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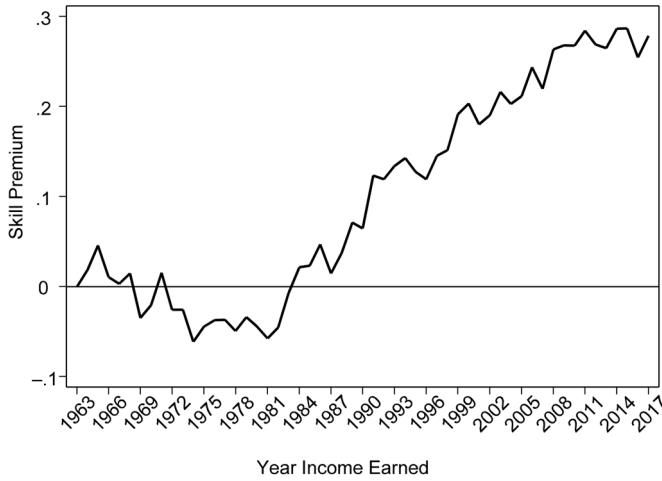
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The skill premium and inequality, more generally, have increased dramatically in the United States since 1980; see the top panel of figure 1. This rise has coincided with a substantial increase in the relative supply of skilled workers; see the bottom panel of figure 1. To the extent that relative supply and demand shape relative prices, these patterns reveal a sizable skill-biased shift in relative demand. A large literature across a range of subfields within economics investigates the roles of various economic forces in generating such a shift. This literature emphasizes in particular two broad categories of observable shocks: a fall in the quality-adjusted cost of capital equipment that is relatively more substitutable for less skilled labor (including computers, software, industrial robots, etc.) and demand shocks biased toward jobs that are relatively intensive in skilled labor (induced by international trade, offshoring, structural transformation, etc.). One central goal of this broad literature is to quantify how important each shock is in explaining the evolution of the skill premium and how much remains unexplained (often referred to as “skill-biased technological change”).

“Trading Up and the Skill Premium” does a good job of empirically motivating the potential importance of a particular channel that has not featured prominently (or at all) in this literature: a within-industry version of the link between structural transformation and inequality. The authors provide evidence that higher-income consumers disproportionately purchase higher-quality varieties within industries and that higher-quality varieties within industries are skill intensive. This evidence suggests that an increase in income will generate a skill-biased demand shock (i.e., an increase in relative expenditure on skill-intensive varieties at fixed prices) within industries.¹

The main point of our discussion is that this first pass at quantification is missing two key elements. First, the connection between the model

A. Evolution of the Skill Premium



B. Evolution of Relative Skill Supply



Fig. 1. The evolution of the composition-adjusted skill premium and the composition-adjusted relative supply of skilled hours.

and the data can be strengthened: the baseline model can be taken to the data analogously to the “canonical model” (described in the paper) with the same data used to estimate the canonical model and an almost identical identification assumption. And when it is, the resulting parameter values differ substantially from those to which the authors calibrate

their model. Second, the baseline model lacks sufficient theoretical flexibility in a particular sense that we clarify in the following.

Solving the Model

The baseline “Trading Up” (TU) model links changes in the skill premium, denoted by $\omega_t \equiv w_{Ht}/w_{Lt}$, to four primitive shocks: changes in the supply of skilled labor (H_t), changes in the supply of unskilled labor (L_t), Hicks-neutral technical change (A_t), and skill-biased technical change (S_t). How important are changes in each of these shocks for generating the observed evolution of the skill premium?

Two equations are sufficient to characterize the impact of all primitive shocks on the skill premium in the TU model. The first equation links changes in the skill premium ($d \ln \omega_t$) to changes in the relative supply of skilled labor ($d \ln H_t/L_t$), skill-biased technical change ($d \ln S_t$), and endogenous changes in quality ($d \ln q_t$),

$$d \ln \omega_t = \rho d \ln S_t + (\rho - 1) d \ln \left(\frac{H_t}{L_t} \right) + \gamma \rho d \ln q_t.$$

This equation is a simple extension of the canonical model, incorporating one additional term associated with the impact of changes in endogenous quality ($d \ln q_t$). The second equation links changes in quality to changes in Hicks-neutral productivity ($d \ln A_t$), factor supplies ($d \ln H_t$ and $d \ln L_t$), and the skill premium ($d \ln \omega_t$) for any $\gamma > 0$,

$$\gamma \rho d \ln q_t = \rho d \ln A_t + \nu_t d \ln H_t + (\rho - \nu_t) d \ln L_t + \nu_t d \ln \omega_t,$$

where $\nu_t \equiv H_t w_{Ht} / (H_t w_{Ht} + L_t w_{Lt})$ is the share of labor payments accruing to skilled labor. Combining these two equations and solving for the change in the skill premium yields

$$d \ln \omega_t = \frac{\rho - 1 + \nu_t}{1 - \nu_t} d \ln H_t + d \ln L_t + \frac{\rho}{1 - \nu_t} (d \ln S_t + d \ln A_t). \tag{1}$$

Equation (1) connects changes in the skill premium to the underlying shocks and clarifies two points. First, the value of the parameter γ plays no role in the response of the skill premium to the underlying shocks (as long as $\gamma \neq 0$) for given values of ρ , ν_t , and shocks; we return to this below.² Second, as noted in the paper, only the sum of $d \ln S_t$ and $d \ln A_t$ matters rather than either directly.

Equation (1) also provides a more direct link between the model and the data than taken in the paper, a point to which we now turn.

Estimation

We can approximate the level of the skill premium as

$$\ln \omega_t \approx c_1 + \frac{\rho - 1 + \nu_t}{1 - \nu_t} \ln H_t + \ln L_t + \frac{\rho}{1 - \nu_t} (\ln A_t + \ln S_t),$$

where c_1 is the constant of integration and then reexpress this as

$$y_t \approx c_2 + (\rho - 1) \ln H_t + \rho (\ln A_t + \ln S_t),$$

where $y_t \equiv (1 - \nu_t)(\ln \omega_t - \ln L_t) - \nu_t \ln H_t$ is observable (because ν_t is observable), and $c_2 \equiv (1 - \nu_t)c_1$. Exactly as in the canonical model, we can express

$$\ln A_t + \ln S_t \equiv c_3 + gt + \tilde{\varepsilon}_t$$

without loss of generality, where g is trend growth in the combination of Hicks-neutral and skill-biased productivities. Combining the previous two expressions, we obtain

$$y_t = \alpha + \beta \ln H_t + \gamma t + \varepsilon_t, \quad (2)$$

where $\alpha \equiv c_2 + \rho c_3$, $\beta \equiv \rho - 1$, $\gamma \equiv g\rho$, and ε_t contains both $\rho\tilde{\varepsilon}_t$ and approximation error.

Equation (2) resembles the estimating equation in the canonical model—which we replicate in the following—except the independent variable $\ln(H_t/L_t)$ in the canonical model is replaced with $\ln(H_t)$ here and the dependent variable $\ln \omega_t$ in the canonical model is replaced by y_t here. We estimate equation (2) using annual data from the March Current Population Survey (CPS) covering working years from 1963 through 2017, composition adjusting the skill premium and factor supplies, and instrumenting for H_t —which depends on hours worked—using the population of those with college education. We obtain estimates of $\beta = -0.345$ (with standard error 0.044) and $\gamma = 0.016$ (with standard error 0.0017). These coefficients imply parameter values $\rho = 0.655$ and $g = 0.025$.

To understand the extent to which the mapping from data to parameters differs between the TU model and the canonical model, which the authors use to calibrate their model, we estimate the canonical model

$$\ln \omega_t = \alpha' + \beta' \ln \left(\frac{H_t}{L_t} \right) + \gamma' t + \varepsilon'_t$$

on our data and using our approach to composition adjusting. We obtain estimates of $\beta' = -0.522$ (with standard error 0.053) and $\gamma' = 0.020$ (with standard error 0.001). The mapping from coefficients to parameters in

the canonical model is $\rho = 1 + \beta'$ and $g = \gamma'/\rho$ so that we infer parameter values $\rho = 0.478$ and $g = 0.041$.

Implications

There are four implications that we can reach at this point. First, taking a value of ρ that is estimated from the canonical model, which has a different mapping from primitive shocks to the skill premium, is inconsistent with the TU model. Second, it is also unnecessary. The TU model can be estimated directly under an identification assumption that is analogous to that in the canonical model.

Third, when estimated in an internally consistent manner, the TU model continues to dramatically reduce the required strength of the time trend relative to the canonical model, from $g = 4.1\%$ per year in the canonical model to $g = 2.5\%$. Indeed, for any value of $d \ln A_t > 0$, the required growth rate of skill-biased technology is strictly less than 2.5% per year, as the time trend in the TU model—unlike in the canonical model—is generated by the sum of the growth rates of $d \ln A_t$ and $d \ln S_t$. This is the key point of the quantitative model, and we find that it is robust.

Fourth, the TU model is not sufficiently flexible in two respects. The parameter that appears to control the importance of quality upgrading, γ , plays no role (for any value $\gamma \neq 0$). It does not shape the elasticity of the skill premium to any shock, which depends only on ρ and ν_t .³ It does not shape the measurement of these elasticities, as ν_t is data and ρ is estimated as shown above. Finally, γ does not shape the measurement of the underlying primitive shocks, as H_t and L_t are data and A_t and S_t are not measured.

In addition, the fact that γ plays no role in shaping the impact of shocks on the skill premium implies that a single parameter, ρ , shapes the response of the skill premium to skill supply, whereas there is no flexibility whatsoever regarding the impact of unskilled labor supply. Because of these restrictions, the TU model appears inconsistent with the data. The following estimating equation is structural in both the TU and canonical models:⁴

$$\ln \omega_t = \alpha'' + \beta_H \ln H_t + \beta_L \ln L_t + \gamma''t + \varepsilon_t'' \tag{3}$$

The canonical model predicts that $\beta_H = -\beta_L$. The TU model predicts that $\beta_L = 1$ and that $\beta_{Ht} = (\rho - 1 + \nu_t)/(1 - \nu_t)$ so that the average treatment effect estimated by the equation above is approximately $\beta_H = 0.02$ (evaluating β_{Ht} at the average value across time of ν_t) or $\beta_H = 0.05$ (evaluating

the average value across time of β_{Ht}).⁵ Estimating equation (3) using the same data as previously described, we obtain estimates $\beta_H = -0.53$ (standard error 0.057) and $\beta_L = 0.54$ (standard error 0.094). These estimates are consistent with the prediction of the canonical model but inconsistent with either prediction of the TU model.

In summary, we find the empirical motivation compelling. The authors provide the first empirical evidence of which we are aware that higher-income consumers disproportionately purchase higher-quality varieties within industries and that higher-quality varieties within industries are skill intensive. This evidence suggests that an increase in income will generate a skill-biased demand shock within industries, raising the relative demand for skilled workers within industries and, therefore, raising the skill premium. We look forward to the next generation of quantification.

Endnotes

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1. This is a within-industry version of the mechanism emphasized in Buera, Kaboski, and Rogerson (2015); Caron, Fally, and Markusen (2017); and He (2018), each of which focuses on reallocation across industries.

2. Note that given the value of ρ , the evolution of v_t is pinned down by the evolution of the shocks.

3. In equation (9), the authors demonstrate a related result that the value of γ is irrelevant for shaping the value of $A_t S_t$ conditional on the skill premium.

4. The estimate of β_H in the TU model is the average treatment effect, as the impact of changes in H_t is heterogeneous across time given changes in v_t .

5. The TU model features an increasing relationship between H_t and the skill premium, like models of directed technical change, for sufficiently high ρ or v_t ; this is satisfied for later years in the sample when v_t has risen sufficiently.

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