careers, Heckman, Lochner, and Taber (1998) show that it is possible to identify changes in skill prices by looking at wage changes among older workers.[13] Explicitly incorporating age a, log wages for older workers satisfy the following:

$$\begin{aligned} E[\ln(\pi_{L,t+1} l_{i,a+1,t+1})] - E[\ln(\pi_{L,t} l_{i,a,t})] &= \ln(\pi_{L,t+1}) - \ln(\pi_{L,t}), \quad \text{for } i \in \mathcal{L}, a \in [\underline{a}_L, \bar{a}_L] \\ E[\ln(\pi_{H,t+1} h_{i,a+1,t+1})] - E[\ln(\pi_{H,t} h_{i,a,t})] &= \ln(\pi_{H,t+1}) - \ln(\pi_{H,t}), \quad \text{for } i \in \mathcal{H}, a \in [\underline{a}_H, \bar{a}_H], \end{aligned}$$

where $\underline{a}_S$ and $\bar{a}_S$ reflect skill type-specific $S \in \{H, L\}$ lower and upper age limits, respectively, that

[13] The level of skill prices cannot be separated from the level of skills, requiring a normalization on one or the other for each of the two broad skill groups, $\mathcal{L}$ and $\mathcal{H}$, in a single period.

characterize periods of no skill investment or accumulation. As discussed in BR, changes in median rather than mean log wages for older workers can also be used to identify skill price variation over time. It is important to note that this approach, referred to as the "flat spot" approach by BR, does not require observing the same workers repeatedly, since it only requires estimating differences in average (or median) log wages. However, it does require following the same cohort of workers over consecutive years, with the implicit assumption that the underlying population of workers across the years remains the same. Thus, it is important to consider older ages at which workers' skills are no longer changing, yet ages at which there is not selection into retirement based on skills.

The flat spot method follows the basic assumptions of the canonical model in that within broad skill types, workers of different ages or gender are assumed to be perfectly substitutable. That is, workers within skill type $\mathcal{L}$ or $\mathcal{H}$ all supply the same type of human capital but may supply different amounts.[14] Critically, the approach does not require any assumptions about within-group stability of skill levels across cohorts or over time (except among older workers as implied by theory).

Once skill prices π_{Lt} and π_{Ht} have been estimated from older workers, aggregate low- and high-skill supplies in period t, L_t and H_t, can then be obtained each period by dividing the total low- and high-skill wage bills by the respective estimated skill prices that period. Using relative skill prices and aggregate supplies obtained by this approach, the canonical skill premium equation (5) can be estimated directly.[15]

Estimation of the canonical model using composition-adjusted wages and skill supplies requires modification of equation (5) when within-cell skill levels have changed over time. To see why, it is useful to first define the time-varying constants $q_{Lt} \equiv L_t/L_t^c$ and $q_{Ht} \equiv H_t/H_t^c$. If $\bar{l}_j$ and $\bar{h}_j$ are normalized to represent long-run time averages for $\bar{l}_{jt}$ and $\bar{h}_{jt}$, respectively, then q_{Lt} and q_{Ht} reflect the (n_{jt} weighted) deviations of average within-cell skill levels $\bar{l}_{jt}$ and $\bar{h}_{jt}$, respectively, from their long-run averages.[16] Therefore, an increase in the average amount of skill supplied per worker hour within cells would not be reflected in L_t^c or H_t^c, but would instead imply an increase in q_{Lt} or q_{Ht} over time. Furthermore, since composition-adjusted wages are simply $w_{Lt}^c = W_{Lt}/L_t^c = q_{Lt}\pi_{Lt}$ and

[14] Carneiro and Lee (2011) report a very high elasticity of substitution across ages when accounting for differences in skill levels across cohorts. We discuss this issue further in Section 3.2. See BR and Bowlus and Robinson (2020) for a full discussion of substitutability by gender and its implications for females.

[15] After describing our data and measurements in greater detail below, we comment on potential concerns about measurement error in both composition-adjusted and BR relative skill prices and supplies.

[16] For example, for low skill define the deviation $l_{jt}^d \equiv \bar{l}_{jt} - \bar{l}_j$, where $\bar{l}_j \equiv \sum_{t=1}^{T} n_{jt}\bar{l}_{jt} / \sum_{t=1}^{T} n_{jt}$. Then, $q_{Lt} = 1 + \sum_{j\in\mathcal{J}_L} n_{jt} l_{jt}^d / L_t^c$. If for any t, $\sum_{j\in\mathcal{J}_L} n_{jt} l_{jt}^d = 0$, then $q_{Lt} = 1$ and $L_t^c = L_t$. The same is true for high skill.

$w_{Ht}^c = W_{Ht}/H_t^c = q_{Ht}\pi_{Ht}$, they also differ from actual skill prices whenever average skill levels vary within different subgroups.

Substituting the composition-adjusted wages and supplies into equation (5) and defining relative worker quality, $Q_t \equiv q_{Ht}/q_{Lt}$, relative log wages can be re-written as

$$\ln(w_t^c) \equiv \ln(w_{Ht}^c/w_{Lt}^c) = \left(\frac{\sigma-1}{\sigma}\right)\ln(A_{Ht}/A_{Lt}) + \left(\frac{\sigma-1}{\sigma}\right)\ln(Q_t) - \left(\frac{1}{\sigma}\right)\ln(H_t^c/L_t^c), \qquad (8)$$

where the addition of $\ln(Q_t)$ accounts for discrepancies between composition-adjusted relative wage and skill measures and actual relative skill prices and supplies. Note that log relative worker quality, $\ln(Q_t)$, plays exactly the same role in determining the composition-adjusted wage premium, $\ln(w_t^c)$, as the SBTC term, $\ln(A_{Ht}/A_{Lt})$; however, they reflect very different economic forces. The former reflects changes in the relative human capital per worker of high- vs. low-skilled workers, while the latter reflects changes in relative demand due to technology shifts in production. We refer to equation (8) as the augmented canonical model.

The standard approach to the canonical model estimates equation (8) using composition-adjusted relative wages and skill supplies while omitting the term for relative quality, $\ln(Q_t)$. Failure to account for changes in relative worker quality (within age-gender-education groups) across cohorts in this way effectively attributes those changes to estimated SBTC profiles. This approach also produces biased estimates of σ whenever changes in $\ln(Q_t)$ are correlated with changes in $\ln(H_t^c/L_t^c)$ conditional on the assumed time path for SBTC.

If an estimated series for $\ln(Q_t)$ is available, it can simply be included in equation (8) to account for the cohort differences in worker relative quality levels, estimating the model with the composition-adjusted relative wage and supply series used by the literature. Alternatively, equation (5) can be estimated directly using skill prices (π_{Lt}, π_{Ht}) and supplies $(H_t,\, L_t)$ — obtained from the BR approach — that account for unobserved skill differences across cohorts. This enables estimation of both demand and supply effects on the evolution of relative skill prices, $\ln(\pi_t)$. If desired, these estimates can then be combined with the path of $\ln(Q_t)$ — estimated from BR skill supplies (L_t, H_t) and composition-adjusted measures (L_t^c, H_t^c) — to decompose composition-adjusted relative wages into supply effects, demand effects (i.e. SBTC), and changes in relative worker quality using equation (8).

3 Data and Measurement of Relative Skill Prices and Supplies

To estimate the canonical model, we use March Current Population Survey (CPS) data from 1963–2017, extending the period used in BR and Acemoglu and Autor (2011) beyond 2008 by almost 10 years. We follow the literature in defining two broad skill types based on the educational attainment of workers: high-skilled (i.e., college graduates) and low-skilled (i.e., high school graduates). In creating aggregate skill supplies, we follow most studies in allocating all college graduate cell hours and 50% of some college cell hours to the high-skill type and the remainder to the low-skill type.

For the composition-adjustment approach, we closely follow the methodology and definitions laid out in Autor, Katz and Kearney (2008), which are also used in Acemoglu and Autor (2011). To compute composition-adjusted supplies for high- and low-skilled labor, we first compute a measure of detailed gender-education-experience average skill levels relative to a base subgroup. In calculating these "efficiency units", we take average subgroup-specific wages relative to average wages for the base subgroup (male high school dropouts with 10 years of experience) each year, then average these across all years. Next, we calculate high- and low-skill composition-adjusted aggregate supplies for each year (H_t^c and L_t^c) by summing the "efficiency units" for the relevant subcategories of workers multiplied by total hours worked by everyone in that subgroup that year. To compute composition-adjusted log wages (and $\ln(w_t^c)$), log wage regressions run separately by year and gender are first used to obtain predicted log wages by gender, year, and detailed experience and education categories.[17] Then, composition-adjusted log wages for high- and low-skilled workers are computed separately as weighted averages of all gender and experience subcategories for college graduates and high school graduates, respectively, where the weights are based on total hours worked within each subgroup (averaged over all years).

To calculate prices and supplies that adjust for cohort and other differences within detailed observable subgroups of workers, we employ the flat spot approach of BR. We effectively extend through 2017 the BR estimated price series for college graduates and high school graduates as our measures of high- and low-skill prices, π_{Ht} and π_{Lt}, respectively. Following the description in Section 2.2, these prices are estimated using median wages from full-time, full-year male workers in 10-year flat spot ranges: ages 50–59 for college graduates and ages 46–55 for high school graduates.[18]

[17] We carefully follow Autor, Katz, and Kearney (2008) by also controlling for race and region indicators, including interactions of most characteristics with a quartic in experience.

[18] BR note that using changes in median, rather than average, log wages addresses problems associated with changes

Next, the ratio (H_t/L_t) is obtained by dividing the ratio of total wage payments (W_{Ht}/W_{Lt}) by the price ratio (π_{Ht}/π_{Lt}) obtained using the BR approach. Finally, we construct a series for Q_t using the ratio of the BR (H_t/L_t) and composition-adjusted (H_t^c/L_t^c) relative skill supplies.[19]

3.1 Relative Prices, Wages, and Supplies: 1963–2017

Figure 1 shows the evolution of composition-adjusted relative wages, $\ln(w_t^c)$, and BR relative prices, $\ln(\pi_t)$, over the 1963–2017 period. For comparison purposes, the extended relative price series from BR, $\ln(\pi_t)$, is normalized to the same initial (1963) value as $\ln(w_t^c)$. The two series diverge slightly in the late-1960s with $\ln(w_t^c)$ increasing and then declining in the late-1970s and $\ln(\pi_t)$ showing only a slight downward trend. Both series start to grow in the early-1980s with $\ln(w_t^c)$ growing much faster than $\ln(\pi_t)$. In the mid-1990s, $\ln(\pi_t)$ reverses and declines until leveling off in the 2010s, while $\ln(w_t^c)$ increases throughout the 1980s, 1990s, and early-2000s before stabilizing.

The difference between the paths for $\ln(\pi_t)$ and $\ln(w_t^c)$ reflects changes in the relative quality of college graduates compared to high school graduates, $\ln(Q_t)$, as shown in Figure 2. Following the late-1970s, as documented in BR, the relative quality of college graduates compared to high school graduates increases over time. The implied rise in $\ln(Q_t)$ and modest increase in relative skill prices, $\ln(\pi_t)$, suggests that much of the increase in the college wage premium, $\ln(w_t^c)$, is due to an improvement in the relative quality of college-educated workers rather than SBTC. As is evident from equation (8), the importance of the secular increase in $\ln(Q_t)$ for (composition-adjusted) relative wages depends on the elasticity of substitution, σ.

The time path for $\ln(Q_t)$ also implies a difference in the two measures of estimated relative supplies, $\ln(H_t^c/L_t^c)$ and $\ln(H_t/L_t)$, as shown in Figure 3. Both measures exhibit a strong increasing secular trend in the relative supply of skill; however, the composition-adjusted relative supplies, $\ln(H_t^c/L_t^c)$, flatten markedly beginning in the early-1980s as noted by Card and DiNardo (2002) and Acemoglu and Autor (2011).[20] By contrast, the BR relative skill supplies, $\ln(H_t/L_t)$, show little

in CPS topcoding over time. See BR for a detailed analysis and justification for the flat spot age ranges. Our main results are robust to alternative flat spot age ranges shifted by 1–2 years in either direction.

[19] We can also define wage-based relative quality ratios obtained as $q_{Ht}^w \equiv \pi_{Ht}/w_{Ht}^c$ and $q_{Lt}^w \equiv \pi_{Lt}/w_{Lt}^c$. If skill prices and composition-adjusted wages are both constructed from total wage payments (W_{Ht}, W_{Lt}) divided by corresponding aggregate supply measures, then $q_{Ht}^w/q_{Lt}^w = q_{Ht}/q_{Lt}$ by construction. However, since we follow the literature and do not calculate composition-adjusted wage measures in this way, this equality need not hold. In theory, this implies the following relationship in place of equation (8): $\ln(w_t^c) = \frac{\sigma-1}{\sigma}\ln(A_{Ht}/A_{Lt}) + \ln(q_{Ht}^w/q_{Lt}^w) - \frac{1}{\sigma}\ln(q_{Ht}/q_{Lt}) - \frac{1}{\sigma}\ln(H_t^c/L_t^c)$. In practice, we find very minor differences between q_{Ht}^w/q_{Lt}^w and q_{Ht}/q_{Lt}, which we ignore going forward.

[20] Focusing on the periods analyzed by Acemoglu and Autor (2011), we find that annual growth drops from 4.4% over 1963–1982 to 1.9% from 1982 to 2008. Figure 3 shows that the slower rate of growth extends to the end of our

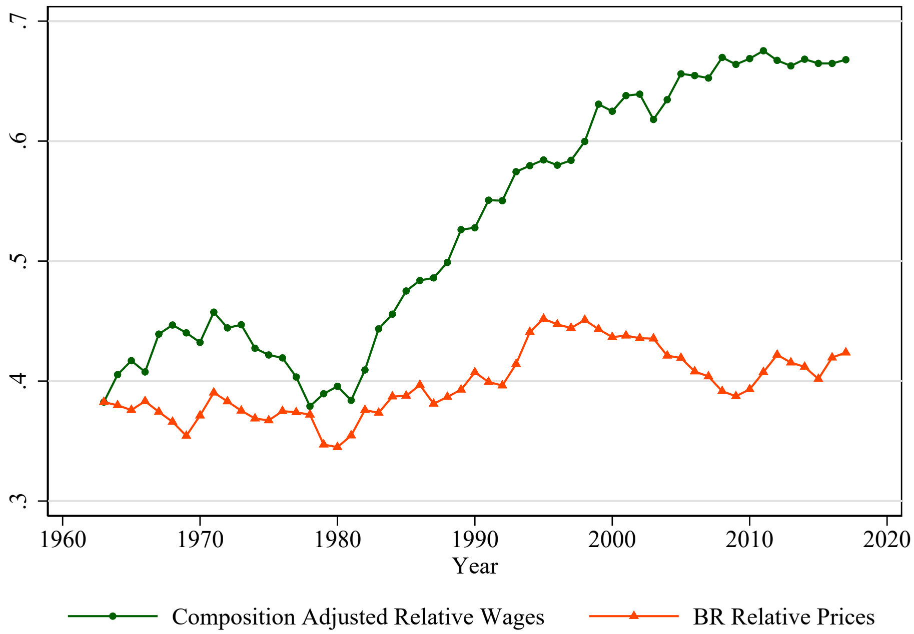


Figure 1: Composition-Adjusted Log Relative Wages and BR Log Relative Prices

Notes: Log relative skill prices, $\ln(\pi_t)$*, are normalized to the same 1963 value as composition-adjusted log relative wages,* $\ln(w_t^c)$*.*

evidence of a break in trend due to the sharp increase in worker quality for college graduates relative to high school graduates, $\ln(Q_t)$, beginning in the early-1980s (see Figure 2).

3.2 Substitutability Across Age Groups and Cohort Effects

Consistent with the canonical model, our approach for measuring skill prices and supplies implicitly assumes perfect substitutability across age groups. Workers of different ages but from the same broad skill type ($\mathcal{H}$ or $\mathcal{L}$) are assumed to possess the same type of labor market skill (i.e. the same input into production), face the same skill price, and only differ in the amount of skill they provide to the market. This assumption has been challenged by Card and Lemieux (2001) and Acemoglu and Autor (2011), who point to the faster growth in the (composition-adjusted) college – high school wage premium over the 1980s for younger workers compared to older workers as evidence against perfect substitutability across age/experience. Based on this, they argue for a generalization of the canonical model that incorporates imperfect substitutability across age or experience groups within

sample period, 2017.

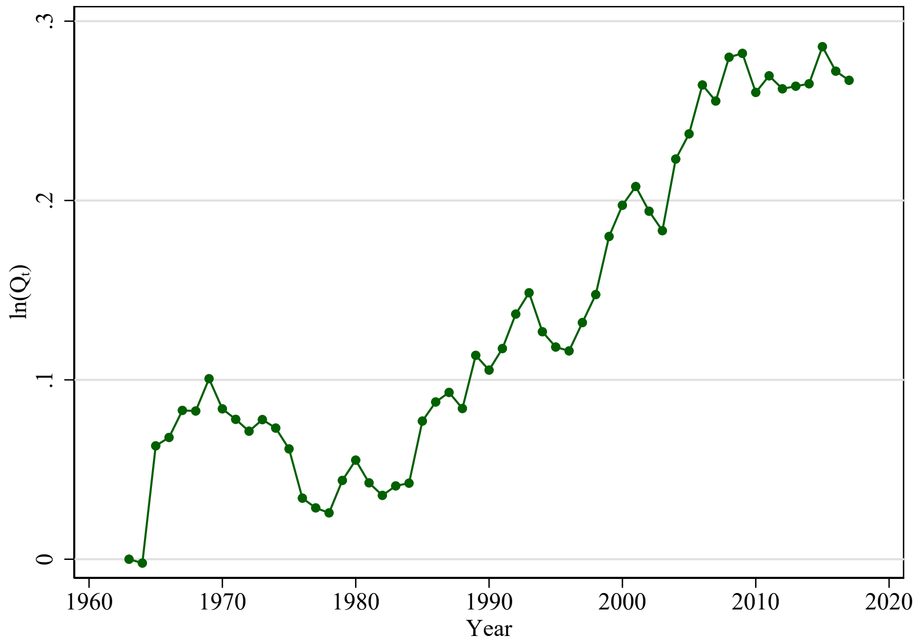


Figure 2: Log Relative Quality, $\ln(Q_t)$

Notes: This figure reports deviations in log relative skill quality, $\ln(Q_t) = \ln(H_t/L_t) - \ln(H_t^c/L_t^c)$*, from the 1963 value.*

high school- and college-educated types.

Yet, the evolution of composition-adjusted wages need not reflect changes in skill prices when worker skill levels are changing across cohorts. In fact, BR show that the rapid growth in relative wages for young workers in the 1980s is consistent with the improvement in quality for college cohorts born over the 1950s, largely due to selection effects associated with declining college attendance rates over these cohorts. Consistent with this cohort quality explanation, Figure 4 shows that the dramatic increase in college relative to high school wages that appears in the 1980s for workers with 5 years of experience was first followed by workers with 15 years of experience and then by workers with 25 years of experience.[21] Moreover, the sharp increase in relative wage ratios appears to stop around

[21] In Figure 4, the younger group in 1980 corresponds to workers born in the late 1940s. These cohorts have the largest fraction of college graduates, suggesting strong negative selection effects on their per capita skill levels. Subsequent cohorts of college graduates likely improve as college enrolment rates decline (about 5 percentage points between 1950 and 1960 cohorts according to BR), implying increasingly positive selection (BR, Carneiro and Lee 2011). BR argue that there were also secular improvements in the production of skill among the more recent cohorts of college graduates. Altogether, they estimate an 11% upward shift in the lifecycle human capital profiles for college graduates between the 1949 and 1961 birth cohorts, much more than observed for cohorts born during the decades before or after.

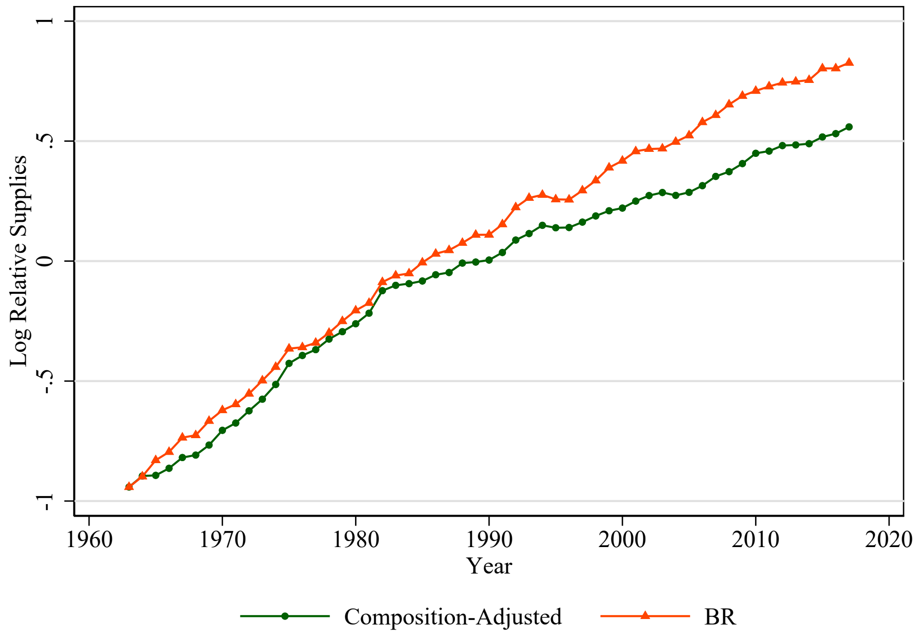


Figure 3: Composition-Adjusted and BR Log Relative Supplies

Notes: BR log relative skill supplies, $\ln(H_t/L_t)$*, are normalized to the same 1963 value as composition-adjusted log relative skill supplies,* $\ln(H_t^c/L_t^c)$*.*

1990 for those with 5 years of experience, 2000 for those with 15 years of experience, and 2010 for those with 25 years experience. In light of these patterns, the different time series for college – high school relative wages by worker age/experience appear to reflect differences in relative skill levels across cohorts rather than differences in relative skill prices by age/experience.

Carniero and Lee (2011) attempt to directly measure changes in cohort quality using observed test score measures. Accounting for cohort differences based solely on selection of ability among college students, they estimate very strong substitutability across age groups (elasticity of substitution of roughly 10). BR further show that using skill prices estimated from the log wages of older workers (based on the flat spot approach described above) implies prototypical lifecycle human capital profiles that shift up (down) for more recent cohorts of college (high school) graduates, consistent with the cohort selection effects highlighted by Carneiro and Lee (2011) and other long-run trends in the education sector and labor market.[22] Altogether, these studies suggest that the parsimonious

[22]For example, Hanushek and Zhang (2009) estimate that the quality of post-secondary education improved over time while the quality of primary and secondary education declined. Bowlus and Robinson (2020) document important improvements in the skills of college-educated relative to non-college-educated women over the past few decades.

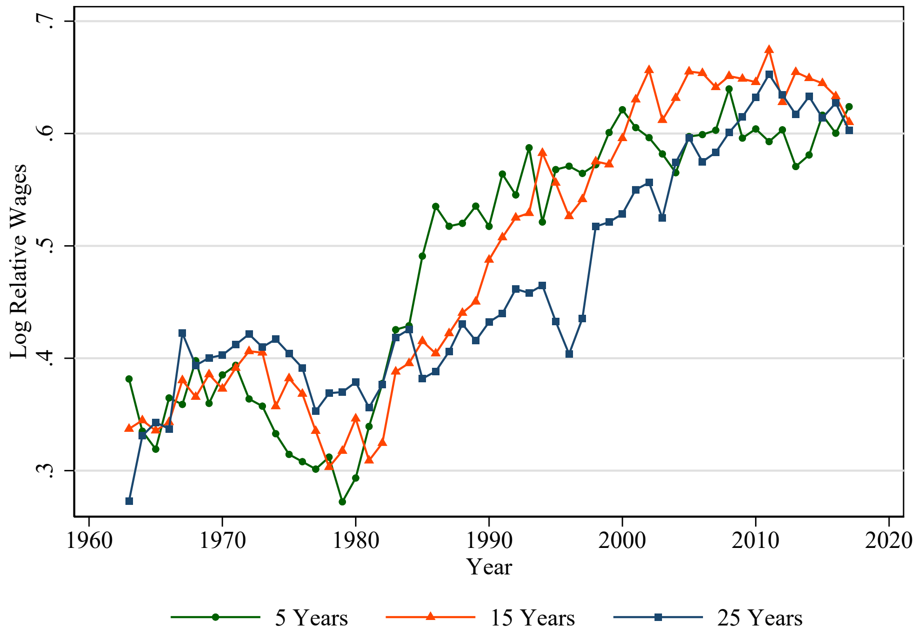


Figure 4: Composition-Adjusted Log Relative Wages by Experience

Notes: This figure reports composition-adjusted log relative wages, $\ln(w_t^c)$*, for workers with 5, 15, and 25 years of experience.*

canonical model and our general approach to measuring skills and skill prices, which assumes perfect substitutability across age/experience groups, provides a good approximation to US wage patterns as long as cohort effects are taken into account. Put another way, the problem raised by Card and Lemieux (2001) and Acemoglu and Autor (2011) is likely one of measurement more than a failure of the basic canonical model.

4 Estimates from Parametric Canonical Models

Figure 3 shows that the estimated skill supply ratio has increased substantially. This should have reduced the skill premium, but obviously did not (see Figure 1). The canonical framework accounts for the simultaneous increase in relative skill prices and supplies by introducing SBTC through a time-varying relative productivity constant $\ln(A_{Ht}/A_{Lt})$. Empirically, the increased demand through SBTC must dominate the effects of rising relative skill supply.

Since the technology coefficients A_{Ht} and A_{Lt} are not directly observed and it is not possible to simultaneously estimate σ and allow for completely unrestricted year-to-year variation in

$\ln(A_{Ht}/A_{Lt})$, an assumption must be made regarding the time trend for $\ln(A_{Ht}/A_{Lt})$. Using data from 1963–1987, Katz and Murphy (1992) employ the simplest assumption of a linear trend for SBTC: $\ln(A_{Ht}/A_{Lt}) = \alpha_0 + \alpha_1 t$. This linear trend specification and the assumption that relative skill levels do not change within cells (i.e. $\ln(Q_t) = 0$) yields the standard estimating equation from the literature:

$$\ln(w_t^c) = \tilde{\alpha}_0 + \tilde{\alpha}_1 t - \frac{1}{\sigma} \ln(H_t^c/L_t^c). \tag{9}$$

where $\tilde{\alpha}_j \equiv \alpha_j(\sigma - 1)/\sigma$ for $j = 0, 1$.

Replicating Katz and Murphy (1992) for the 1963–1987 period, Acemoglu and Autor (2011, p. 1108) estimate that $\tilde{\alpha}_1 = 0.027$ and $\sigma = 1.634$. This simple specification implies a modest elasticity of substitution between high school- and college-educated labor and captures the sharp reversal of the trajectory in relative log wages coinciding with the deceleration in the growth of (composition-adjusted) relative skill supply in the late-1970s. SBTC increases the college wage premium by 2.7% per year.

Acemoglu and Autor (2011) highlight a number of problems that arise when the sample period is extended from 1963–1987 to 1963–2008.[23] In our analysis, we first replicate the estimates of Acemoglu and Autor (2011) for their sample period, defining $t = year - 1962$. Columns (1) to (5) in Table 1 report estimation results that are almost identical to those in Table 8 of Acemoglu and Autor (2011). Inspection of columns (1) and (3) shows that, as reported in Acemoglu and Autor (2011), a linear time trend imposed over the extended 1963–2008 period results in a higher estimated elasticity of substitution (2.96 vs. 1.60) and a weaker SBTC time trend (1.64% vs. 2.74%). This is consistent with a poor out of sample fit for the model using the original Katz and Murphy (1992) estimates. Autor, Katz, and Kearney (2008) and Acemoglu and Autor (2011) explore more flexible specifications for SBTC to see whether they are better able to fit the data over the entire time period while producing positive estimates for σ similar in magnitude to the original estimate in Katz and Murphy (1992). Columns (4) and (5) show analogous results for these more flexible specifications. Column (4) allows for a break in the time trend after 1992, while column (5) allows for a cubic time trend throughout the period. These specifications produce an elasticity of substitution for the 1963–2008 period that is similar to that for 1963–1987 estimated by Katz and Murphy (1992). However, the estimated time trends for SBTC imply that relative demand for high-skilled workers decelerated

[23]These concerns were also previously documented in Autor, Katz, and Kearney (2008).

	1963–1987	1988–2008	1963–2008			1963–2017
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(H_t^c/L_t^c)$	-0.626	0.285	-0.339	-0.645	-0.559	-0.452
	(4.86)	(1.96)	(7.88)	(9.87)	(5.95)	(5.61)
t	0.027	0.002	0.016	0.029	0.020	0.016
	(5.08)	(0.83)	(12.61)	(11.69)	(3.58)	(3.14)
$t^2 \times 100$	.	.	.	.	0.036	0.029
	.	.	.	.	(2.93)	(2.89)
$t^3 \times 1000$	.	.	.	.	-0.007	-0.005
	.	.	.	.	(4.37)	(5.07)
$\mathbb{1}(year \geq 1992) \times t$	.	.	.	-0.010	.	.
	.	.	.	(5.45)	.	.
implied σ	1.598	-3.505	2.955	1.549	1.789	2.212
R^2	0.568	0.948	0.935	0.962	0.960	0.970
number of years	25	21	46	46	46	55

Notes: Table reports estimates (absolute value of t-statistics) based on regressions of composition-adjusted log relative wages, $\ln(w_t^c)$, on composition-adjusted log relative skill supplies, $\ln(H_t^c/L_t^c)$, and other reported variables.

Table 1: Canonical Model Estimated Using Composition-Adjusted Wages and Supplies

in the 1990s, which Acemoglu and Autor (2011, p. 1109) argue "...does not accord with common intuitions regarding the nature or pace of technological change occurring in this era."

Estimating both SBTC and σ using aggregate time series variation in relative wages and supplies is complicated by the absence of a direct measure of SBTC and the consequent identification problem. The results in column (2) of Table 1 highlight the challenges. Estimating the linear trend model over 1988–2008 yields the "wrong" sign for σ and no evidence of SBTC. Expanding the sample to use data from 1980 to 2008 produces an even more negative and statistically significant value for σ (not shown in table). Unless the sample period includes enough pre-1980 data to cover both sides of the break in the trend for composition-adjusted relative supplies (see Figure 3), estimates of σ have the wrong sign. Even then, estimates of σ are highly sensitive to the chosen sample period.

Column (6) in Table 1 extends the data period to 2017. In this case, σ is 2.21 and SBTC is even weaker than that in column (5).[24] Finally, Autor, Katz, and Kearney (2008) and Acemoglu and Autor (2011) show that the model estimated on the 1963–1987 period produces a poor out-of-sample fit predicting the relative log wage series out to 2008. Figure 5 shows this poor out-of-sample fit

[24] A linear specification for SBTC (not reported) produces an even higher value for σ at 4.70 and still weaker SBTC.

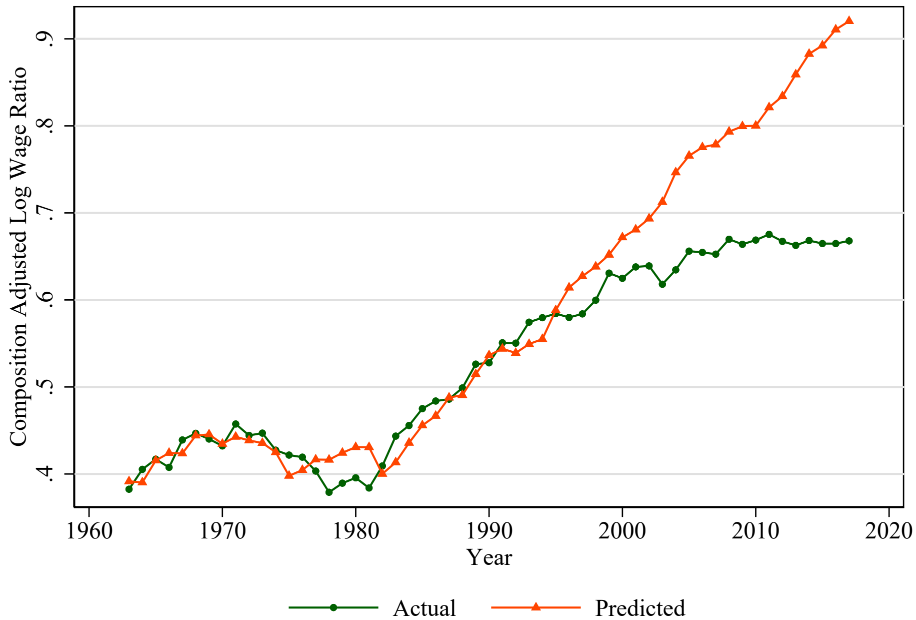


Figure 5: Predicted Log Relative Wages based on 1963–1987 Basic Canonical Model

Notes: This figure reports actual and predicted composition-adjusted log relative wages, $\ln(w_t^c)$*, where the predicted values are based on estimates reported in column (1) of Table 1.*

worsens when extending out to 2017. Based on estimates from the 1963–1987 data, the predicted increase in relative log wages is much larger after 1987 than occurs in the data.

4.1 Accounting for Unobservable Skill Differences Across Cohorts

We now show that the results reported in Table 1 are quite sensitive to the implicit maintained assumption that cohort differences in relative quality are time invariant (i.e., $\ln(Q_t) = 0$ for all periods). This assumption can be easily relaxed by using the BR relative skill prices and supplies ($\ln(\pi_t)$ and $\ln(H_t/L_t)$) to directly estimate equation (5). Alternatively, one could estimate the augmented model using composition-adjusted relative wages and supplies ($\ln(w_t^c)$ and $\ln(H_t^c/L_t^c)$) while incorporating estimates of $\ln(Q_t)$ as in equation (8). In both cases, differences in unobserved relative skill levels across cohorts can be accounted for while continuing to use the same parametric forms for SBTC as in Table 1 and the previous literature.

Table 2 reports the results from estimating equation (5) using BR relative skill prices, $\ln(\pi_t)$, and supplies, $\ln(H_t/L_t)$. The problem of the wrong sign for σ when estimated for the 1988–2008 sub-

	1963–1987	1988–2008	1963–2008			1963–2017
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(H_t/L_t)$	-0.175	-0.261	-0.127	-0.437	-0.262	-0.355
	(1.28)	(1.29)	(2.44)	(5.85)	(3.04)	(3.88)
t	0.007	0.008	0.006	0.019	0.004	0.014
	(1.29)	(1.40)	(3.34)	(6.40)	(0.89)	(2.77)
$t^2 \times 100$	.	.	.	.	0.042	0.011
	.	.	.	.	(4.76)	(1.43)
$t^3 \times 1000$	.	.	.	.	-0.007	-0.003
	.	.	.	.	(6.34)	(3.56)
$\mathbb{1}(year \geq 1992) \times t$	.	.	.	-0.007	.	.
	.	.	.	(4.99)	.	.
implied σ	5.714	3.828	7.865	2.288	3.822	2.821
R^2	0.070	0.121	0.603	0.751	0.831	0.726
number of years	25	21	46	46	46	55

Notes: Table reports estimates (absolute value of t-statistics) based on regressions of BR log relative skill prices, $\ln(\pi_t)$, on BR log relative skill supplies, $\ln(H_t/L_t)$, and other reported variables.

Table 2: Canonical Model Estimated Using BR Prices and Supplies

period (see column (2) of Table 1) is now eliminated. More generally, estimates using the BR relative skill prices and supplies lead to notably larger estimates of σ, implying stronger substitutability between skill groups. They also indicate much weaker SBTC over the entire sample period. While the estimated path for SBTC still appears to decline in the 1990s — counter to conventional wisdom about the pace of innovation — the slowdown is less dramatic (see column (4)).

Why are the results in Table 2 so different from those reported in Table 1? As shown in Figure 1, there is much weaker long-term growth in BR relative prices, $\ln(\pi_t)$, than in composition-adjusted relative wages, $\ln(w_t^c)$. Less SBTC is, therefore, needed to explain the modest increase in relative skill prices. Further, a weaker correlation between deviations from trends in relative skill prices and supplies compared to their composition-adjusted counterparts is responsible for the larger estimates for σ in Table 2.[25]

[25]Since both the composition-adjusted relative wage and skill supply series and the BR relative skill price and supply series are estimated using CPS data, they may be measured with error. As discussed in the Appendix, estimates of σ in Table 1 are likely to be upward biased in the presence of classical measurement error in composition-adjusted relative wages and skills when abstracting from unobserved quality differences across cohorts (i.e., assuming $\ln(Q_t) = 0$ for all t). In contrast, estimates of σ using the BR approach (Table 2) are likely to be downward biased by classical measurement error in relative skill prices. The difference in biases arises, because the measurement errors for composition-adjusted

4.2 The Great Recession and the Canonical Model

Accounting for unobserved differences in cohort relative quality levels helps address some of the previously documented problems with the canonical model. However, better measurement of relative skill prices and supplies does not resolve the puzzling decline in SBTC in the 1990s, and extending the data period to cover the Great Recession and its aftermath produces non-trivial changes in estimates of σ and SBTC even when using the BR-based measures. Model fit is also a concern. Figure 6 shows the model fit for relative skill prices, $\ln(\pi_t)$, for the 1963–2008 period when assuming a cubic time trend for SBTC (Table 2, column 5). It misses the dip around the early 1980s recession, but otherwise fits quite well. By contrast, Figure 7 shows a noticeably worse fit when the cubic-trend model is extended to the 1963–2017 period: the model cannot fit the relative skill price path through and after the 2008 Great Recession. The sharp changes in relative skill prices around 1980, 2000, and 2009 cannot be explained by sharp changes in relative skill supplies (see Figure 3), rendering as futile efforts to model SBTC using smooth low-order polynomials. Rather than continuing with arbitrary functional form assumptions for SBTC, we consider two new approaches to modeling SBTC in the next section.

5 New Approaches to Estimating SBTC in the Canonical Model

SBTC is central to the canonical model, so parametric assumptions about its evolution not only affect conclusions about the timing of SBTC but also impact estimates of σ. This raises problems of identification in the absence of good information on the appropriate functional form for SBTC. The previous literature and estimates in Section 3 rely on *ad hoc* parametric forms — typically low-order polynomials — for the time path of technological skill-bias. In this section, we draw on insights from research on technological change to aid in modeling and estimation of SBTC in the canonical model. Given the important benefits from accounting for changes in unobserved cohort differences in relative skills, the analysis in this section utilizes the BR measures for relative skill prices, $\ln(\pi_t)$, and supplies, $\ln(H_t/L_t)$.

relative wages and skill supplies are likely to be independent (since these relative wage and skill supply measures are constructed independently), while the measurement errors for BR relative skill prices and supplies are negatively correlated (since relative supplies are obtained from relative total wage payments divided by relative skill prices). Thus, estimation error in our relative price and supply series are unlikely to explain the larger estimated elasticities in Table 2; indeed, these biases go in the opposite direction. Given the sample sizes in the CPS, we expect that the biases are quite small in both cases.

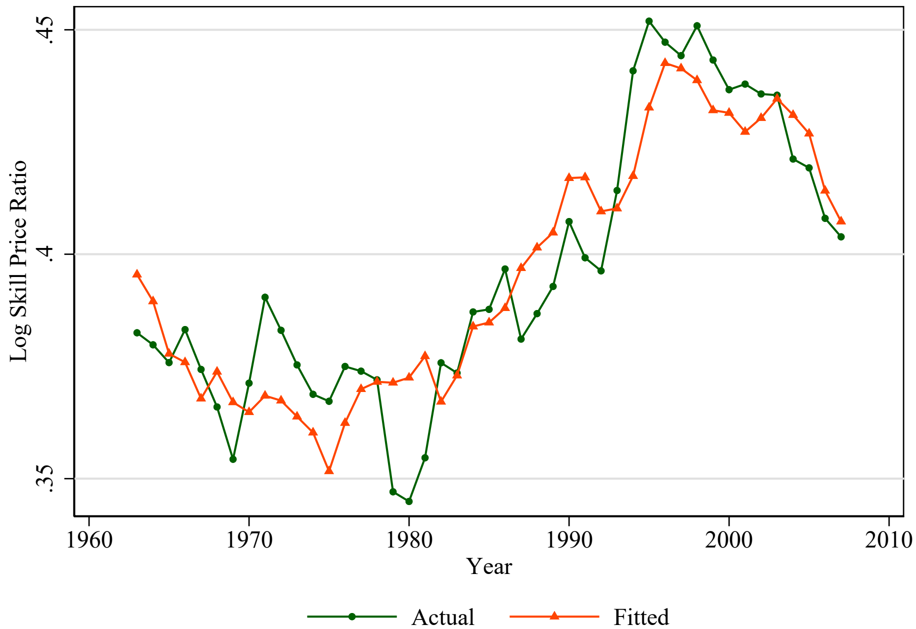


Figure 6: Actual and Fitted Log Relative Price Ratios: 1963–2008

Notes: This figure reports actual and predicted log relative skill prices, $\ln(\pi_t)$*, where the latter are obtained from estimates reported in column (5) of Table 2.*

To gain basic insights on the path for SBTC over the past several decades, we begin by exploring implied patterns for SBTC based on relative skill prices and supplies under different assumptions about the elasticity of substitution, σ. Inspection of the paths for SBTC obtained in this way suggest a special role for recessions. Moreover, the patterns are consistent with the (previously discussed) theoretical and empirical literatures, which find that significant changes in production methods are more common during recessions. The patterns are also consistent with a reversal in the relative demand for skill after the 2001 recession associated with the "Dot Com" Bust (Beaudry, Green, and Sand, 2016). We incorporate these features into the canonical model by allowing for jumps and trend changes in the skill-bias of technology centered around recessions.

We also take an alternative approach that models SBTC as a function of well-documented measures of IT private investment expenditures. These direct measures of investment in new technology were used by Beaudry, Green, and Sand (2016) to argue that the relative demand for skill fell sharply after 2000.

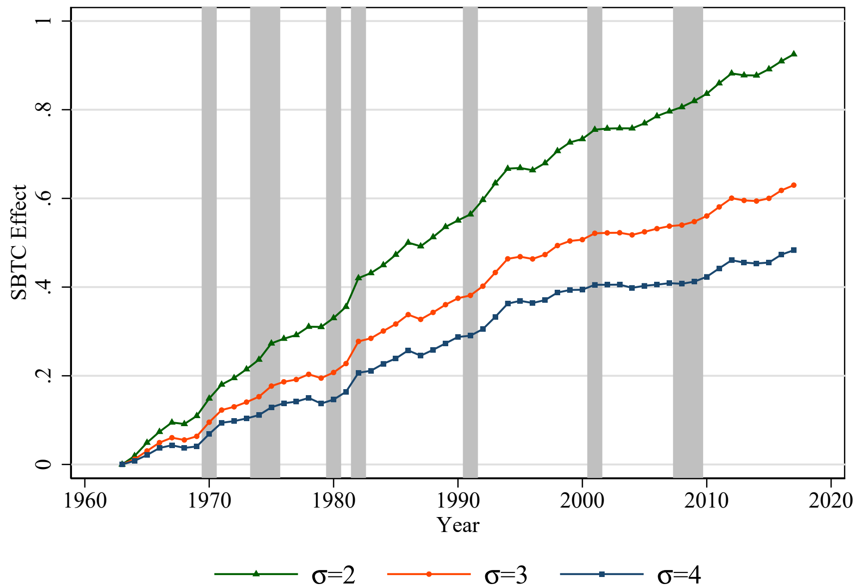
Figure 7: Actual and Fitted Log Relative Price Ratios: 1963–2017

Notes: This figure reports actual and predicted log relative skill prices, $\ln(\pi_t)$*, where the latter are obtained from estimates reported in column (6) of Table 2.*

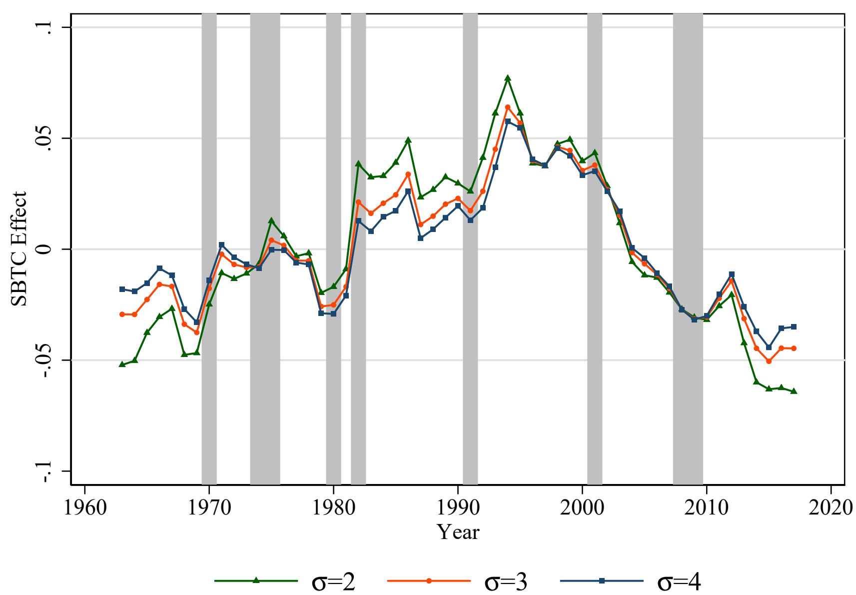
5.1 Implied Non-parametric SBTC Paths in the Canonical Model

Following Katz and Murphy (1992), equation (5) can be re-arranged to calculate the implied path for technology skill bias as a function of relative skill prices and supplies for any given elasticity of substitution: $\frac{\sigma-1}{\sigma}\ln(A_{Ht}/A_{Lt}) = \ln(\pi_t) + \frac{1}{\sigma}\ln(H_t/L_t)$. This reflects the effects of SBTC on relative skill prices (and wages), imposing no functional form on its estimated path. Figure 8(a) plots this implied skill bias path for three assumed values of σ suggested by the estimates in Table 2. (All series use BR relative supplies and prices and are normalized to zero in 1963.) The most notable feature of Figure 8(a) is the systematic long-term growth in skill bias over more than 50 years. While the long-term rate of SBTC is clearly more modest for high values of σ, the consistency in growth rates over time — regardless of the assumed elasticity — suggests that the implied "slowdown" in SBTC during the early-1990s based on previous estimates (and those reported in Tables 1 and 2) may simply reflect mis-specification of the SBTC time path.

Figure 8(b) de-trends these SBTC series, clearly demonstrating that, while the actual value of σ



(a) SBTC Effect



(b) De-Trended SBTC Effect

Figure 8: Implied SBTC Effects on Relative Skill Prices: 1963–2017

Notes: Panel (a) reports deviations in $\frac{\sigma-1}{\sigma}\ln(A_{Ht}/A_{Lt}) = \ln(\pi_t) + \frac{1}{\sigma}\ln(H_t/L_t)$ *from its 1963 value for three different assumed elasticities of substitution,* σ*. Panel (b) reports the same measure after removing a linear time trend.*

is intimately related to the long-run growth rate for SBTC, it has little to do with deviations around the long-run trend. The de-trended series highlight the important effects of recessions (denoted by shaded vertical bars in this and subsequent figures) on SBTC — regardless of σ — exhibiting occasional dips and jumps initiated (almost entirely) around recessions.[26] Still, deviations from the long-run trend rarely exceed 3–4 percentage points over the five decades we study. Most notably, we observe an acceleration of SBTC in the 1980s and 1990s, followed by a sharp reversion back to the long-run trend beginning around 2000. The declining pace of SBTC after 2000 lasts for about a decade before partially recovering after the Great Recession.

Not all recessions are equal in terms of their relationship with SBTC. Based on Figure 8(b), the 1970 recession coincides with a jump in skill bias from 1969 to 1971, while the rate of SBTC changed very little over the 1974-75 recession. The double-dip recession of the early-1980s was accompanied by a very clear fall and then jump in skill bias, followed by a resumption of the previous trend. The next recession, in 1991, appears to have led to an acceleration in SBTC, which reversed itself in the mid-1990s, before plummeting after the 2001 recession. The slower rate of SBTC persists until the Great Recession, after which it begins to increase again, at least for a few years.[27]

5.2 Recessions and SBTC in the Canonical Model

To account for the apparent changes in technology surrounding recessions, we re-estimate the canonical model allowing for permanent effects of recessions on SBTC. Table 3 reports results from three specifications, all of which include a linear time trend for SBTC. Column (1) also allows for permanent jumps in skill bias during each year of a recession, while column (2) only includes jumps for the first year of the 1974–75 and 2008–09 recessions. Column (3) allows for both jumps and trend changes in skill bias at the beginning of each recession.[28] These specifications identify σ from changes in relative prices and supplies between recessions. The results are similar for all three specifications and fit the relative price series, $\ln(\pi_t)$, quite well as shown in Figure 9 (and confirmed by R-squared

[26] We define recessions by years with negative growth in GDP per capita (based on the World Development Indicators), plus 2001, which had an annual GDP per capita growth rate of 0.004. See https://data.worldbank.org/indicator/NY.GDP.PCAP.KD.ZG?locations=US. We include 2001, because there was a widely agreed upon recession during that year. For example, the NBER reports an eight month contraction from March to November in 2001. See https://www.nber.org/cycles.html.

[27] Figure 8 suggests that SBTC is not likely to be well-represented by a simple function of aggregate economic growth. Indeed, Autor, Katz, and Kearney (2008) estimate a weak correlation between SBTC and the unemployment rate.

[28] Specifications that only allow for a linear time trend and transitory (rather than permanent) effects of recessions fit the data quite poorly and produce implausible estimates for σ. Such specifications cannot account for the SBTC patterns observed in Figure 8.

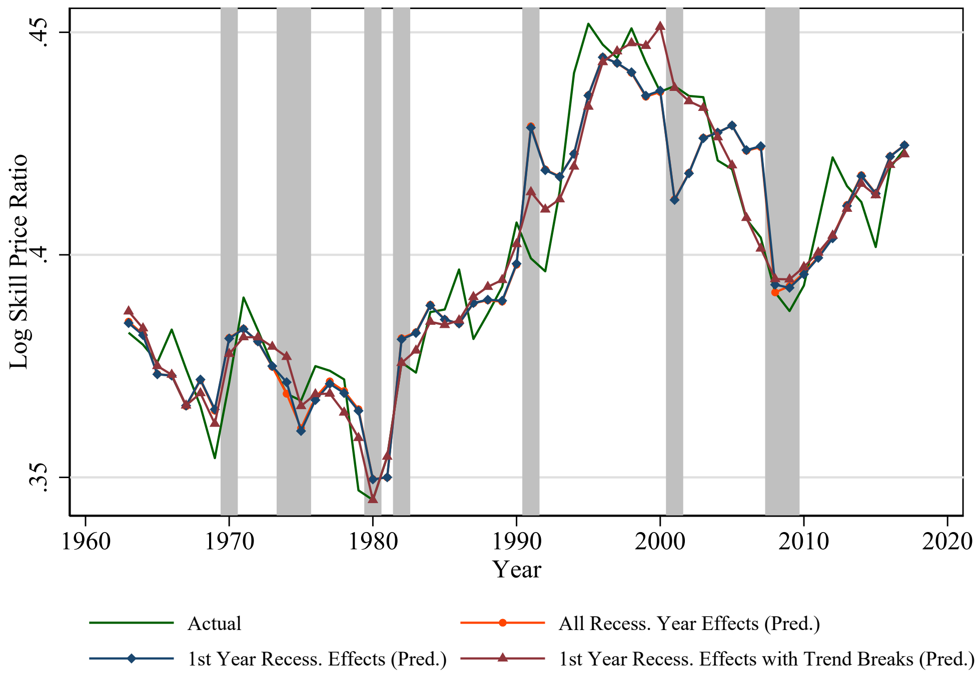


Figure 9: Actual and Predicted Log Relative Price Ratios, Recession Specifications

Notes: This figure reports actual and predicted log relative skill prices, $\ln(\pi_t)$*, where predicted values are based on estimates reported in Table 3.*

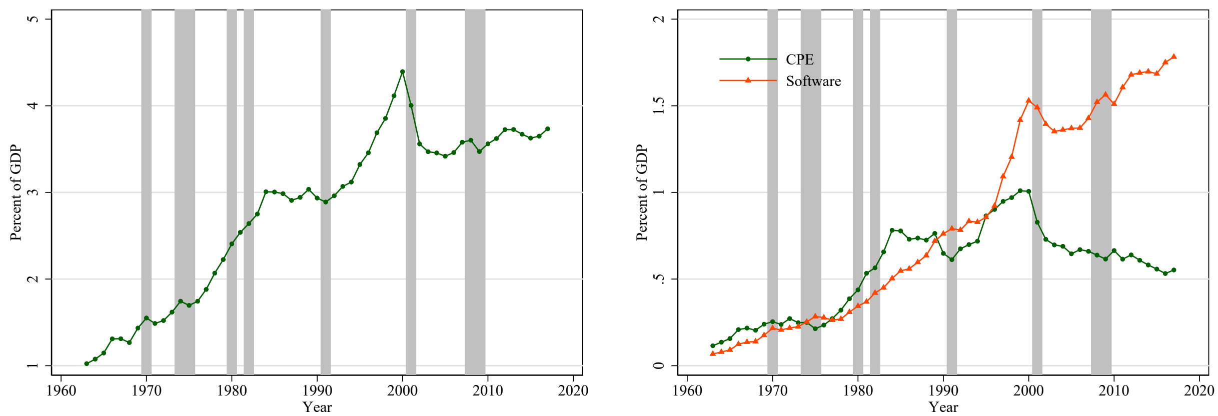
statistics above 0.85). Based on the most general specification of column (3), we observe positive long-run SBTC with a sizeable jump up in the relative demand for skill during the 1970 and 1982 recessions followed by a slightly smaller drop during the 2001 recession, which also led to a 1.1% reduction in the SBTC growth rate. Finally, we see a 0.8% increase in the rate of SBTC growth following the Great Recession. We further discuss the estimated SBTC patterns in Section 5.4.

These results show that a much richer specification for SBTC is needed to explain relative wage patterns than the low-order polynomials favored in the previous literature. Despite the flexibility of our recession-based specifications for SBTC, there is still sufficient covariation in relative skills and prices between recessions to identify σ. Estimated elasticities of substitution range from about 4.0 in columns (1) and (2) to 5.2 in column (3), much higher than previous estimates in the literature obtained using composition-adjusted measures and *ad hoc* specifications for SBTC. Indeed, these estimates are even higher than those using BR prices and supplies but assuming a cubic polynomial in time for SBTC (see columns (5) or (6) of Table 2). This suggests that failure to account for sharp

	(1) All Recession Year Effects	(2) 1st Year Recession Effects	(3) 1st Year Recession Effects with Trend Breaks
$\ln(H_t/L_t)$	-0.2545	-0.2525	-0.1933
	(3.701)	(3.875)	(2.424)
t	0.0083	0.0084	0.0047
	(4.355)	(4.620)	(1.168)
$\mathbb{1}(year \geq 1970)$	0.0194	0.0189	0.0197
	(1.859)	(1.882)	(1.800)
$\mathbb{1}(year \geq 1974)$	-0.0000	0.0023	0.0001
	(0.004)	(0.220)	(0.007)
$\mathbb{1}(year \geq 1975)$	0.0034		
	(0.251)		
$\mathbb{1}(year \geq 1980)$	-0.0127	-0.0125	-0.0091
	(1.199)	(1.211)	(0.721)
$\mathbb{1}(year \geq 1982)$	0.0451	0.0446	0.0221
	(4.077)	(4.169)	(1.020)
$\mathbb{1}(year \geq 1991)$	0.0338	0.0332	0.0120
	(3.823)	(3.954)	(1.359)
$\mathbb{1}(year \geq 2001)$	-0.0224	-0.0229	-0.0159
	(2.652)	(2.847)	(1.779)
$\mathbb{1}(year \geq 2008)$	-0.0298	-0.0283	0.0028
	(2.253)	(3.509)	(0.280)
$\mathbb{1}(year \geq 2009)$	0.0022		
	(0.165)		
$\mathbb{1}(year \geq 1970) \times (year - 1970)$			0.0039
			(0.866)
$\mathbb{1}(year \geq 1974) \times (year - 1974)$			-0.0048
			(1.020)
$\mathbb{1}(year \geq 1980) \times (year - 1980)$			0.0120
			(0.916)
$\mathbb{1}(year \geq 1982) \times (year - 1982)$			-0.0077
			(0.589)
$\mathbb{1}(year \geq 1991) \times (year - 1991)$			0.0017
			(1.088)
$\mathbb{1}(year \geq 2001) \times (year - 2001)$			-0.0110
			(5.465)
$\mathbb{1}(year \geq 2008) \times (year - 2008)$			0.0080
			(3.795)
implied σ	3.929	3.961	5.173
R^2	0.8593	0.8591	0.9258
number of years	55	55	55

Notes: Table reports estimates (absolute value of t-statistics) based on regressions of BR log relative skill prices, $\ln(\pi_t)$, on BR log relative skill supplies, $\ln(H_t/L_t)$, and other reported variables.

Table 3: Canonical Model with Permanent Recession Effects on SBTC



(a) IPES

(b) CPE and Software

Figure 10: IPES, CPE, and Software: 1963–2017

Notes: IPES reflects investment in information processing and equipment as a fraction of GDP. CPE (software) reflects non-residential private fixed investment expenditures on computers and peripheral equipment (software) as a fraction of GDP.

changes in skill demand associated with the implementation of new technologies during (some) recessions leads to under-estimates of the elasticity of substitution between high school- and college-educated labor.[29]

5.3 Direct Measures of SBTC and the Canonical Model

One of the clearest pieces of evidence offered by Beaudry, Green, and Sand (2016) in support of a reversal in the demand for skill is a series on private fixed investment in information processing and equipment as a percent of GDP (*IPES*). This series, shown in Figure 10(a), reveals a sharp fall in investment after 2000. However, it then begins to rise again in 2010, which is after the period studied by Beaudry, Green, and Sand (2016). The decline, followed by a rebound after the Great Recession, is broadly consistent with the pattern for implied SBTC in Figure 8.

Figure 10(b) shows that the fast rise in *IPES* during the 1990s and even sharper fall in the early 2000s is also observed for two of its key subcomponents (also considered by Beaudry, Green, and Sand (2016)): non-residential private fixed investment expenditures on computers and peripheral equipment (*CPE*) and on *Software* (both reported as a percent of GDP).[30] By contrast, the rise in

[29]Substantially higher estimates of the elasticity of substitution are also obtained when using composition-adjusted wages and supplies to estimate the more flexible SBTC specifications in Table 3.

[30]*IPES* is based on Federal Reserve Economic Data (FRED) series "Private fixed investment in information

IPES following the Great Recession is only evident for expenditures on software; *CPE* expenditures continued to fall over this period. The accelerated increase in *IPES* in the late-1970s and early-1980s, followed by a slight decline in the late-1980s, is driven more by the pattern for *CPE* expenditures.

We explore the extent to which these direct measures of IT investment can explain the SBTC patterns implied by the canonical model. Specifically, we re-estimate our model using BR-estimated prices and supplies specifying SBTC as a function of either *IPES* or its subcomponents, *CPE* and *Software*. Given well-documented quality improvements in *IPES* and the well-known declining price of computers and IT equipment over time, we also include a linear time trend.[31] Because the precise mapping from these investment expenditure measures to SBTC in the canonical model is unknown, we consider several specifications in Table 4.

The first two columns of Table 4 report estimates for specifications that assume SBTC is a linear function of *IPES* or its subcomponents *CPE* and *Software*, while columns (3) and (4) incorporate quadratic terms in our technology measures.[32] All four specifications produce estimates for σ ranging from 5.0 to 6.3, consistent with those from our flexible recession-based specification reported in Table 3, column (3). Figure 11 presents relative skill prices, $\ln(\pi_t)$, along with its predicted values based on the quadratic specifications. Both specifications do a good job of reproducing the general patterns for relative skill prices, including the rise in relative skill prices over the 1980s and 1990s, followed by the sharp fall after 2000 and rebound after the Great Recession. The more general quadratic specification in *CPE* and *Software* performs better in the 1980s and 1990s.

Figure 11 also reveals that trends in these IT measures cannot explain the sharp drops or jumps in relative skill prices surrounding some of the recessions in our sample period. Therefore, columns (5) and (6) of Table 4 add indicators for each recession year to allow for temporary deviations in SBTC from the trends implied by *IPES* or its subcomponents. We only allow for temporary deviations to ensure that all longer-term changes in SBTC continue to be explained by the direct technology measures. Table 4 shows that incorporating temporary jumps in technology at recessions has only modest impacts on the estimated elasticity of substitution. However, it improves the model fit

processing equipment and software" (A679RC1Q027SBEA), *CPE* is based on FRED series "Private fixed investment: Non-residential: Information processing equipment and software: Computers and peripheral equipment" (B935RC1Q027SBEA), and *Software* is based on FRED series "Private fixed investment: Non-residential: Intellectual property products: Software" (B985RC1Q027SBEA). All three series are scaled by FRED series "Gross Domestic Product" (GDP) and multiplied by 100 (after aggregating quarterly to annual measures).

[31]The linear time trend accommodates a linear decline in the price of information processing equipment relative to all other goods, since our measures reflect total expenditures relative to GDP.

[32]Cubic specifications offered only marginal improvements in fit.

	(1) Linear IPES	(2) Linear CPE & Software	(3) Quadratic IPES	(4) Quadratic CPE & Software	(5) Quadratic IPES with Recession Indicators	(6) Quadratic CPE & Software with Recession Indicators
$\ln(H_t/L_t)$	-0.1965	-0.1963	-0.1582	-0.2013	-0.1529	-0.1870
	(4.078)	(3.479)	(1.742)	(3.638)	(1.404)	(2.787)
t	0.0049	0.0056	0.0038	0.0067	0.0037	0.0067
	(3.707)	(2.430)	(1.592)	(3.435)	(1.304)	(2.866)
IPES	0.0491		0.0296		0.0343	
	(5.788)		(0.740)		(0.724)	
Software		0.0220		0.1628		0.1671
		(0.976)		(3.389)		(3.229)
CPE		0.1078		-0.1619		-0.2070
		(6.514)		(2.088)		(2.236)
IPES-squared			0.0030		0.0019	
			(0.500)		(0.271)	
Software-squared				-0.0750		-0.0811
				(4.093)		(4.200)
CPE-squared				0.1658		0.1898
				(2.897)		(2.862)
$\mathbb{1}(year = 1970)$					-0.0047	-0.0030
					(0.268)	(0.238)
$\mathbb{1}(year = 1974)$					-0.0025	-0.0039
					(0.140)	(0.299)
$\mathbb{1}(year = 1975)$					0.0059	-0.0060
					(0.304)	(0.395)
$\mathbb{1}(year = 1980)$					-0.0406	-0.0205
					(2.294)	(1.631)
$\mathbb{1}(year = 1982)$					-0.0094	0.0132
					(0.528)	(1.016)
$\mathbb{1}(year = 1991)$					0.0061	-0.0051
					(0.347)	(0.396)
$\mathbb{1}(year = 2001)$					0.0012	0.0215
					(0.064)	(1.529)
$\mathbb{1}(year = 2008)$					-0.0220	-0.0195
					(1.236)	(1.539)
$\mathbb{1}(year = 2009)$					-0.0183	-0.0195
					(1.001)	(1.510)
implied σ	5.088	5.093	6.322	4.968	6.541	5.347
R^2	0.6632	0.7426	0.6649	0.8292	0.7225	0.8688
number of years	55	55	55	55	55	55

Notes: Table reports estimates (absolute value of t-statistics) based on regressions of BR log relative skill prices, $\ln(\pi_t)$, on BR log relative skill supplies, $\ln(H_t/L_t)$, and other reported variables. IPES reflects investment in information processing and equipment as a fraction of GDP. CPE (software) reflects non-residential private fixed investment expenditures on computers and peripheral equipment (software) as a fraction of GDP.

Table 4: Canonical Model Estimated with Direct Technology Measures

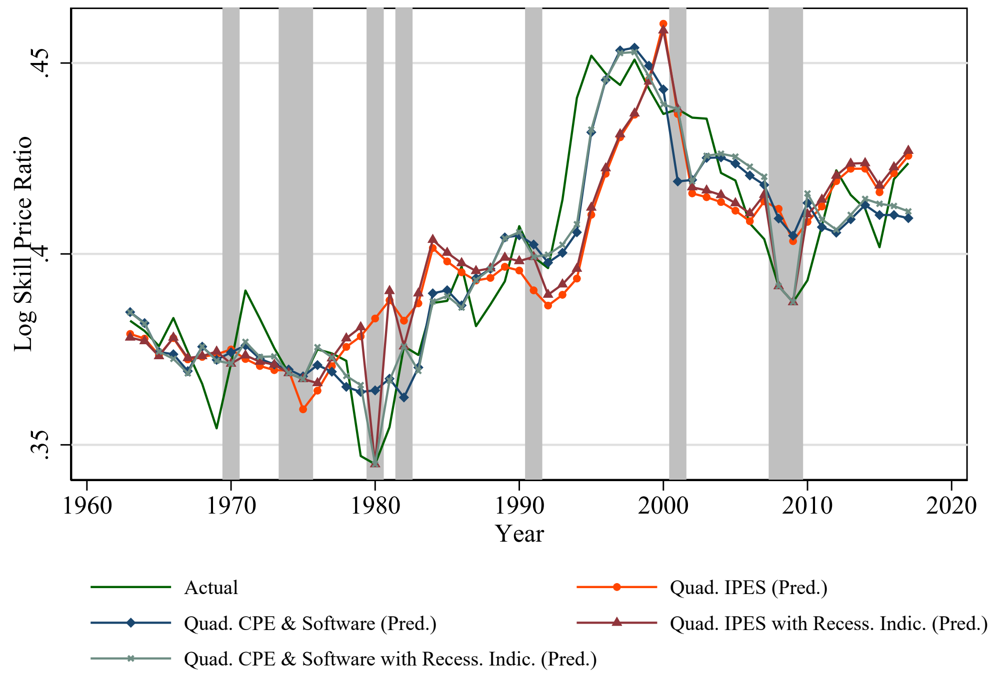


Figure 11: Actual and Predicted Log Relative Price Ratios, Direct Technology Specifications

Notes: This figure reports actual and predicted log relative skill prices, $\ln(\pi_t)$*, where predicted values are based on estimates reported in columns (3)–(6) of Table 4.*

noticeably as evidenced by the R-squared statistics and as shown in Figure 11. This model fits almost as well as allowing for permanent jumps and trend changes in skill bias during each recession (Table 3, column 3). While we include indicators for all recession years, Table 4 and Figure 11 make clear that only the 1980 recession and Great Recession (combining estimates for 2008 and 2009) have quantitatively important effects on SBTC that are not reflected in our IT measures.

5.4 Estimated SBTC Paths

We conclude this section by discussing the predicted SBTC paths from our two 'new' approaches for modeling SBTC. Figure 12 shows the predicted SBTC paths for the most general recession-based specification (Table 3, column 3) and for our most general specification using direct technology measures (Table 4, column 6). Since the estimated σ values are nearly identical for these two specifications, Figure 12 also shows the SBTC path implied by BR relative prices and supplies using

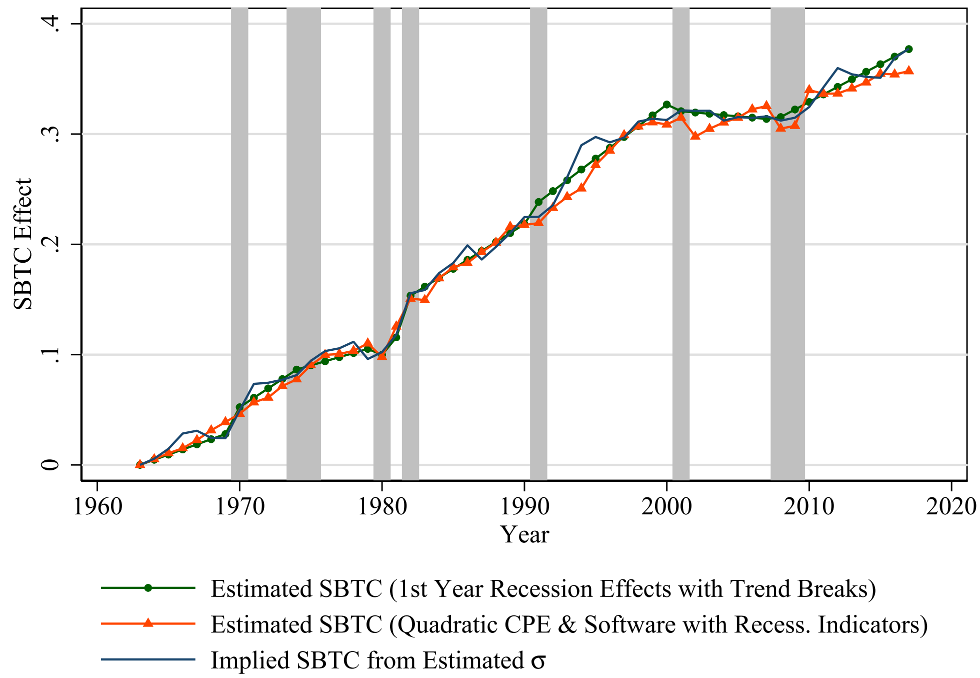


Figure 12: Implied and Estimated SBTC for Recession and Direct Technology Specifications

Notes: This figure reports SBTC profiles (deviations from 1963 values) predicted by specifications reported in column (3) of Table 3 and column (6) of Table 4, as well as the implied SBTC path, $\frac{\sigma-1}{\sigma}\ln(A_{Ht}/A_{Lt}) = \ln(\pi_t) + \frac{1}{\sigma}\ln(H_t/L_t)$*, for* $\sigma = 5.26$.

the average of these two σ estimates.[33] As in Figure 8, this imposes no structure on SBTC.

It should not be surprising that both estimated SBTC paths accurately reproduce the unrestricted SBTC series given the high R-squared statistics for both specifications. We, therefore, discuss a few notable features of SBTC as estimated by both of our models. First, Figure 12 shows a clear slowdown in SBTC around 2000, consistent with Beaudry, Green, and Sand (2016). However, this is followed by a recovery after the Great Recession to the previous long-run trend. The "Great Reversal" in demand for skill emphasized in Beaudry, Green, and Sand (2016) — whose analysis did not cover the period of the Great Recession — appears to have been a temporary phenomenon.

Second, our estimated SBTC paths show no evidence of a decline in demand beginning in the early-1990s. Cad and DiNardo (2002) and Acemoglu and Autor (2011) argue that a significant weakness of the canonical model is that efforts to extend it beyond the original 1963–1987 period

[33] As in Figure 8, the implied SBTC plots $\ln(\pi_t) + \frac{1}{\sigma}\ln(H_t/L_t)$, where Figure 12 uses $\sigma = 5.26$ (i.e. average of 5.173 and 5.347). All three SBTC series in Figure 12 subtract off the 1963 values, such that the series start at zero.

(assuming that SBTC follows a cubic time trend or contains a trend break in 1992) imply a slowdown in SBTC in the early-1990s, contrary to conventional wisdom and other evidence on computer use and the IT revolution. Our analysis suggests that, while their failure to take into account cohort changes in unobserved skill levels played some role in this puzzling result, a more serious problem arises from their *ad hoc* functional form assumptions for SBTC. Specifications assuming a low-order polynomial or single trend break are far too limiting as is clear from inspection of Figures 8 and 12. As the latter figure shows, our two approaches imply an *increasing* (rather than decreasing) rate of SBTC in the 1990s, helping reconcile the model with conventional wisdom and other evidence on technological change.[34]

Finally, we note that our theoretically motivated and more flexible approaches reveal a modest but systematic long-run shift in technology favoring skilled workers with relatively minor and short-lived deviations from this trend. The most notable shift occurs in the early-2000's as highlighted by Beaudry, Green, and Sand (2016); however, even that slowdown lasts less than a decade.

6 Conclusion

The canonical model has proven popular and powerful for understanding the importance of supply shifts for relative wage patterns by education over time and across countries. Changes in relative wages that cannot be explained by relative supply shifts have typically been attributed to SBTC, motivating an enormous literature on technological innovation and its impacts on the economy (e.g., see the survey of Acemoglu (2002)). The elasticity of substitution between college and high school workers estimated from the canonical framework also plays a critical role in determining the general equilibrium effects of policies that impact educational attainment (Heckman, Lochner and Taber 1998a, 1998b, Autor 2014, Abbott, *et al* 2019).

For all its influence (or because of it), the canonical model has faced several major challenges. First, estimates of the elasticity of substitution are unstable across periods and sometimes of the wrong sign (Beaudry and Green 2005, Acemoglu and Autor 2011). Second, estimated technology profiles tend to suggest a deceleration of SBTC in the 1990s, conflicting with conventional wisdom and direct measures of technological innovation (Card and DiNardo 2002, Autor, Katz, and Kearney

[34]The estimated slowdown in SBTC during the 1990s obtained when using composition-adjusted relative wages and supplies also disappears when adopting the more flexible forms for SBTC used in Tables 3 and 4, underlining the general importance of new approaches to modeling SBTC of the kind used in this paper.

2008, Acemoglu and Autor 2011). Third, the college wage premium rose only for young workers during the 1980s, leading Card and Lemieux (2001) to argue for a more flexible framework that distinguishes between worker types not only based on education but also based on age/experience.

We show that these important challenges can be explained by problems with standard approaches to measuring unobserved skill levels and prices and with inadequate functional form assumptions about the path for SBTC. The standard composition-adjustment approach for measuring skill levels and prices implicitly assumes that workers within narrowly defined observable groups (by education, age/experience, gender) possess the same skill levels over time — i.e., there are no differences across cohorts. Yet, recent research argues against this over the period typically used to estimate the canonical model. Using the BR approach to estimate skill levels and prices, which accounts for unobserved differences in worker quality over time and across cohorts, we obtain elasticities of substitution that are notably higher than previous estimates and always of the correct sign. Accounting for unobserved differences in relative skill levels across cohorts also explains the differential skill wage premiums by age/experience highlighted by Card and Lemieux (2001). Relative wages rose first for younger workers, followed by mid-career workers, and then by older workers, consistent with the rise in relative skill levels for more recent cohorts.

Although accounting for unobserved cohort differences in relative skill levels continues to suggest a slight slowdown in SBTC during the 1990s (when using functional form assumptions standard in the literature), we show that two new, better-motivated specifications for SBTC resolve this remaining puzzle. Our first approach is motivated by an abundance of research, both theoretical and empirical, which suggests that major technological changes are more likely to occur during recessions. This research raises concerns about identifying the effects of relative supply shifts using relative wage movements that occur over the course of an economic downturn. We, therefore, move away from the *ad hoc* polynomial 'approximations' for SBTC of past research and, instead, estimate an extremely flexible specification that allows for jumps and trend changes in SBTC during recessions. Our second approach is entirely data-driven and models SBTC as a function of direct measures of IT investment used previously in the literature. We show that this approach captures medium- and long-run trends in SBTC quite well. Further, when we allow for transitory jumps in technology during recessions, it explains the entire time series of SBTC (from 1963–2017) nearly as well as our more flexible recession-based specifications.

Our two new specifications for SBTC, combined with BR skill supplies and prices that account for unobserved worker quality differences across cohorts, explain the college vs. high school relative price (and wage) series from 1963–2017 remarkably well. Both sets of estimates imply much stronger substitutability between high school- and college-educated labor (with σ around 5.3 rather than 1.5) and a weaker, though important, role for SBTC compared to the current consensus. The stronger skill substitutability implies weaker equilibrium wage responses to skill-promoting policies, suggesting that the inequality-reducing benefits of such policies may be weaker than previously thought (Autor 2014). This further implies that general equilibrium impacts of tuition policies may also be more closely aligned with estimated partial equilibrium responses than suggested by Heckman, Lochner, and Taber (1998b) and Abbott, et al. (2019).

Estimated SBTC paths are nearly identical for both of our novel specifications and suggest a modest and systematic positive rate of SBTC with mostly minor and short-lived deviations from the long-run trend. Importantly, we find no evidence of a slowdown in SBTC during the 1980s or early- to mid-1990s. The most notable disruption to the long-run trend in SBTC occurs after the bursting of the "Dot Com" Bubble in 2000–2001, which led to a dramatic reversal in SBTC as highlighted by Beaudry, Green, and Sand (2016). Yet, even this derailment lasts less than a decade with SBTC returning to its long-run trend after the Great Recession. Between 1963 and 2017, SBTC accounts for a 35–40% increase in the relative wages of college vs. high school workers.

The most rapid increase in the college wage premium occurred between 1980 and 2000. Over this period, (composition-adjusted) relative wages rose by about 23 log points. Changes in the relative quality of workers — neglected by standard measurement approaches — explains about two-thirds of this rise, while the traditional supply and demand explanations together only account for the remaining one-third. The rise in demand due to SBTC accounts for a roughly 20 log point increase in relative wages but is partially offset by the increase in relative supply over this period (accounting for a 12 log point decrease in relative wages).[35] Over the 1980s and 1990s, the dramatic increase in the college wage premium is, therefore, explained almost entirely by SBTC, with the effects of increasing relative supply offset by improvements in relative worker skill levels across cohorts.

We hope our analysis provides renewed confidence in the canonical model as a useful and practical framework for studying the evolution of wage differentials by education. Our analysis clearly

[35]The decomposition of composition-adjusted relative wage changes is based on equation (8) using $\ln(Q_t)$ from Figure 2 and estimated σ value of 5.2 from Table 3 column 3. (Results are nearly identical when using $\sigma = 5.3$ from Table 4 column 6.) The first term in equation (8) reflects SBTC, the second reflects the effects of relative quality changes, and the third reflects relative supply effects.

demonstrates the importance of accounting for changes in unobserved skill levels across cohorts and can serve as a guide for future analyses. We also provide new approaches to modeling SBTC, which future work can naturally build upon to study whether there are systematic explanations for how and why SBTC changes across recessions or which types of investments or technological innovations are most related to SBTC. Data from multiple countries or cross-region variation within countries may prove useful in these more targeted endeavors.

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Appendix: Measurement Error in Skill Supplies and Prices

This appendix discusses the effects of measurement error in skill prices and supplies when using ordinary least squares (OLS) to estimate equation (5). Let η_t reflect measurement error in relative skill supplies and ϵ_t reflect measurement error in relative skill prices. Here, we assume these measurement errors (ϵ_t, η_t) are independent of the "true" measures for relative skill supplies and prices and abstract from any unobserved differences in relative skills across cohorts (i.e., assume $\ln(Q_t) = 0$ for all t). For simplicity, we assume that technology is constant over time with $\alpha \equiv ((\sigma - 1)/\sigma) ln(A_{Ht}/A_{Lt})$.[36]

Since the standard composition-adjusted approach we follow calculates relative wages and skills independently, their measurement errors are likely to be independent of each other, $\eta_t \perp\!\!\!\perp \epsilon_t$. In this case, measurement error in composition-adjusted relative wages would have no effect on OLS estimates of $\beta = -1/\sigma$ (and, therefore, σ); however, classical measurement error in relative skill supplies would lead to the standard attenuation bias in OLS estimates of β.[37] Thus, OLS estimates of σ using composition-adjusted relative wages and skill supplies will tend to be biased upward (for $\sigma > 0$).

Measurement error is slightly more complicated for the BR skill prices and supplies, since any error in measures of relative skill prices will directly contribute to measurement error in skill supplies. To see this, suppose relative prices derived from the BR approach, π_t^m, are measured with error such that:

$$ln(\pi_t^m) = \ln(\pi_t) + \epsilon_t.$$

Since the measured relative skill supply, $(H_t/L_t)^m$, is obtained by dividing the total wage payment to H_t relative to the total wage payment to L_t by the estimated relative measured price, the log relative skill supply will be measured with the same error, but opposite in sign (i.e., $\eta_t = -\epsilon_t$), so

$$ln(H_t/L_t)^m = \ln(H_t/L_t) - \epsilon_t.$$

This implies the following estimating equation based on equation (5):

$$ln(\pi_t^m) = \alpha + \beta \ln(H_t/L_t)^m + (1 + \beta)\epsilon_t.$$

Unless $\sigma = 1$, measurement error in skill prices will bias OLS estimates of σ towards 1, since $plim\,\hat{\beta}$ is a weighted average of β and -1:

$$plim\,\hat{\beta} = \theta\beta + (1 - \theta)(-1),$$

where $\theta = Var(ln(H_t/L_t))/[Var(ln(H_t/L_t)) + Var(\epsilon_t)]$. As $Var(\epsilon_t) \to 0$, $plim\,\hat{\beta} \to \beta$.[38]

[36]Incorporating time trends in SBTC would simply replace expressions related to the variance of $\ln(H_t/L_t)$ with the variance of deviations in $\ln(H_t/L_t)$ from the specified time trends.

[37]Specifically, OLS estimates of β using composition-adjusted relative wages and skills will converge in probability to $\theta^c\beta$, where $\theta^c = Var(ln(H_t/L_t))/[Var(ln(H_t/L_t)) + Var(\eta_t)]$.

[38]A similar upward bias would apply if composition-adjusted supplies were obtained from the relative total wage payment to high- and low-skilled workers divided by relative composition-adjusted relative wages (or if composition-adjusted wages were obtained by dividing relative total wage payments by relative composition-adjusted supplies).