Reassessing the Trends in the Relative Supply of College-Equivalent Workers in the U.S.: A Selection-Correction Approach

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Reassessing the Trends in the Relative Supply of College-Equivalent Workers in the U.S.: A Selection-Correction Approach*

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Abstract

Among better-educated employed men, the fraction of full-time full-year (FTFY) workers is quite high and stable—around 90 percent—over time in the U.S. Among those with lower education levels, however, this fraction is much lower and considerably more volatile, moving within the range of 62–82 percent for high school dropouts and 75–88 percent for high school graduates. These observations suggest that the composition of unobserved skills may be subject to sharp movements within low-educated employed workers, while the scale of these movements is potentially much smaller within high-educated ones. The standard college-premium framework accounts for the observed shifts between education categories, but it cannot account for unobserved compositional changes within education categories. Our paper uses Heckman's two-step estimator on repeated Current Population Survey cross sections to calculate a relative supply series that corrects for unobserved compositional shifts due to selection into and out of the FTFY status. We find that the well-documented deceleration in the growth rate of relative supply of college-equivalent workers after mid-1980s becomes even more pronounced once we correct for selectivity. This casts further doubt on the relevance of the plain skill-biased technical change (SBTC) hypothesis. We conclude that what happens to the within-group unobserved skill composition for low-educated groups is critical for fully understanding the trends in the relative supply of college workers in the United States. We provide several interpretations to our selection-corrected estimates.

JEL codes: J23, J24, J31, I24, O33.

Keywords: Wage inequality; self selection; relative supply index; college premium; SBTC; FTFY.

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1 Introduction

The college premium in the U.S. increased substantially after the late 1970s until mid-1980s. Researchers investigating the sources of this increase have built their analyses on a framework featuring the interactions between the relative demand for skills and the relative supply of skills. This "market" framework has been influential in explaining the U.S. data until the late 1980s, as, in this period, the relative supply of college-equivalent workers increased sharply and steadily, implying a similar upward trend in the relative demand. This phenomenon has been hypothesized as the existence of a steady technological progress—the skill-biased technical change (SBTC)—in the U.S. labor markets, corresponding to a shift in the relative demand for labor favoring the skilled over unskilled.[1] Based on this definition, the SBTC is associated with increased investment in computerized technologies.

After the late 1980s, however, the rate of increase in the relative supply of college-equivalent workers decelerated, which was accompanied by a parallel slowdown in the rate of increase in the college premium. According to the predictions of the canonical college-premium equation, the relative demand for skilled workers should also have slowed down after the mid-1980s in the U.S. However, this is in stark contrast with the story linking SBTC to computer investments. In fact, the computer investments have continued to grow even more rapidly during the 1990s, while the college-premium equation implies the opposite. This observation led to the consensus in the literature that the pure "market" explanation fails to fully capture the evolution and determinants of college premium in the U.S. The role of "non-market" (or institutional) factors has been investigated with the hope of providing an alternative explanation [Bound and Johnson (1992)]. Specifically, the decline in real minimum wages is argued to account for how wage inequality has evolved after the mid-1980s in the U.S.[2] Other factors such as business fluctuations [Hoynes, Miller, and Schaller (2012)] and foreign outsourcing of less-skilled jobs [Feenstra and Hanson (1999)] are also argued to affect the

[1]See Davis and Haltiwanger (1991), Mincer (1991), Katz and Murphy (1992), Krueger (1993), and Autor, Katz, and Krueger (1998) for different versions of this hypothesis. See also Katz and Autor (1999), Violante (2008), and Acemoglu and Autor (2011) for extensive surveys of the related literature.

[2]See Lee (1999), Card and DiNardo (2002), Lemieux (2006), and Autor, Katz, and Kearney (2008). See also DiNardo, Fortin, and Lemieux (1996) for a different line of research summarizing the effects of institutional factors other than real minimum wages.

trends in college premium. These findings have led the literature toward the conclusion that market and non-market factors jointly determine the college premium.

The key construct in the traditional college premium analysis is the variable describing the supply of college equivalent workers relative to the supply of high school equivalent workers. This variable is called the *relative supply index* and it enters the wage inequality estimations as the key regressor. Roughly speaking, the supply of college-equivalent workers is calculated from the aggregate hours supplied by full-time full-year (FTFY) workers sorted into the following three education categories "weighted" by the mean wage—in the entire data horizon—for the corresponding education category: (*i*) workers with graduate education (COL+), (*ii*) college graduates (COL), and (*iii*) some college education (SC2) who earn more than the median wage within the some college category. The supply of high school equivalent workers, on the other hand, is calculated from the aggregate hours worked by workers sorted in the remaining three education levels "weighted" by the mean wage—in the entire data horizon—for the corresponding education category: (*i*) high school dropouts (HSD), (*ii*) high school graduates (HSG), and (*iii*) workers with some college education (SC1) who earn less than the median wage within the some college category.[3] The ratio of these two aggregates gives the relative supply of college-equivalent workers.

The weighting procedure captures the basic "efficiency units" idea in the sense that an hour supplied by a relatively higher educated worker counts more than an hour supplied by a lower educated worker. This setup successfully addresses the effect of the observed changes in the educational composition of the working population on wage inequality.[4] But it has two deficiencies: **first**, most papers focus only on the FTFY workers (i.e., those who self-select into the FTFY status)[5] and, **second**, it does not capture the potential changes in the efficiency units (i.e., relative efficiency of college hours versus high school hours) over time, since the weights are fixed.

[3] Katz and Murphy (1992) and Autor, Katz, and Kearney (2008) explain the construction of this index in great detail. See also our data appendix [Appendix B].

[4] For example, an increase in the fraction college educated workers with a parallel decline in the fraction of lower educated workers implies an increase in the relative supply index.

[5] For example, Autor, Katz, and Kearney (2008) and many others focus only on the FTFY workers. Katz and Murphy (1992) focus on full-time workers and provide only a partial treatment of the part-year workers.

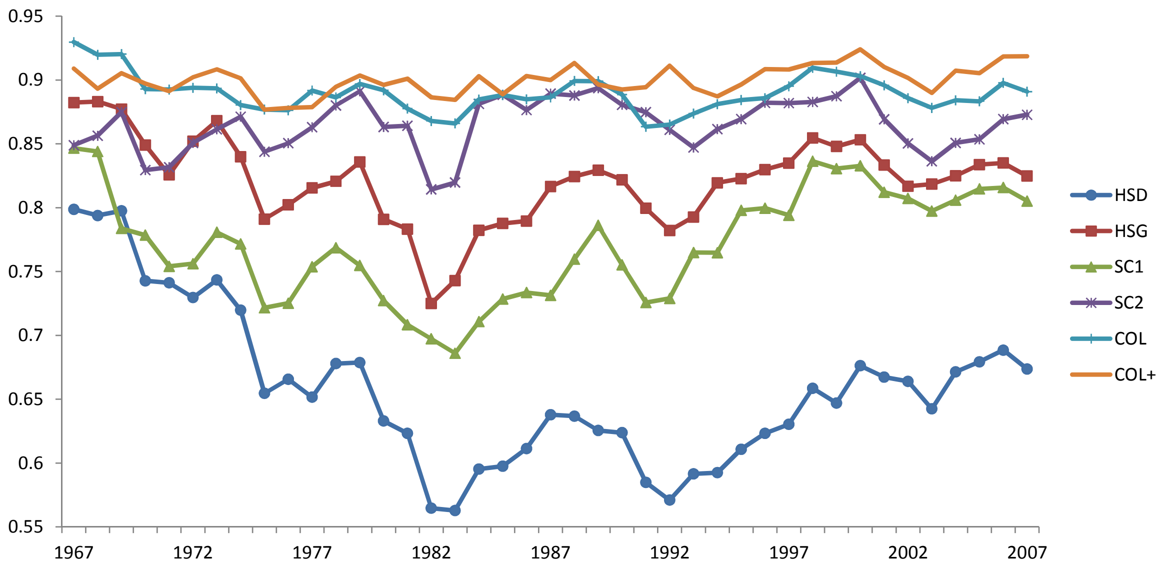

Figure 1: Fraction of the FTFY workers by education categories.

Our main purpose in this paper is to develop a method to revise the relative supply index in such a way that these two issues are corrected. To achieve this goal, we use Heckman's two-step estimator on repeated Current Population Survey cross sections to calculate a relative supply series that corrects for unobserved compositional shifts due to selection into and out of the FTFY status. Why do we do this? Our starting point is the observation that most studies in the U.S. wage inequality literature focus on the FTFY workforce, i.e., the ones who self-select into the FTFY status. Among employed workers, selection into the FTFY status has exhibited distinct trends between education categories since the late 1960s [see Figure (1)]. The fraction of the FTFY status among high-skill workers stays in a narrow range around 90% over the data horizon. The fraction of the FTFY status among low-skill workers, on the other hand, exhibits significant time variation. For example, among high school dropouts, around 80% of the employed workers have had FTFY status in the late 1960s, while the FTFY ratio has sharply gone down to 60% and made a double-dip in 1982 and 1992. Then it has picked up and reached to 70% in 2007. Similar trends are also observed for other less-skilled workers, including the high school graduates and workers with some college education who earn less than the median wage. These divergent patterns between low-and high-skill workers in terms of the labor supply patterns on the FTFY margin motivate this study.

These patterns raise some concerns that the existing estimates may be misrepresenting the evolution of the relative supply series. The ***first*** step in our analysis is to investigate if a significant selection bias exists or not. We calculate a selection-corrected relative supply series. We then compare this corrected series with the uncorrected series. We find that selectivity is significant and that, under selection-correction, the rate of growth in the relative supply of college workers is even sharper before the mid-1980s and it is even slower afterwards; that is, the deceleration is even more pronounced after correcting for selectivity. This suggests that the predicted SBTC slowdown is even more mysterious.

At the ***second*** step, we investigate the sources of this bias. To perform this task, we take a deeper look at the composition of the bias across education and experience groups. We show that selectivity operates over the lower educated and less experienced workers. More precisely, we find that high-school dropouts and the workers with 0–9 years of experience select into the FTFY status until late 1980s and they select out afterwards. The same tendencies have been reported for the high-school graduates and the workers with 10–19 years of experience, though in a much weaker magnitude. There are signs of selectivity also for the more skilled workers, but their patterns of selectivity do not change over time; that is, they do not affect the trends in the relative supply. To sum up, accounting for selectivity alters the trends in the relative supply of skills and the main source of these changes is the shift in the self-selection patterns of the low-skill workers. This suggests that low-skill workers are overrepresented in the FTFY workforce before the mid-1980s and they are underrepresented afterwards. Correcting for these patterns makes the trend in the relative supply of skills steeper before the mid-1980s and flatter after the mid-1980s. As a result, the deceleration in the relative supply of skills after the mid-1980s is sharper under selection correction.

We then question what triggers the shifts in the selectivity patterns of the low-skill workers. We conjecture that the interaction between the (endogenous) direction of technical change [see, e.g., Acemoglu (1998)] and the minimum wage laws is potentially the triggering mechanism. Profit generating motives by producers endogenously determine the amount of innovative effort (i.e., R&D expenditures, patents etc.) to be devoted to different factors of production. These factors of production include skilled and unskilled labor. Thus, the direction of technical progress can lead to *unskill-bias* (e.g., England in the eighteenth and nineteenth centuries) or *skill-bias* (e.g., Unites States after World War II). Institutions (i.e., the non-market factors) can lead to amplification or attenuation of the strength of the technical change. To understand this mechanism better, think of the following example. Suppose that the relative supply of college workers grows at a constant rate. The government raises the level of real minimum wages permanently. This makes unskilled labor more expensive, triggering investments in skilled-labor favoring technologies. This raises the relative returns to college education leading the society to invest in college education at a faster rate. The reverse logic holds when real minimum wages are reduced permanently. The trends in real minimum wages in the U.S. perfectly fit the self-selection structure that we document. We conclude that the real minimum wage can affect wage inequality not only directly, but through its observed and unobserved effects on the relative supply of college workers.

The plan of the paper is as follows. Section 2 compares our paper to the related papers in the literature. Section 3 describes the theoretical framework, outlines how the relative supply measure is computed from the CPS data, and explains how we calculate the selection-corrected relative supply series. Section 4 presents our empirical results along with an in-depth discussion of the potential effects of real minimum wages and several related policy implications. Section 5 concludes.

2 Related Literature

This paper directly contributes to the U.S. college-premium (or skill-premium) literature, the main point of which is to show that rising college education in the U.S. is a consequence of a steady technological progress—called the SBTC—favoring the demand for skilled workers over the unskilled ones. Thus, rising U.S. wage inequality—defined in terms of the wage gap between skilled and unskilled workers—is a by product of this relationship. There is no need to review this literature, as there are already quite comprehensive literature surveys including

Katz and Autor (1999), Violante (2008), and Acemoglu and Autor (2011).

The SBTC hypothesis has substantially affected the direction toward which growth, education, and inequality literatures have moved in the past 20 years.[6] The main problem with this hypothesis is that, based on the standard college-premium framework, we should have observed a slowdown in the growth rate of demand for skilled workers after the mid-1980s; however, the main proxies to measure the demand for skilled workers, such as the pace of computerization in manufacturing, say the opposite. This remains as a puzzle in the literature—although there is some room for explanations featuring the role of institutional, or the so-called "non-market" factors.

This paper establishes that the traditional method used to measure the relative supply of college workers—which is a key construct in the empirical analysis of SBTC and wage inequality—is subject to selection bias. Then, the big question is: will the SBTC puzzle be resolved after correcting for selectivity? Our answer is no, the break in the estimated SBTC trend becomes even more pronounced after correcting for selectivity. We discuss the potential implications of this result on SBTC and wage inequality further in Section 4.

The idea that assuming fixed efficiency labor supply units in the construction of the relative supply series may lead to miscalculations is related to Carneiro and Lee (2011) and Bowlus and Robinson (2012). Carneiro and Lee (2011) argue that time variation in school quality may be used as a proxy to endogenize the fixed efficiency units. They show that quality of college education in the U.S. has been declining over time; thus, an hour supplied by a worker received college education in, say, 1980s produces more output than an hour supplied by a worker received college education more recently. As a result, the fixed efficiency units setup overestimates the growth rate of relative supply of college workers, which means that the slope of the SBTC trend has been overestimated in the literature. Bowlus and Robinson (2012) show that estimating the changes in the efficiency units over time poses a serious challenge of identification.[7] They find that both quality and quantity changes are important and should

[6] See, e.g., Acemoglu (1998, 1999), Ciccone and Papaioannou (2009), and Iranzo and Peri (2009).

[7] Separating the changes in quality from those in quantity has been a difficult identification problem in the empirical human capital literature [Weiss and Lillard (1978)]. Bowlus and Robinson (2012) develop an identification strategy motivated by a

be accounted for.

Our paper is similar to both of these papers in the sense that we also argue that ignoring time variation in the efficiency units may lead to miscalculations. Different from these papers, we obtain time variation through an explicit self-selection framework that allows for unobserved compositional changes within education categories. In particular, we argue that the bias term, which characterizes the unobserved traits diffusing into the labor supply decisions, changes over time. This term is often interpreted in the literature as a form of unobserved ability or worker "quality."[8] Thus, we proxy quality with this bias term, while Carneiro and Lee (2011) use school quality and Bowlus and Robinson (2012) estimate the quality dimension within a life-cycle human capital accumulation model.

One important difference between Carneiro and Lee (2011) and Bowlus and Robinson (2012) is that the former find that the relative quality of skilled workers have been almost monotonically declining over time, meaning that the college-premium framework overestimates the SBTC trend, while the latter document that the relative quality of skilled labor has been monotonically going up, suggesting that the college premium literature underestimates the SBTC. In terms of the results, our results differ from these two papers in that the quality adjustments that our model produces are nonmonotonic. In particular, our selection-correction procedure implies that the relative quality has improved before the mid-1980s and it has deteriorated afterwards. This suggests that the college-premium framework underestimates the SBTC trend before the mid-1980s, while it overestimates the SBTC trend afterwards.

The idea that selection into and out of the FTFY status might be affecting wage inequality has been introduced by Mulligan and Rubinstein (2008). They focus on the changes in women's self-selection into the FTFY status, correct for selectivity using Heckman's two-step estimator, and propose this mechanism as an explanation for closing gender wage gap in the U.S. Although we have been motivated by the method they develop, we apply it to an entirely

version of the Ben-Porath (1967) model of the human capital investments over the life course. The main motivation behind their strategy is that the efficiency units ought to behave on a flat path toward the end of the working life. Along this range, changes in wages are assumed to fully reflect changes in quality and, thus, the quality dimension can be identified this way. Carneiro and Lee (2011) uses school quality as an auxiliary factor in their identification strategy. In this paper, we use the selectivity terms as auxiliary factors in identifying quality adjustments.

[8] See, e.g., Willis and Rosen (1979) and Heckman, Lochner, and Taber (1998).

different area: the college-premium framework. As Figure (1) suggests, concentrating on male workers, we document that there are systematic differences between the FTFY choices of the low-skill and high-skill workers. To be concrete, we show that the FTFY fraction is stable for high-skill employed workers, while it fluctuates wildly for the low-skill ones.

Although our results do not produce direct implications for the effect of non-market factors, we argue that the non-market factors might have generated the differential selectivity patterns across the skill categories. We focus on a particular institutional factor: the real minimum wage. The idea that the movements in the real minimum wage may have triggered substantial unobserved compositional changes in the workforce is closely related to Lemieux (2006). He argues that movements in the real value of the minimum wage can be linked to the movements in the extent of residual inequality in the U.S. More specifically, he shows that the magnitude of residual inequality is negatively related to the real minimum wage. Similar to his work, we also discuss the potential effects of the real minimum wage on the composition of the workforce. Different from Lemieux (2006), we argue that the real value of the minimum wage may have led to unobserved compositional changes in the workforce that affect the relative supply of college-equivalent workers in the U.S. In other words, we say that real minimum wages have indirect as well as direct effects on the structure of the U.S. college premium.

Overall, our paper makes three contributions to the related literature. *First*, we develop a method that can be used to adjust for the changes in the relative quality of skilled versus unskilled workers "within" the standard college-premium framework. Other papers, including Carneiro and Lee (2011) and Bowlus and Robinson (2012), either employ different models or auxiliary equations to correct for quality adjustments. Performing these adjustments within the college-premium framework is desirable, because the strongest aspect of this framework is that it provides an intuitive platform using which one can jointly understand the empirical and theoretical underpinnings of the skill-premium concept.[9] Second, Carneiro and Lee (2011) and Bowlus and Robinson (2012) present conflicting results: the former shows that the relative quality of skilled workers has deteriorated, while the latter documents that it has

[9] Section 3 clearly presents the links between the theoretical and empirical aspects of the skill-premium problem.

improved. Both papers find that quality adjustments are almost monotonic over time. Our paper is the first to document non-monotonic effects; that is, we show that the relative quality of skilled workers has improved before the mid-1980s, while it has deteriorated afterwards. *Finally*, we argue that this non-monotonicity might be related to institutional factors. The literature argues that changes in the relative supply trend might be due to the changes in non-market factors—such as the changes in the minimum wage laws. Our paper says that the institutional factors might also be driving the selectivity patterns and, thus, the unobserved quality adjustments over time.

3 The Analytical Framework

3.1 Theory

Existing research on the U.S. skill premium relies on a simple aggregate production model with two basic assumptions: (1) the aggregate production function is of the Constant Elasticity of Substitution (CES) form with two factors; college equivalent labor and high school equivalent labor, and (2) college and high school equivalents are paid their marginal products.[10] The standard practice is to derive a college-premium (or college-high school wage gap) equation and to perform empirical analysis based on this equation. The goal is to capture the movements in the wage premium paid to skills in the labor market. The labor market is assumed to consist of two types: the skilled and the unskilled. The former is defined by the college-equivalent workers and the latter by the high school equivalents. In this framework, the skill premium can be thought of as a proxy of how the labor market values skills.[11]

The aggregate production model is of the following CES form:

$$Y_t = A_t \left[\phi_t \left(a_t C_t \right)^{\frac{\sigma-1}{\sigma}} + \left(1 - \phi_t\right) \left(b_t H_t \right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}, \tag{3.1}$$

where C_t and H_t are college and high school equivalents employed at time t, A_t is the Hicks-

[10] See, for example, Katz and Murphy (1992), Katz and Autor (1999), Autor, Katz, and Krueger (1998), Card and Lemieux (2001), and Autor, Katz, and Kearney (2008).

[11] See Acemoglu and Autor (2011) for an excellent discussion of the foundations of this framework.

neutral technical change, a_t and b_t respectively correspond to skilled and unskilled labor-augmenting technical change, ϕ_t is the time-varying weight parameter characterizing the work load allocated to skilled labor, and $\sigma \geq 0$ is the elasticity of substitution between college and high school equivalents. Wages are determined based on the assumption that college and high school equivalents are paid their marginal products. We first calculate the marginal products of C_t and H_t using the production function described by Equation (3.1), then we equate wages to the corresponding marginal products and, finally, we take the ratio of these two decision rules. Taking the natural logarithms of this final ratio yields the following skill-premium equation:

$$\ln\left(\frac{w_{C,t}}{w_{H,t}}\right) = \ln\left(\frac{\phi_t}{1-\phi_t}\right) + \frac{\sigma-1}{\sigma}\ln\left(\frac{a_t}{b_t}\right) - \frac{1}{\sigma}\ln\left(\frac{C_t}{H_t}\right), \tag{3.2}$$

which can be rearranged as

$$\ln\left(\frac{w_{C,t}}{w_{H,t}}\right) = \frac{1}{\sigma}\left[D_t - \ln\left(\frac{C_t}{H_t}\right)\right], \tag{3.3}$$

where D_t collapses the time-varying skilled labor augmented relative demand shifts into a single variable measured in logs [Katz and Murphy (1992) and Autor, Katz, and Kearney (2008)]. Equation (3.3) says that college premium is determined by the combined effect of the relative demand measure, D_t, the relative supply measure, $\ln(C_t/H_t)$, and the elasticity of substitution between high school and college equivalents, σ.

Following Autor, Katz, and Kearney (2008), we formulate the relative demand measure as

$$D_t = \beta_0 + \beta_1 t + \beta_2 \ln(RMW_t), \tag{3.4}$$

where t represents the SBTC trend and RMW denotes real minimum wages.[12] This structure says that the relative demand shifts favoring the skilled against unskilled workers have two components: SBTC and changes in log real minimum wages, where the expected signs of β_1 and β_2 are positive and negative, respectively. Thus, the final equation that we estimate

[12]The U.S. federal minimum wage is deflated by the personal consumption deflator.

becomes

$$\ln\left(\frac{w_{C,t}}{w_{H,t}}\right) = \beta_0 + \beta_1 t + \beta_2 \ln(RMW_t) + \beta_3 \ln\left(\frac{C_t}{H_t}\right) + \varepsilon_t, \tag{3.5}$$

where β_0 is a constant term, ε_t is an error term, and β_3 provides an estimate of $1/\sigma$. Note that there may be additional institutional factors—other than the real minimum wage—that can potentially diffuse into the process determining the relative demand for skills. These factors include, but are not limited to, business cycles and foreign outsourcing of jobs with low skill requirements. For simplicity and for the purpose of compliance with Autor, Katz, and Kearney (2008), we focus on real minimum wages as the only institutional factor driving the demand for skills. The key problem in this setup is the formulation of $\ln(C_t/H_t)$, the relative supply measure (or index), which we describe next.

3.2 The Relative Supply Measure

The conventional relative supply measure used in the wage inequality literature is calculated as follows. There are five education categories: high school dropouts (HSD), high school graduates including the GEDs (HSG), some college (SC), college graduates (COL), and post college graduates (COL_+). The SC category is further divided into two categories: SC1 and SC2. SC1 describes those who earn less than the median wage in the SC category, while SC2 describes those who earn more than the median wage in the SC category.[13] In our notation, $J \in \{\text{HSD}, \text{HSG}, \text{SC1}, \text{SC2}, \text{COL}, \text{COL}_+\}$. Two more general education categories are constructed from these six categories: high school equivalents (HSD + HSG + SC1) and college equivalents (SC2 + COL + COL_+). We denote the labor supplies of high school equivalents and college equivalents by H and C, respectively. Roughly speaking, H and C are calculated by aggregating the hours supplied for the respective categories weighted by the "efficiency units." The details of how we construct the related series are described in the data appendix [Appendix B]. But, to understand the basic logic, it is possible to simply consider

[13] Some papers use mean rather than median. But the choice of the division criterion is not critical at all for the results.

the main mechanism as follows. We formulate

$$J_t = \bar{\omega}^J h_t^J, \tag{3.6}$$

where J_t denotes the weighted hours supplied by the education category J, h_t^J is the total hours of work for the education category J at time t, and $\bar{\omega}^J$ is a weight parameter for category J calculated using the following formula:

$$\bar{\omega}^J = \frac{1}{T}\sum_{t=1}^{T} \frac{\int_{\mathcal{I}_J} \ln(w)_{i,t}^J dF_{J,t}(i)}{\int_{\mathcal{I}_{HSG}} \ln(w)_{i,t}^{\text{HSG}} dF_{\text{HSG},t}(i)}. \tag{3.7}$$

Here $\ln(w)_{i,t}^J$ is the log real wage for individual i, $i \in \mathcal{I}_J$, belonging to the category J at time t, $t = 1, ..., T$, where T is the length of the sample period, and $\mathcal{I}_J$ is the support for the relevant population in the corresponding education category. $F_{J,t}(i)$ describes the cdf of individual-level wage observations at time t. Note that the weight $\bar{\omega}^J$ is calculated relative to the real mean wage for the benchmark education category, which is high school graduates (HSG), at time t. To put it differently, the fixed weight $\bar{\omega}^J$ is incorporated to capture the fact that higher educated workers supply larger efficiency labor units per unit of time than the lower educated workers do. The efficiency units of labor supply are calculated by multiplying the total hours supplied with this fixed weight. Based on this logic, one can simply construct

$$H_t = \sum_{J=\text{HSD,HSG,SC1}} J_t \quad \text{and} \quad C_t = \sum_{J=\text{SC1,COL,COL}_+} J_t. \tag{3.8}$$

Finally, the relative supply measure is constructed by calculating the ratio C_t/H_t and, then, taking the natural logarithm of this ratio to get $\ln(C_t/H_t)$. We would like to emphasize at this stage that all the calculations are carried out for the workers reporting a FTFY status.

In this paper, our main focus is on the efficiency units, $\bar{\omega}^J$. Under this formulation, there are six efficiency unit coefficients, one for each education category. The one for the HSG category is 1 due to the normalization described above. These coefficients capture the standard idea that the labor units supplied by skilled workers per unit of time is larger than the labor units supplied by unskilled workers per unit of time. For example, ω_J is expected to be greater than 1 for college educated workers, because their wages are, on average, larger than the wages earned by typical high school graduates, which means that the market assigns a greater value to the labor hours supplied by the higher educated workers than those supplied by the lower educated ones. The opposite is true for high school dropouts, i.e., for them, $\omega_J < 1$ is expected. This logic has been frequently used in many different contexts in economics.[14]

Although, the fixed efficiency units idea is a good first approximation, it misses how the relative labor supply contributions of each education category evolve over time. This is particularly important for the point we make in this paper. We mainly argue that the share of the FTFY status fluctuates within education categories over time, which suggests that there may be unobserved compositional shifts due to selection into and out of the FTFY status. The literature focuses exclusively on the FTFY workers without dealing with this issue. Accounting for these unobserved compositional changes can alter the estimated trends in the relative supply of college equivalent workers and, thus, can have implications on the analysis of wage inequality.

3.3 Incorporating Selectivity

This subsection introduces a simple selection-correction algorithm to account for the unobserved compositional shifts due to selection into and out of the FTFY status. Since we deal with time variation in the compositional factors that are "unobserved" to the econometrician, it is possible to interpret our method as an attempt to control for the variation in the unobserved quality or skill level in the worker population over time. Such an exercise hasn't been performed in the traditional college-premium literature and our main purpose is to explore whether accounting for these shifts can alter the results featured in the literature. Below we describe our method in two steps: first, we explain the intuition behind our method by a simple example and, then, we describe the details of the econometric procedure we employ.

[14] See Browning, Hansen, and Heckman (1999) for an excellent discussion of the efficiency units idea.

3.3.1 Intuition

Suppose that we want to calculate the trends in the relative supply of skilled versus unskilled workers in a country. We have access to nationally-representative repeated cross-section data for T consecutive years. There is publicly available information on education levels, hours worked (h), and wages (w). For simplicity, assume that there are two worker types: high-educated (s) and low-educated (u), which means that we proxy skills with education level. So, we observe $h_{s,t}$, $h_{u,t}$, $w_{s,t}$, and $w_{u,t}$. Think of these quantities as the yearly averages of micro-level observations, where $t = 1, \ldots, T$. Let $\bar{w}_s = (1/T)\sum_{t=1}^{T} w_{s,t}$ and $\bar{w}_u = (1/T)\sum_{t=1}^{T} w_{u,t}$ denote the means of $w_{s,t}$ and $w_{u,t}$, respectively. Let $\omega = \bar{w}_s/\bar{w}_u$ describe the relative efficiency of skilled versus unskilled hours supplied. Clearly, $\omega > 1$.

In calculating the trends in the relative supply of skilled workers, the literature compares the evolution of skilled hours supplied, $\omega h_{s,t}$, versus that of the unskilled hours supplied, $h_{u,t}$. Obviously, ω serves as a level shifter and it does not affect the trends in the log series. There are two problems with this setup. First, ω does not evolve over time; that is, this setup does not account for the fact that the relative efficiency of skilled versus unskilled workers may have changed over time. And, second, ω is a noisy measure of relative efficiency due to potential selectivity bias, since most papers in the traditional literature restrict their samples to the FTFY workers only. As Figure (1) suggests, different skill categories have potentially exhibited different selectivity patterns over time. This means that $\omega = \omega_{\text{true}} + \omega_{\text{bias}}$. Our purpose is to calculate ω_{bias} and then subtract this from ω to approximate the corrected efficiency weight ω_{true}. The method we develop performs this correction in such a way that ω_{bias} is calculated for each year in our sample, i.e., it is time-varying. Thus, when we adjust ω with these time-varying bias terms, the resulting corrected weights become time varying too. So, we propose a joint solution to these two problems. Next we present the full details of the econometric method we develop to account for the potential biases that can arise from focusing on the FTFY wages in the weighting procedure.

3.3.2 Method

Let w_i^* denote the real hourly wages received by a worker under the FTFY status. The empirical wage equation can be characterized simply as

$$\ln(w_i^*) = \boldsymbol{x}_i'\beta^* + \epsilon_i^*, \tag{3.9}$$

where ϵ_i^* is normally distributed with zero mean and non-zero variance σ^2 and it is i.i.d across individuals. The binary variable D_i describes the labor force status of the workers in the sample. $D_i = 1$ if the worker has a FTFY status and $D_i = 0$ otherwise (i.e., if the worker is employed, but has a part-time part-year, part-time full-year, or full-time part-year status). The FTFY wage $\ln(w_i^*)$ is observed only if $D_i = 1$ and is latent otherwise. In fact, a wage is observed under part-time and/or part-year status, but it is not the FTFY wage and, therefore, we assume that the FTFY wage is latent even though the worker is employed part-time and/or part-year.

To formulate the choice, the worker is assumed to observe two offers: one for the FTFY job ($\ln(w_i^*)$) and the other for a non-FTFY job ($\ln(w_i)$). He chooses $D_i = 1$ if $\ln(w_i^*) > \ln(w_i)$ and $D_i = 0$ if $\ln(w_i^*) \leq \ln(w_i)$. Let the latent wage equation be $\ln(w_i) = \boldsymbol{x}_i'\beta + \epsilon_i$. Then, the first-step (choice) regression can be formulated as (i subscripts are suppressed)

$$\begin{aligned}
\mathbb{P}[D = 1|\boldsymbol{x}, \boldsymbol{z}] &= \mathbb{P}[\ln(w^*) > \ln(w)|\boldsymbol{x}, \boldsymbol{z}] \\
&= \mathbb{P}[\eta > -\boldsymbol{z}'\gamma] \\
&= \Phi\left(\frac{\boldsymbol{z}'\gamma}{\sigma_\eta}\right),
\end{aligned} \tag{3.10}$$

where $\boldsymbol{x}$ is the restricted version of the $\boldsymbol{z}$ (i.e., $\boldsymbol{z}$ is a vector of regressors in the choice equation, while $\boldsymbol{x}$ is that in the outcome equation), $\gamma = \beta^* - \beta$, $\eta = \epsilon^* - \epsilon$, and σ_η is the standard deviation of η.[15] The second-step (outcome) equation is therefore

$$\mathbb{E}[\ln(w^*)|\ln(w^*) > \ln(w)] = \boldsymbol{x}'\beta^* + \frac{\sigma^*}{\sigma_\eta}\lambda\left(-\frac{\boldsymbol{z}'\gamma}{\sigma_\eta}\right), \tag{3.11}$$

where σ^* is the covariance between ϵ^* and η, and λ is the inverse Mills ratio. The selection-corrected version can either be estimated via the full-information maximum likelihood method or the two-step estimator developed by Heckman (1979). If there is no selection bias, the estimated wage equation takes the form

$$\mathbb{E}[\ln(w^*)|\boldsymbol{x}] = \boldsymbol{x}'\beta^*. \tag{3.12}$$

However, if selectivity is statistically significant, then the wage regressions pick up the bias term expressed in Equation (3.11). In our context, the term

$$\Lambda = \frac{\sigma^*}{\sigma_\eta}\lambda\left(-\frac{\boldsymbol{z}'\gamma}{\sigma_\eta}\right) \tag{3.13}$$

is the component of the FTFY wages due to the correlation between the unobserved determinants of choices and outcomes. We let this term represent the evolution of the unobserved compositional factors driven by self-selection in and out of the FTFY status.

Note that Λ consists of two components: (*i*) the selectivity component, $\lambda\left(-\frac{\boldsymbol{z}'\gamma}{\sigma_\eta}\right)$, characterizing the systematic correlation between the FTFY choice and wage outcomes and (*ii*) the coefficient σ^*/σ_η—can be positive or negative depending on the sign of the covariance σ^*—that converts the selectivity component into wage units. In other words, Λ is a part of the wage equation and it measures how big the selectivity bias is. The conventional college-premium literature have ignored the role of Λ in calculating the trends in the relative supply of skills; that is, the literature ignores the potential selection bias—measured by Λ—due to selection into and out of the FTFY status. Below, we demonstrate the details of our attempt to remove

[15] The vector of regressors $\boldsymbol{z}$ describes the variables that affect the worker's decision of whether to work or not, while the variables in $\boldsymbol{x}$ describe the factors affecting earnings of the worker, given that she has chosen to work. These variables often overlap, but there are some classical examples for typical variables in $\boldsymbol{z}$ and $\boldsymbol{x}$. In the typical Mincerian earnings equations, the years of schooling and years of work experience are the typical variables in $\boldsymbol{x}$, while variables like marital status, number of children, or the number of employed individuals in the household are typical variables in $\boldsymbol{z}$, but not in $\boldsymbol{x}$. See Heckman (1974) for an in depth discussion of this issue.

the selectivity problem.

Let $\widehat{\Lambda}^J_{i,t}$ denote the predicted inverse Mills ratio (for individual i in education category J observed at time t) multiplied by its estimated coefficient. To calculate these predicted values, we run separate year-by-year regressions for each of the six education categories. This means that the predicted selectivity term captures the year-by-year differences in labor market conditions that affect the decision to work FTFY or not. It also captures the possibility that workers with different capabilities make the FTFY decision differently. Based on this structure, selectivity is incorporated by employing the following formula:

$$\bar{\omega}^J_t = \bar{\omega}^J - \frac{\int_{\mathcal{I}_J} \widehat{\Lambda}^J_{i,t} dF_{J,t}(i)}{\int_{\mathcal{I}_{HSG}} \widehat{\Lambda}^{HSG}_{i,t} dF_{HSG,t}(i)}. \tag{3.14}$$

To understand the intuition behind this equation, remember the formula that we use to calculate $\bar{\omega}^J$ [see Equation (3.7)]. Equation (3.7) gives us six numbers, which are fixed over time, describing the relative efficiency of skilled versus unskilled hours. This is the baseline setup used in the college-premium literature. The observed wages used to calculate $\bar{\omega}^J$ embody selectivity, so they are potentially biased. The direction of the selectivity is governed by the sign of the coefficient σ^*/σ_η, which can differ across years and education categories. So, if there is positive (negative) selection embodied in $\bar{\omega}^J$ at time t, then our correction exercise subtracts (adds) this bias term to obtain the corrected weight.

In this exercise, we make two related, but distinct, assumptions: symmetry and separability. The symmetry assumption suggests that the aggregate selectivity term is calculated in the same way as we calculate $\bar{\omega}^J$ [i.e., compare Equation (3.7) with the second term in Equation (3.14)]. To impose symmetry, we have to assume that the observed wage component $\bar{\omega}^J$ and the aggregate selectivity term are additively separable. Notice that the predicted $\widehat{\Lambda}^J_{i,t}$ terms are used to adjust the fixed efficiency weights ($\bar{\omega}^J$) in such a way that, in the end, we obtain time varying weights that can account for the effect of unobserved compositional shifts on efficiency units. The time varying efficiency weights, $\bar{\omega}^J_t$, are then used to calculate the "corrected" relative supply measure. Notice also that the aggregate selectivity term is measured in wage units, which is ensured via multiplying the inverse Mills ratios by their coefficients in the corresponding wage equations. Hence, we are comparing apples with apples in Equation (3.14).

It is worthwhile to mention at this stage that the symmetry and separability assumptions are invoked to demonstrate the main intuition behind the selection-correction exercise in a clear way and they do not otherwise affect the main results of the paper qualitatively. The symmetry assumption is not restrictive at all and, in fact, it ensures that our formulation is internally consistent. The separability assumption might be more delicate. To check robustness, Appendix A relaxes the separability assumption and shows that the qualitative results remain almost unaltered.

To summarize, we use the standard latent variable selection-correction methods to control for selection into and out of the FTFY status. The main motivation was given in Figure (1). We observe a lot of variation in the FTFY fraction among low-skill workers, whereas the FTFY fraction among the high-skill workers is quite stable. This variability is potentially due to discrepancies in the labor supply decisions across different skill groups. The fixed weight is just a mean relative wage estimated by the OLS. We mechanically incorporate the mean relative inverse Mills ratio's—multiplied by the respective coefficients to convert them into wage units—to capture what is going on selection-wise. A similar approach has been adopted by several papers in different contexts in the labor economics literature [see Section 2 for details]. However, this is the first paper in the college-premium literature to implement this strategy to test the role of the FTFY choice on the trends in relative skills and wage inequality.

The next section provides a detailed presentation of our estimates along with a careful comparison of the results with and without selection-corrected relative supply series.

4 Results and Discussion

4.1 Estimates

We first compare the estimated relative supply series with and without selectivity. The version with no selection-correction is identical to the estimates provided by Autor, Katz, and Kearney (2008). The selection-corrected version controls for self-selection in and out of the FTFY status. Before discussing the results, it will perhaps be useful to discuss the identification of selection patterns. There are three main practical methods to obtain selection-corrected estimates. **First**, if there exists a variable affecting the choice but not the outcome, then this variable might serve as an exclusion restriction (or instrument). **Second**, if the data offer no exclusion restriction, then one can still perform selection correction exercise and calculate the inverse Mills ratios. However, the source of identification in this case will rely on the functional form of the error structure, which is assumed to be distributed normally. **Finally**, one can employ an "identification at infinity" strategy, which relies on the existence of an independent variable, which is almost fully correlated with the individuals' choice. In other words, it requires focusing on a group of workers who would anyway choose $D = 1$ under any circumstance. See also Mulligan and Rubinstein (2008) for a discussion of these alternative methods.

The third method is proposed by Chamberlain (1986) and Heckman (1990), and is often regarded as the most reliable of the three methods summarized above. The main disadvantage is that finding such a group of individuals is very hard and, even if such a group exists, the sample size will be extremely small. The problem we study necessitates working with the full sample, since we study relative education trends in the entire U.S. So, we drop the third strategy so as not to pick up new biases in exchange for eliminating the selection bias.

To calculate the selection-corrected series, we run the algorithm described in Section 3: basically, we run year-by-year probit regressions of the FTFY choice for each of the education categories. Then, we use the predicted inverse Mills ratios to adjust the efficiency units in wage regressions so as to correct for selectivity. We obtain the predicted inverse Mills ratios

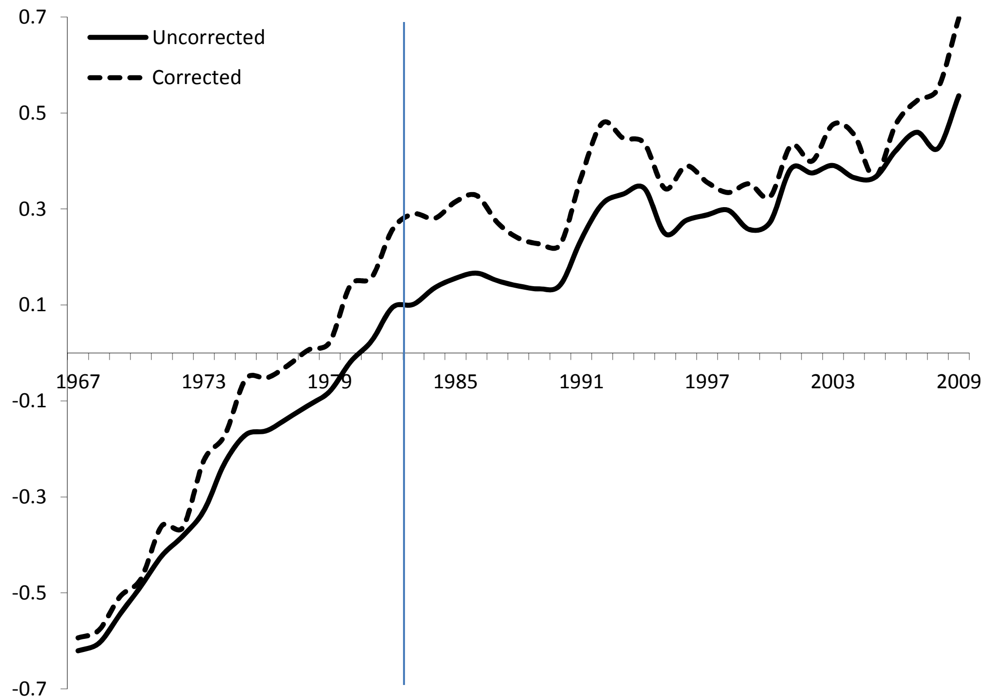

Figure 2: Uncorrected versus corrected relative supply series.

with the first and second methods mentioned above. To be specific, first we use the variable "being married or not" as an instrument affecting the choice of the FTFY status but not affecting the wages. This is one of the standard instruments often utilized in the correction exercises performed using the CPS data. And, second, we do not use an exclusion restriction and instead we rely on identification through functional form. Since the second exercise is restrictive due to the normality of the error structure, we try alternative monotone transformations of the inverse Mills ratios as suggested by Moffitt (1999) and Newey (1999). We find that both methods yield very similar results.[16]

Figure (2) compares the relative supply series with and without selection correction. The dashed line plots the corrected series, while the solid line plots the uncorrected series. Clearly, the corrected series is steeper than the uncorrected series before 1982. After 1982, however, it is flatter.

[16]This similarity can be interpreted in two ways. First, it might suggest that our results are robust. And, second, the similarity might be due to a coincidence. However, since we try monotone transformations of the inverse Mills ratios, and the results have not changed much, we believe that the probability of such a coincidence is very small. So, we interpret the consistency of the results obtained through employing these two distinct methods as a sign of robustness.

We start our discussion with the uncorrected series. The observed deceleration in the uncorrected series is argued to point out a puzzle in the literature [see Autor, Katz, and Kearney (2008)]. In terms of the mechanisms that the canonical college-premium equation features, the deceleration in the relative supply series brings together a puzzling deceleration in the relative demand for skilled workers. This is a consequence of the slowing of the growth of overall wage inequality. But, given the fact that computerized technologies have been invested heavily during the 1990, the slowing of the SBTC trend is a source of confusion in the literature. The consensus is that the canonical supply-demand framework motivating the college-premium framework falls short of explaining the trends after mid 1980s. A strand of the literature, called the "revisionists", highlighted the importance of several institutional factors in explaining this puzzle. The real minimum wage is often pronounced as a key factor driving these results.

The corrected series tell a somewhat different story. We still observe a decline in the growth rate of the relative supply of skills after 1982. But the growth rate until 1982 is sharper and the deceleration after 1982 is more pronounced. This is because of the selection-correction procedure we follow. The motivation is provided in Figure (1), which plots the fraction of the FTFY workers among all employed workers by each education category. The data reveal that the fraction of the FTFY status is quite stable around 90 percent among the high-educated employed workers. In other words, better-educated workers tend to work full-time full-year and this tendency does not vary a lot over time.

For lower-educated workers, however, the fraction of FTFY exhibits a time-varying pattern. In particular, we observe that the fraction of FTFY status declines until 1982 and it picks up thereafter. To interpret these trends, it is instructive to think of distributions of unobserved ability (or productivity) for each education category. FTFY status is a choice and a change in the fraction of the FTFY status can be related to systematic changes in the distribution of unobserved skills over time. To understand the structure of selectivity, suppose that the demand for part-time and/or part-year jobs is constant over time. When the demand for college education is high, there will be an increased transition from high-school to college education among those who prefer to work FTFY. These are the more able guys and they are the ones who are more likely to succeed in college. As a result, as the FTFY fraction goes down among the low-educated workers, the mean unobserved ability also goes down.

This suggests that the uncorrected series underestimate the growth rate of the relative supply series before 1982. The reason is that the skill gap should be higher in this period after correcting for selectivity. The opposite logic should hold after 1982; that is, a rise in the FTFY status among low-educated workers suggests that the more able ones among FTFY status choose to stay low educated (due to decreased demand for college education). As a result, the deceleration in the relative supply series is even more pronounced after correcting for self-selection due to choices in and out of the FTFY status.

What is the explanation? Observe that selection operates through the unobserved ability composition of the low educated. This suggests that we should focus on factors affecting the lower tail of the wage distribution in seeking a suitable explanation for the selectivity patterns. The real minimum wage is a good candidate. Lemieux (2006) argues that trends in the real minimum wage can potentially generate compositional effects. Our findings suggests that changes in minimum wage laws may be the driving force behind the unobserved compositional shifts. To be specific, we think that the interaction between the direction of endogenous technical change [see, e.g., Acemoglu (1998)] and the minimum wage laws is potentially the triggering mechanism. Profit generating motives by producers endogenously determine the amount of innovative effort (i.e., R&D expenditures, patents etc.) to be devoted to different factors of production. These factors of production include skilled and unskilled labor. Thus, the direction of technical progress can lead to *unskill-bias* (e.g., England in the eighteenth and nineteenth centuries) or *skill-bias* (e.g., Unites States after World War II). Institutions (i.e., the non-market factors) can lead to amplification or attenuation of the strength of the technical change. To understand this mechanism better, think of the following example. Suppose that the relative supply of college workers grows at a constant rate. The government raises the level of real minimum wages permanently. This makes unskilled labor more expensive, triggering investments in skilled-labor favoring technologies. This raises the relative returns to college education leading the society to invest in college education at a faster rate. The reverse logic holds when real minimum wages are reduced permanently. The trends in real minimum wages in the U.S. perfectly fit the self-selection structure that we document. We conclude that the real minimum wage can affect wage inequality not only directly, but through its effect on the relative supply of college workers.

The following three main points should perhaps be re-emphasized. **First**, that the deceleration in the relative supply series is more pronounced after correcting for selectivity suggests that the slow down in the SBTC trend is even sharper, which makes the puzzle deeper. **Second**, the selectivity patterns do not explain the puzzle; instead, it offers a mechanism that amplifies the deceleration. **Finally**, the relative supply series can itself be affected from the institutional factors.

The next question is: how does the correction exercise affect the estimates that the college premium equation yields. Table (1) reports the estimates for both the corrected and uncorrected relative supply series. The first column reports the estimates using the uncorrected relative supply series for the 1967 to 2009 period. The estimated elasticity of substitution is 2.75 (1/0.363) and the estimated trend growth in the wage gap is 1.5% per annum. These are in line with the literature. The second column—which we estimate using the selection-corrected relative supply series—gives an estimated elasticity of substitution 3.73 (1/0.268) and an estimated trend growth in the wage gap of 1.3% per annum. Thus, the uncorrected series understate the substitutability of skilled and unskilled workers. This pattern also implies that the relative demand growth is stronger when the uncorrected series is used. This suggests that, when the selection-corrected weights are used, the slowdown in the SBTC trend is more pronounced.

The role of minimum wages is examined in the third and the fourth columns. The natural logarithm of the real minimum wage has additional explanatory power as suggested by Card and DiNardo (2002) and Autor, Katz, and Kearney (2008). But the inclusion of this variable does not alter our main conclusion that the literature overestimates the relative demand

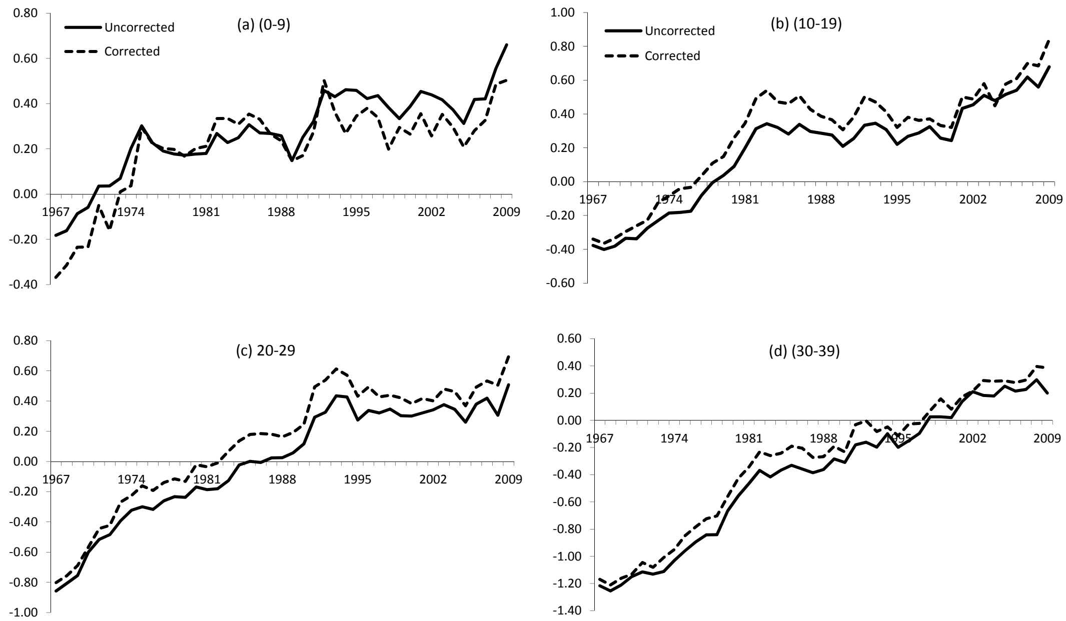

Figure 3: Educational attainment trends in the United States measured by the log relative supply of college equivalents. Panels (a), (b), (c), and (d) plot the specific trends for experience groups 0–9, 10–19, 20–29, and 30–39, respectively.

growth. Thus, our conclusion is robust to the inclusion of non-market (i.e., institutional) factors. We also observe that the estimated coefficients of the real minimum wage supports the story we explain above. Before the correction exercise, the coefficient of the minimum wage is relatively large and statistically significant, while the magnitude gets smaller and the degree of its statistical significance diminishes after correcting for selectivity. This suggests that the developments in the real minimum wage are correlated with the unobserved compositional shifts and, thus, the magnitude of the effect of the real minimum wage on skill premium gets smaller once we correct for selectivity. In other words, the changes in the relative (unobserved) quality of the skilled versus unskilled workers are partly driven by institutional factors. This result can be observed in all of our regressions [see Tables (1)–(4)].

It is well-known that the college premium has significantly varied by age/experience groups over recent decades, with the rise in the skill gap concentrated among less experienced workers in the 1980s [Autor, Katz, and Kearney (2008)]. The return to college education has increased much more substantially since 1980 for younger workers than for older ones. Card and Lemieux (2001) utilize these differences to construct a model in which workers with similar education but with different experience levels enter as imperfect substitutes into the production technology. To take this idea into account, we follow [Autor, Katz, and Kearney (2008)] and modify the college premium equation by estimating a model which includes own experience group relative skill supplies. Specifically, the modified model is

$$\ln\left(\frac{w_{C,t,e}}{w_{H,t,e}}\right) = \beta_0 + \beta_1 t + \beta_2 \ln(RMW_t) + \beta_3 \left[\ln\left(\frac{C_{t,e}}{H_{t,e}}\right) - \ln\left(\frac{C_t}{H_t}\right)\right] + \beta_4 \ln\left(\frac{C_t}{H_t}\right) + \varepsilon_t, \tag{4.1}$$

where e indexes experience groups. There are four experience groups: those with 0–9, 10–19, 20–29, and 30–39 years of experience. This specification can be derived from a model in which the aggregate inputs are themselves CES subaggregates of college and high school workers by experience group as in Card and Lemieux (2001). In this specification, $1/\beta_3$ represents the aggregate elasticity of substitution, and $1/\beta_4$ describes the partial elasticity of substitution between different experience groups within the same education group. We run this regression for both corrected and uncorrected aggregate series.

Table (2) presents the estimates for regressions in which experience groups are pooled and Tables (3) – (4) presents the results of the regressions for each experience category. Table (2) shows that both own-group and aggregate relative supply indices have significant effects on the college premium. Estimates for both the aggregate elasticity of substitution the partial elasticity of substitution between experience groups are larger than the aggregate estimates presented in Table (1). This suggests that accounting for the substitutability of experience groups can potentially alter the results. To sum up, estimates by experience groups communicate important messages. First, for almost all experience groups, the correction exercise makes the college and high-school workers more substitutable; therefore, leaves less room for SBTC trend to operate. Second, the increase in substitutability is more pronounced for less-experienced group (i.e. for workers with 0–9 and 9–19 years of experience). Finally, the effect is much less pronounced in high-experience groups. We conclude that the selectivity operates through the less-experienced workers (see Figure (3).

5 Concluding Remarks

In this paper, we argue that the canonical college premium framework has two disadvantages. First, most papers in the literature focus on the labor hours supplied by only those who self select into working full-time full-year (FTFY). FTFY is a choice variable and this procedure may bias the estimates. Second, it assumes fixed efficiency units of labor supply. In other words, it assumes that the relative efficiency of an hour worked by a college graduate versus an hour worked by a high school graduate is constant in the entire sample period (1967 – to date). This assumption ignores potential changes in the quality dimension.

We are interested in the question how these two strong assumptions affect the estimates reported in the U.S. wage inequality literature. We employ a standard Heckman selection-correction procedure to model FTFY as a choice variable. We find that ignoring this choice may bias the results. In particular, we find that the fraction of FTFY workers remains stable—around 90 percent—for high-educated workers along the data horizon, while it significantly fluctuates over time for the low-educated. This suggests that the selectivity operates over the low-educated workers. We also show that, among the low educated, the fraction of the FTFY status declines until mid-1980s and it picks up afterwards. This means that the direction of selectivity is reversed after mid-1980s.

We then use the inverse Mills ratios—the output from the selection correction procedure—and use them as if they were the time-varying components of the efficiency units. In other words, we assume that the differential selection in and out of the FTFY status can describe how efficiency units might have moved over time. A new relative supply series is constructed based on the selectivity-corrected estimates. The new series is more steeper than the old one before mid-1980s and is flatter afterwards. This suggests that the relative efficiency of college units increased until mid-1980s and it declines later. In terms of the SBTC hypothesis, this suggests the well-known deceleration observed in the relative supply of college workers after 1980s is even more pronounced after correcting for selectivity. This result casts further doubt on the relevance of the plain SBTC story. Finally, we ask what may be triggering the changes in the selectivity patterns. We conjecture that the interaction between the (endogenous) direction of technical change and the minimum wage laws is potentially the triggering mechanism. In other words, institutional changes affect wage inequality not only directly, but also through its indirect effects on the relative supply of college workers.

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A Robustness Check

In this appendix, we relax the separability assumption that we invoke in constructing Equation (3.14). Upon relaxing this assumption, the Equation (3.14) can be reformulated as follows:

$$\bar{\omega}_t^J = \frac{\int_{\mathcal{I}_J} \ln[(w^*)_{i,t}^J] dF_{J,t}(i) - \int_{\mathcal{I}_J} \widehat{\Lambda}_{i,t}^J dF_{J,t}(i)}{\int_{\mathcal{I}_{HSG}} \ln[(w^*)_{i,t}^{HSG}] dF_{HSG,t}(i) - \int_{\mathcal{I}_{HSG}} \widehat{\Lambda}_{i,t}^{HSG} dF_{HSG,t}(i)}, \tag{A.1}$$

where T is the sample period. The advantage of using Equation (3.14) instead of (A.1) is that it offers an intuitive comparison between $\bar{\omega}^J$, the weight that the traditional literature uses, and our selectivity-corrected weight $\bar{\omega}_t^J$. This alternative formula corrects for selectivity on a year-by-year basis, while Equation (3.14) performs this task over averages. We use our dataset to check whether using Equation (3.14) versus (A.1) makes any difference. Figure (4) displays the results—the figure basically plots the relative supply series calculated using (A.1) as an additional line over Figure (2). Comparing the black dashed line [the corrected series based on Equation (3.14)] to the green line [the corrected series based on Equation (A.1)], we observe that the qualitative results are almost unaltered. The black dashed line provides even a more conservative estimate than the green line; that is, the slow down in the growth rate of the relative supply of skills is even more pronounced when this alternative formula is used. As a result, we prefer to advertise Equation (3.14) as our main equation since (*i*) it is more intuitive and (*ii*) it provides more conservative estimates.

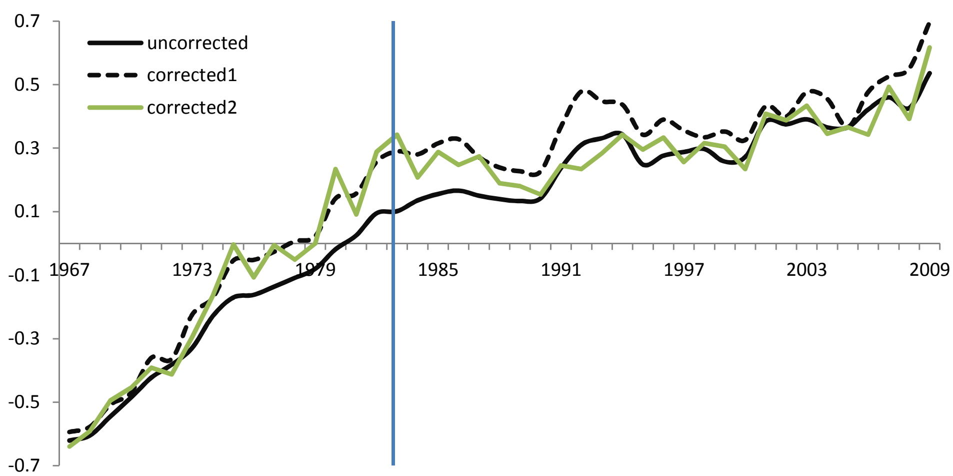

Figure 4: Uncorrected versus corrected relative supply series: An alternative formula.

B Data Appendix

We use the March Annual Social and Economic (ASEC) Supplement of the Current Population Survey (CPS) data for earnings years 1967 to 2009 (referring to raw March files from 1968 to 2010). Since data of a given year is published the next year and labeled with the year of publication, the survey data in one year actually belongs to the year before. Taking this into account, we address the actual year that the data belongs to whenever we mention years. We choose 1967 as the starting year because the content of the survey changed in 1967.

The CPS is a monthly survey conducted among the civilian, non-institutional population in every state of the United States and the District of Columbia. The survey data are collected monthly by interviewing about 60,000 households. Each household is interviewed once a month for four months in turn every year, then interviewed again during the same four months next year. The survey is designed to collect detailed information on employment, earnings, and hours of work in the U.S. It also provides information on a variety of demographic characteristics of the population including age, sex, race, marital status, number of children, area of living, and educational attainment. Over time, supplemental inquiries on special topics have been added to the survey for particular months. Among these supplemental surveys, the ASEC, which constitutes a primary source of detailed information on income and work experience, is the most widely used in the literature. The labor force and work experience data from this survey are used to profile the U.S. labor market.

The CPS data contain three different records: household, family, and person. Each row in the data matrix consists of one of these records while each column characterizes one digit. Therefore, a person's record is reported in the corresponding row by the columns that are determined via the length of the related statistic. The way that the data is arranged can be described as follows. The record for a household is followed by a family record, which in turn is followed by each person's record in that family. Then, related subfamilies, unrelated subfamilies, and non-relatives are recorded as family records, followed by person records under each category. Once the data regarding every family under the same household are collected, a new household record begins. In this study, we utilize only person records. Household and family records are linked to person records whenever necessary.

Our data involve male workers of age 16 to 64, with 0 to 39 years of potential labor market experience. Years of potential labor market experience are calculated by the Mincerian formula: age minus assigned years of education minus 6. We have limited our sample to full-time, full-year workers defined as those who worked at least 35 hours per week and 40-plus weeks in the previous year. We also exclude from the sample those living in group quarters, working part year due to school, retirement, military service, self-employed, or working without pay.

The wage measure that we use is the average weekly wages and salary income. The annual wage and salary income entries in the March CPS are reported in a top coded single variable before March 1987. The top coded values are rearranged by multiplying 1.45 with the reported maximum value of the variable for the corresponding years. However, wage and salary incomes start to be reported in two separate earnings variables: primary and secondary earnings after 1987. Therefore, we impute the top coded values as 1.45 times the maximum top coding value separately for primary and secondary earnings after this year. After correcting for top coding, these values are summed to calculate total wage and salary income. Then the annual wage and salary incomes are deflated to 2000 values using the personal consumption expenditure (PCE) deflator from National Income and Product Accounts (NIPA). Full-time weekly wage and salary income is computed as the natural logarithm of annual earnings divided by the number of weeks worked during the reference year. We drop from the sample workers with weekly earnings below half of the real minimum wage in 1982 ($67/week in 1982 dollars or $112/week in 2000 dollars).

One important point in the computation of weekly wages is that the number of weeks worked during the reference year start to be reported as its exact number only after 1975. Before this year, the number of weeks worked entry is given as a value from 1 to 7 denoting a number of weeks in each group. Therefore, in order to recode the actual number of weeks worked for the previous years to create data in harmony with the post-1975 period, we calculate an average number of weeks for each category using values for 1975, 1976, and 1977, weighted by March Supplement Weights. We use an imputed measure of weeks worked: 22.2 for 14-26 weeks category, 34.4 for 27–39 weeks category, 43.3 for 40–47 weeks category, 48.3 for 48–49 weeks category and 51.9 for 50–52 weeks category.

The definition of data on educational attainment experiences a few changes in its coding within our period of analysis. However, the crucial change occurs in 1991. Before this year, two different questions in the survey provide data on education variable, one is the highest grade or year of regular school attended and other is whether that grade (year) is completed or not. An individual's educational attainment is assumed to be his or her last fully completed year of education. If an individual did not complete his or her last year of school, the years of education are considered without that year. However, beginning in 1991, the survey starts to collect data on educational attainment by combining the two questions mentioned above into the question that ask the highest level of school or degree received. This change in coding means that educational attainment variable starts to focus on the degree received rather than the years of education. In the revised description of the new variable, several years of education of the lower grade levels are grouped into a single category while some new categories start to be used and college degrees begin to be recorded by type. Since the new question revision allows for a more accurate definition of educational attainment, the comparison of the data collected before 1991 with the one belong to subsequent years becomes a bit tricky. In order to make a precise comparison of educational categories across years, we use the general approach proposed in the literature. We construct five different categories of educational attainment. Individuals who have fewer than 12 years of completed schooling are defined as high school dropouts (less than high school category). High school graduates are considered to be those having 12 years of completed schooling. Those with any schooling beyond 12 years and less than 16 completed years are classified in some college category. College graduates are assumed to complete 16 years of schooling while those having more than 16 years of education are counted as college plus graduates.

As we mention above, we calculate years of potential labor market experience for each person.

While doing that, we use the average years of completed schooling derived from the revised educational attainment data following Park (1994). It suggests that calculating potential experience in this way is one of the best options to handle with the revised education variable. Using the CPS data described above, we basically construct two samples: one is a wage sample representing college-high school log relative weekly wages overall and by age groups, and the other is measure, again overall and by age groups. Our wage sample contains average weekly wages for high school and college graduate categories in each year from 1967 to 2009. The logarithm of the ratio of the average weekly wage of college graduates to the average weekly wage of high school graduates provides us college-high school log relative weekly wages.

The sample that we use to measure log relative supply of college-high school is constructed following Katz and Murphy (1992) and Autor, Katz, and Kearney (2008). We form two different components to compute this measure. The first one is a “quantity sample” which refers to total hours of work of all workers in each five education category (high school dropouts, high school graduates, workers with some college, college graduates, and college plus graduates) for each year. Total hours of work are computed by multiplying the imputed weeks of work by the usual weekly hours for each worker in each year and then by summing them up over all workers. The second part of our relative supply measure is a “price sample” including average weekly wages for all workers in each of the five education groups for each year. The construction of these average wages used for a “price sample” is described above. Then, we normalize these average weekly wages for each education group in each year by the average weekly wage (over all periods) of high school graduates. This normalization provides a relative wage measure for a given group in each year. We use these normalized relative wage values (derived from a “price sample”) as weights that are merged to total hours of worked (derived from a “quantity sample”), which in turn creates an “efficiency units” measure of labor supply. (We calculate year-by-year relative wages and five-year moving averages for relative wages as the weights).

Following Katz and Murphy (1992), Card and Lemieux (2001), and Autor, Katz, and Kearney (2008), we use the relative quantity of college equivalent and high school equivalent workers as our relative supply measure. The aggregate high school equivalent labor supply is defined as the total efficiency units of labor supplied by high school graduates (total hours worked by high school graduates), plus the total efficiency units of labor supplied by high school dropouts (total hours worked by high school dropouts weighted by average wage of this group relative to high school graduates), plus a fraction of the hours of workers with some college (total hours supplied by the resultant share of some college workers weighted by average wage of this group relative to high school graduates). The way that we allocate those with some college between high school and college equivalents is as follows: workers in the some college category are sorted on the basis of their weekly wages in each year. We assign those who earns below the median wage as high school equivalents. Similarly the workers receiving above the median wage are merged to college equivalents. The aggregate college equivalent labor supply is described as the total efficiency units of labor supplied by college graduates (total hours worked by college graduates weighted by average wage of this group relative to high school graduates), plus the total efficiency units of labor supplied by college-plus workers (total hours supplied by post college workers weighted by average wage of this group relative to high school graduates), plus the appropriate fraction of the hours of workers with some college (total hours supplied by the corresponding share of those with some college weighted by average wage of this group relative to high school graduates). The natural logarithm of the amount of supply of college equivalents relative to supply of the high school counterpart yields our college-high school log relative supply indicator.

Dependent variable: Log College/High School Hourly Wage Gap				
	[1]	[2]	[3]	[4]
Constant	0.125***	0.191***	0.309***	0.312***
	(0.021)	(0.013)	(0.100)	(0.097)
Time	0.015***	0.013***	0.015***	0.013***
	(0.001)	(0.001)	(0.001)	(0.001)
Log Relative Supply (uncor.)	-0.363***		-0.390***	
	(0.043)		(0.044)	
Log Relative Supply (cor.)		-0.268***		-0.277***
		(0.029)		(0.030)
Log Real Min. Wage			-0.103*	-0.065
			(0.055)	(0.052)
Observations	43	43	43	43
R-squared	0.92	0.92	0.92	0.92

Table 1: Regression results: This table documents the effect of the correction exercise on the estimates that the main college premium equation [i.e., the Equation (3.5)] yields. Robust standard errors are reported in parentheses. ***, **, and * refer to 1%, 5%, and 10% significance levels, respectively.

Dependent variable: Log College/High School Hourly Wage Gap by Experience Groups				
Pooled Regressions				
	[1]	[2]	[3]	[4]
Constant	0.210***	0.256***	0.371***	0.376***
	(0.019)	(0.013)	(0.093)	(0.093)
Time	0.012***	0.011***	0.012***	0.010***
	(0.001)	(0.001)	(0.001)	(0.001)
Aggregate Relative Supply (uncor.)	-0.262***		-0.286***	
	(0.039)		(0.041)	
Aggregate Relative Supply (cor.)		-0.194***		-0.203***
		(0.028)		(0.029)
Own Minus Aggregate Relative Supply	-0.040***	-0.040***	-0.042***	-0.042***
	(0.014)	(0.014)	(0.015)	(0.015)
Log Real Min. Wage			-0.090*	-0.064
			(0.051)	(0.050)
Observations	172	172	172	172
R-squared	0.70	0.70	0.71	0.71

Table 2: Regression results (experience groups as imperfect substitutes): This table documents the effect of the correction exercise on the estimates that the alternative college premium equation [i.e., the Equation (4.1)] yields. This alternative setup assumes that workers in different experience groups are imperfectly substitutable. Robust standard errors are reported in parentheses. ***, **, and * refer to 1%, 5%, and 10% significance levels, respectively.

Dependent variable: Log College/High School Hourly Wage Gap by Experience Groups				
Experience-Group-Specific Regressions				
	[0–9]		[10–19]	
	[1]	[2]	[3]	[4]
Constant	0.715***	0.673***	0.453***	0.448***
	(0.154)	(0.156)	(0.137)	(0.137)
Time	0.014***	0.012***	0.018***	0.015***
	(0.002)	(0.002)	(0.002)	(0.001)
Aggregate Relative Supply (uncor.)	-0.291***		-0.526***	
	(0.072)		(0.060)	
Aggregate Relative Supply (cor.)		-0.211***		-0.369***
		(0.047)		(0.042)
Own Minus Aggregate Relative Supply	0.073	-0.025	-0.250***	-0.172***
	(0.108)	(0.118)	(0.078)	(0.076)
Log Real Min. Wage	-0.320***	-0.249***	-0.183***	-0.130*
	(0.090)	(0.088)	(0.075)	(0.073)
Observations	43	43	43	43
R-squared	0.89	0.88	0.90	0.90

Table 3: Regression results by experience groups 0–9 and 10–19: This table documents the effect of the correction exercise on the "experience-group-specific estimates" that the alternative college premium equation [i.e., the Equation (4.1)] yields. The first two columns focus on the workers with 0–9 years of experience, while the last two columns focus on those with 10–19 years of experience. Robust standard errors are reported in parentheses. ***, **, and * refer to 1%, 5%, and 10% significance levels, respectively.

Dependent variable: Log College/High School Hourly Wage Gap by Experience Groups				
Experience-Group-Specific Regressions				
	[20–29]		[30–39]	
	[1]	[2]	[3]	[4]
Constant	0.018	0.036	0.479***	0.464***
	(0.140)	(0.140)	(0.166)	(0.170)
Time	0.011***	0.010***	0.003	0.003
	(0.001)	(0.001)	(0.002)	(0.002)
Aggregate Relative Supply (uncor.)	-0.214***		-0.060	
	(0.061)		(0.073)	
Aggregate Relative Supply (cor.)		-0.162***		-0.048
		(0.043)		(0.055)
Own Minus Aggregate Relative Supply	-0.091	-0.084	0.091	0.063
	(0.079)	(0.075)	(0.088)	(0.093)
Log Real Min. Wage	0.120	0.131*	-0.021	-0.020
	(0.078)	(0.077)	(0.084)	(0.082)
Observations	43	43	43	43
R-squared	0.79	0.80	0.44	0.44

Table 4: Regression results by experience groups 20–29 and 30–39: This table documents the effect of the correction exercise on the "experience-group-specific estimates" that the alternative college premium equation [i.e., the Equation (4.1)] yields. The first two columns focus on the workers with 20–29 years of experience, while the last two columns focus on those with 30–39 years of experience. Robust standard errors are reported in parentheses. ***, **, and * refer to 1%, 5%, and 10% significance levels, respectively.