Skill-Biased Structural Change*

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Abstract

Using a broad panel of advanced economies we document that increases in GDP per capita are associated with a systematic shift in the composition of value added to sectors that are intensive in high-skill labor, a process we label as skill biased structural change. It follows that further development in these economies leads to an increase in the relative demand for skilled labor. We develop a two-sector model of this process and use it to assess the contribution of skill-biased structural change to the rise of the skill premium in the US and a set of ten other advanced economies, over the period 1977 to 2005. For the US we find that these compositional changes in demand account for 20-27% of the overall increase of the skill premium due to technical change.

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1 Introduction

The dramatic increase in the wages of high skilled workers relative to low skilled workers is one of the most prominent secular trends in the US and other advanced economies in recent decades. Isolating the underlying causes of this trend is important for projecting future trends and evaluating the extent to which policies might be effective or advisable. The literature has consistently concluded that skill-biased technological change (SBTC) is a quantitatively important driver of the increase in the relative demand for high skilled workers.[1] In this paper we argue that a distinct process – which we label skill-biased *structural* change – has also played a quantitatively important role. We use the term skill-biased structural change to describe the *systematic* reallocation of sectoral value-added shares toward high-skill intensive industries that accompanies the process of continued development among advanced economies.

The economic intuition behind our finding is simple. If (as we show is indeed the case in the next section) the process of development is systematically associated with a shift in the composition of value added toward sectors that are intensive in high-skill workers, then the demand for high-skilled workers will increase, independently of whether development is driven by skill-neutral or skill-biased technical change. This channel is absent in analyses that adopt an aggregate production function, since in that case development that comes from skill-neutral technical change has no effect on the relative demand for high-skilled workers.

To assess the quantitative significance of this channel, we develop a simple general equilibrium model of structural transformation that incorporates an important role for skill and use it to study the evolution of the US economy between 1977 and 2005. In order to best highlight the shift in value added to high skill-intensive sectors, we study a two-sector model in which the two sectors are distinguished by their intensity of high-skill workers in production. We allow for sector-specific technological change, which is a (sector-specific) combination of skill-neutral and skill-biased tech-

[1]Important early contributions to the literature on the skill premium that stress skill biased technical change include Katz and Murphy (1992), Bound and Johnson (1992), Murphy and Welch (1992), Berman et al. (1994) and Berman et al. (1998). This is not to say that SBTC is the *only* factor at work, as the literature has also highlighted the effect of other factors on overall wage inequality. For example, DiNardo et al. (1996) argue that labor market institutions such as minimum wages and unionization have played an important role in shaping wage inequality overall, Feenstra and Hanson (1999) emphasize the role of offshoring, and Autor et al. (2013) emphasize the role of trade.

nical change. We show how the model can be used to infer preference parameters and the process for technical change using data on the change in the composition of employment by skill, the change in aggregate output, changes in sectoral factor shares, the skill premium, relative sectoral prices and the distribution of sectoral value added.

In the data, our measure of the skill premium increases from 1.41 to 1.90 between 1977 and 2005, an increase of 49 percentage points. Our calibrated model perfectly matches this increase. We then use the model to decompose this increase into three different components: one part due to the changes in the relative supply of high-skill workers, one part due to skill-biased technical change, and a third part due to other technological changes. If there had been no change in technology, our model predicts that the increase in the relative supply of high-skill workers would have lowered the skill premium to 0.88, a drop of 53 percentage points. It follows that overall changes in technology created an increase in the skill premium of 102 percentage points. In our benchmark specification, between 20 and 27 percent of this increase comes from changes in technology other than skill-biased technical change, operating through their effect on the composition of value added. We conclude that systematic changes in the composition of value added associated with the process of development are an important factor in accounting for the rise in the skill premium. In fact, if skill-biased technical change had been the sole source of technical change over this period, our model predicts that the skill premium would have increased by only 22 percentage points instead of by 49.

Having established the importance of this effect for the US, we repeat the analysis for a set of ten other OECD countries. While there is some variation in the contribution of compositional changes in value added to changes in the skill premium across countries, ranging from around 15 percent to slightly less than 50 percent, the average for this sample is 25 percent, very much in line with our estimates for the US.

Our paper is related to many others in two large and distinct literatures, one on SBTC and the skill premium and the other on structural transformation. Important early contributions to the literature on the skill premium include Katz and Murphy (1992), Bound and Johnson (1992), Murphy and Welch (1992), Berman et al. (1994) and Berman et al. (1998). Given that the increase in the skill premium occurred in the face of a large increase in the supply of high skill workers, all of these papers sought to identify factors that would increase the relative demand for high-skilled workers. In addition to skill-biased technological change, each of them noted compositional changes in demand as a potentially important element of the increased relative demand for skill. Relative to them, our contribution is fourfold. First, we document the importance of compositional effects that are *systematically* related to the process of development. Second, we show how to uncover the different dimensions of technological change in a multi-sector framework. Third, we present a general equilibrium model in which one can assess the driving forces behind compositional changes. Fourth, and perhaps most importantly, our structural approach finds a much larger role for structural change.

An early contribution in the second literature is Baumol (1967), with more recent contributions by Kongsamut et al. (2001) and Ngai and Pissarides (2007). (See Herrendorf et al. (2014) for a recent overview.) Relative to this literature our main contribution is to introduce heterogeneity in worker skill levels into the analysis and to organize industries by skill intensity rather than broad sectors.

Caselli and Coleman (2001) is an early paper linking structural transformation and human capital. Differently than us, they focus on the movement of resources out of agriculture and into non-agriculture, and assume that the non-agricultural sector uses only skilled labor. The paper that we are most closely related to is Buera and Kaboski (2012). Like us, they study the interaction between development and the demand for skill, though their primary contribution is conceptual, building a somewhat abstract model to illustrate the mechanism. Relative to them our main contribution is to build a simple model that can easily be connected to the data and to use the model to quantitatively assess the mechanism. Leonardi (2015) considers a similar mechanism to us, but focuses on how demand varies by education attainment as opposed to income more broadly, and finds relatively small demand effects.[2]

Our model structure is broadly similar to that of Acemoglu and Guerrieri (2008). Like us, they study the relationship between development and structural change in a model that features heterogeneity in factor intensities across sectors. But differently than us, they focus on differential intensities for physical capital and the role of the relative price of physical capital rather than human capital. Their work is also primarily theoretical. Cravino and Sotelo (2018) use a framework similar to ours to show how reductions in trade costs affect demand composition and the demand for

[2] Ngai and Petrongolo (2014) use a similar framework to show that compositional changes in value added associated with development can explain part of the decrease in the gender wage gap that has occured in the US over time.

skill. Cerina et al (2018) Cerina et al. (2018) is a recent paper that incorporates skill biased technical change into a model of structural change. Their focus is on labor market polarization and the role of gender differences.

An outline of the paper follows. Section 2 presents aggregate evidence on the relation between development and the value added share for high skill intensive services in a panel of advanced economies, in addition to some other important empirical patterns. Section 3 presents our general equilibrium model and characterizes the equilibrium. Section 4 shows how the model can be used to account for the evolution of the US economy over the period 1977 to 2005, and in particular how the data can be used to infer preference parameters and the process of technical change. Section 5 presents our main results about the contribution of various factors to the evolution of the skill premium. Section 6 assesses the contribution of skill-biased structural change for relative prices, and in Section 7 we extend our analysis to a set of nine other countries. Section 8 concludes.

2 Empirical Motivation

This section documents the prominence of what we refer to as skill-biased structural change, as well as some of its salient features. In particular, using data for a broad panel of advanced economies, we document two key facts. First, there is a strong positive correlation between the level of development in an economy, as measured by GDP per capita, and the share of value added that is attributed to high skill services. Second, there is also a strong positive correlation between the level of development and the price of high skill services relative to other goods and services. Interestingly, these relationships are very stable across countries, and in particular, the experience of the US is very similar to the average pattern found in the data.

We supplement the above aggregate time series evidence for a panel of countries with some evidence about cross-sectional expenditure shares in the US economy. In particular, we show that the expenditure of higher income households contains a higher share of high skill intensive value-added. This fact will serve two purposes. First, it is suggestive evidence for a non-homotheticity in the demand for high skill services, which is a feature we will include in our model. Second, this cross-sectional moment provides important information about preference parameters that is not readily available from aggregate time series data.

2.1 Aggregate Panel Evidence

The starting point for our analysis is the earlier work of Buera and Kaboski (2012). They divide industries in the service sector into two mutually exclusive groups: a high skill-intensive group and a low skill-intensive group, and show that whereas the value-added share of the high skill-intensive group rose substantially between 1950 and 2000, the value added share of the low skill intensive group actually fell over the same time period. This finding suggests that the traditional breakdown of economic activity in the structural transformation literature, into agriculture, manufacturing and services, is perhaps not well suited to studying the reallocation of economic activity in today's advanced economies. Here we pursue this line of work further, modifying their aggregation procedure to include goods-producing industries, and extending their analysis to a broad panel of advanced economies.

The analysis uses data on value-added and labor compensation. The value-added data come from the EUKLEMS Database ("Basic Table").[3] These data exist in comparable form for a panel of countries over the years 1970-2005. Our focus is on advanced economies' growth experience in the services sector, so following Buera and Kaboski (2012), we focus on the 15 countries with income per capita of at least 9200 Gheary-Khamis 1990 international dollars at the beginning of the panel in 1970.[4] The sectoral value-added data are available at roughly the 1 to 2-digit industry level. We focus on a two-way split of industries into high skill intensive and low skill intensive based on the share of labor income paid to high-skill workers.[5] While one could consider more detailed splits, including more than two skill categories and perhaps interacting skill intensity with goods vs. services, this two-way split both facilitates exposition and allows us to focus on a robust pattern in the cross-country data.

Labor compensation data come from the EUKLEMS Labour Input Data. We define high skill-intensive service sectors as: "Education", "Health and Social Work", "Renting of Machinery and Equipment and Other Business Activities", and "Financial Intermediation". In 1970, the economy-wide average share of labor compensation paid to high-skill workers in the U.S. was 20 percent; the corresponding shares for these

[3]See O'Mahony and Timmer (2009).

[4]These countries are Australia, Austria, Belgium, Canada, Denmark, France, Germany, Ireland, Italy, Japan, the Netherlands, Spain, Sweden, the United Kingdom, and the United States. We exclude Luxembourg given its small size. The U.S. data for value-added go back to only 1977, while the Japan data go back to only 1973.

[5]High-skill is defined as a college graduate and above.

high skill-intensive industries were 76, 32, 72, and 28 percent, respectively. These industries remain well above average throughout the time period.[6] Finally, we demean both the value-added share data and the (log) GDP per capita data by taking out country fixed effects.

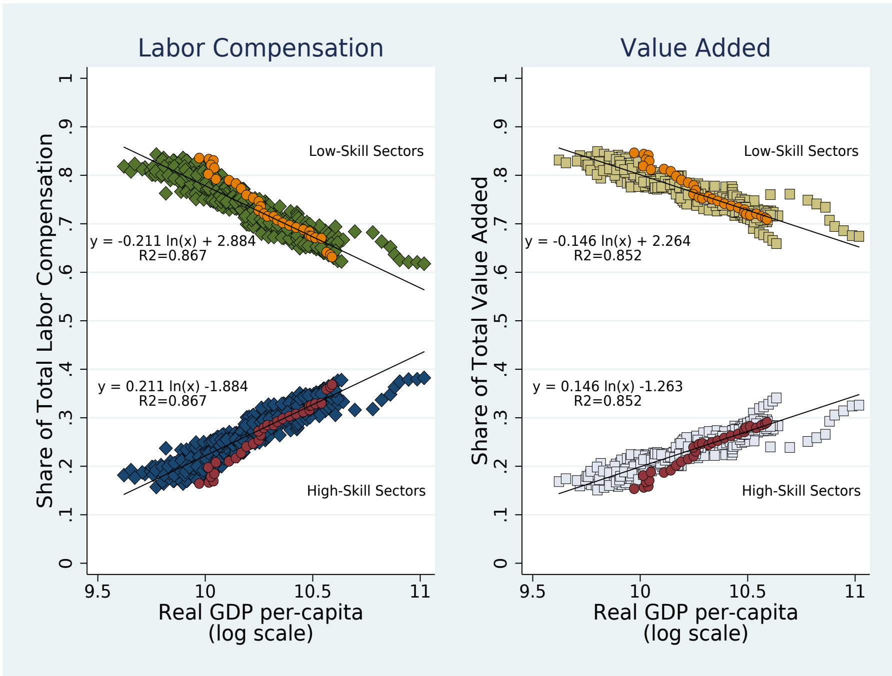

Figure 1: Structural Change by Skill-intensity and Economic Development.

Figure 1 shows the relationship between development, as proxied by real GDP per capita and the rise of the high skill service sector. Real (chain-weighted) GDP per capita data is from the Penn World Tables 9.0. We use two different measures for the size of the high skill service sector: the share of total labor compensation accounted for by this sector, and the share of total value added accounted for by this sector. Labor compensation is more relevant from the perspective of labor demand, but value added is the more typical metric for theories of structural change. The left panel of Figure 1 shows the relationship using labor compensation, while the right panel shows the relationship using value added. The small squares show the relationship for countries other than the US, and the larger circles represent data for

[6]The next highest industries are a mix of goods and service producing industries: "Chemicals and Chemical Products" (27 percent), "Public Admininistration and Defense " (23 percent) "Real Estate " (23 percent), "Coke, Refined Petroleum, and Nuclear Fuel" (21 percent), and "Electrical and Optical Equipment" (20 percent).

the US.

Both panels lead to the same conclusion: the relative size of the high skill service sector increases with log GDP/capita, with highly significant (at a 0.1 percent levels) semi-elasticities of 0.22 and 0.15 respectively. The regression line implies an increase of roughly 30 percentage points of labor compensation and 21 percentage points of value added, as we move from a GDP per capita of $10,000$ to $40,000$ (in 2005 PPP terms). Per capita income alone explains 87 percent of the variation in the labor compensation share data, and 81 percent of the value added share variation. Moreover, we see that the relationship found in the US data is quite similar to the overall relationship. Indeed, the tight relationship suggests that from the perspective of time series changes, cross-country differences in the details for funding of education or health, for example, are second order relative to the income per capita relationship in terms of their effects. (Recall that we have removed country fixed effects in Figure 1.) In sum, the tendency for economic activity to move toward high skill-intensive services as an economy develops is a robust pattern in the cross-country data.

One common explanation for structural change is changes in relative prices (see, for example, Baumol, 1967; Ngai and Pissarides, 2007). Using value-added price indices from the EUKLEMS Database, we can examine the correlation between changes in the relative price of the high-skill service sector and the changes in its value added share that accompanies the process of development.[7] Figure 2 is analogous to Figure 1, but plots the value added price index of the high skill service sector relative to the low-skill intensive sector. We have again taken out country fixed effects, and normalized the relative price indices to 100 in 1995. As before, the larger circles represent the U.S. data.

Figure 2 reveals a strong positive relationship between the relative price of high skill services and development. The linear regression is highly significant, explains 74 percent of the variation in the demeaned data, and is quantitatively important: the relative price of the high skill service sector almost doubles over the range of the data. In this case the relationship in the US data is a bit stronger than in the overall data set, but the strong relationship exists even abstracting from the US. We conclude that changes in relative prices are another robust feature of the structural transformation

[7] We construct sector-level aggregate indices as chain-weighted Fisher price indices of the price indices for individual industries. Calculation details are available in the online data appendix, `http://www3.nd.edu/~jkaboski/SBSC_DataAppendix.zip`.

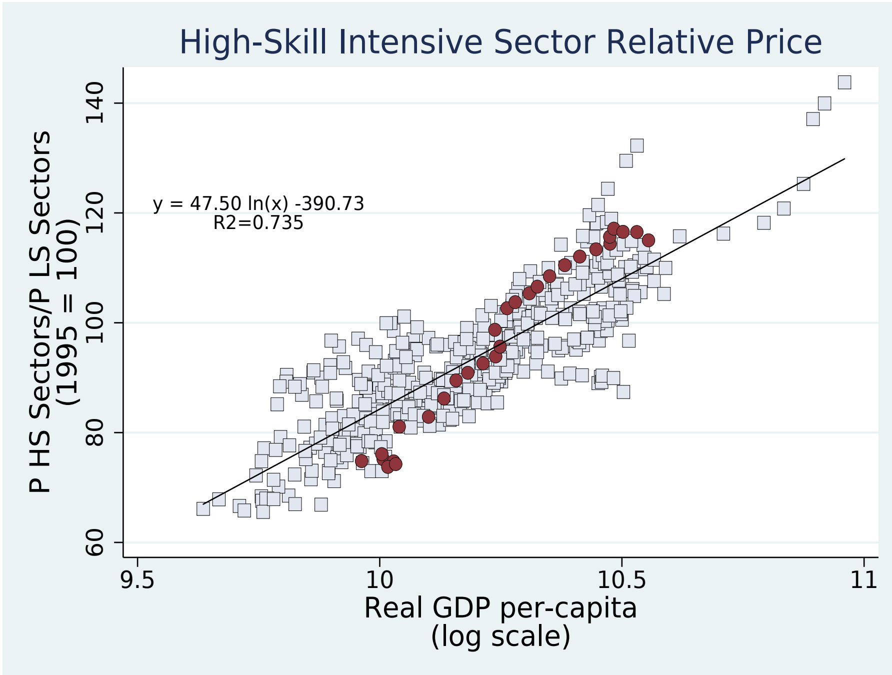

Figure 2: Relative Price of Skill-intensive Sector and Economic Development.

process involving the movement of activity toward the high-skill intensive sector.

2.2 Income Effects: Cross-Sectional Household Evidence

A second common explanation for structural change is income effects associated with non-homothetic preferences (see, for example, Kongsamut et al., 2001). With this in mind it is of interest to ask whether high-skill intensive services are a luxury good, i.e., have an income elasticity that exceeds one. To pursue this we examine the relationship between the skill intensity of value-added consumption and income in the Consumer Expenditure Survey (CEX), a cross-section data set of household expenditure. To the extent that all households face the same prices at a given point in time and have common preferences (or at least preferences that are not directly correlated with income), the cross-sectional expenditure patterns within a country abstract from the relative price relationship in Figure 2 and allow us to focus on the effect of income holding prices constant.

One complication with pursuing this approach is that it involves mapping household expenditure data through the input-output system in order to determine the consumption shares of value added. We briefly sketch the steps of this procedure here, and provide more details in the online appendix. We start with the household level CEX data for the United States from 2012. We adapt a Bureau of Labor Statistics mapping from disaggregated CEX categories to 76 NIPA Personal Consumption Expenditure (PCE) categories and then utilize a Bureau of Economic Analysis (BEA) mapping of these 76 PCE categories to 69 input-output industries that properly attributes the components going to distribution margins (disaggregated transportation, retail, and wholesale categories). Using the 2012 BEA input-output matrices, we can then infer the quantity of value added of each industry embodied in the CEX expenditures. We classify the 69 industries as high skill intensive or low skill intensive using the EUKLEMS data as previously noted.[8]

This procedure generates household-level data for the share of total expenditure that represents valued added by high skill intensive sectors and low skill intensive sectors, which we can regress on household observables, most importantly income or education, and potentially a host of other household level controls. In our empirical work we restrict ourselves to the primary interview sample, and each observation is a household-quarter observation.

Table 1 presents results for regressions of the total share of expenditures that is high skill intensive. The first column presents results from an OLS regression on log after tax income and a set of demographic controls, including age, age squared, dummies for sex, race, state, urban, and month, and values capturing household composition (number of boys aged 2-16, number of girls aged 2-16, number of men over 16, number of women over 16 years, and number of children less than 2 years). The coefficient on log income in the first column indicates that the semi-elasticity of the share of value-added embodied in expenditures is 0.010. The second column replaces log income with the log of total expenditures, and finds a larger semi-elasticity of 0.030.[9]

Both income and expenditure are certainly mismeasured in the micro data, and even if properly measured, income would only proxy for permanent income, leading

[8] The classification of real estate has a substantial impact on these results. We classify it as low skill intensive, while the related industries of finance and insurance are high skill intensive. In general, real estate has very little labor compensation in its value-added, so this categorization not only fits our criterion but is also conservative because the income effects are much weaker using this classification.

[9] The larger coefficient for expenditures may be driven by certain lumpy expenditures like higher educational expenses and car purchases driving both up in particular months. We nonetheless report these coefficients for the sake of completeness.

Table 1
Household High-Skill Intensive Expenditure Share vs. Income or Total Expenditures

	OLS	OLS	IV	IV	OLS
Ln Income	0.010***	.	0.029***	.	.
SE	0.000	.	0.001	.	.
Ln Expenditures	.	0.030	.	0.045***	.
SE	.	0.001	.	0.002	.
High Skill Head	.	.	.	.	0.023***
SE	.	.	.	.	0.002
R^2	0.11	.	0.05	.	0.12
Observations	24,213	27,318	24,213	27,318	8,883

[1] *** indicate significance at the 1 percent level.; [2] Controls include: age; age squared; dummies for sex, race, state, urban, and month; number of boys (2-16 year); number of girls (2-16 years); number of men (over 16 years); number of women (over 16 years);and number of infants (less than 2 years). High skilled is defined as 16 years of schooling attained, while low skilled is defined as 12 years attained.

to a likely attenuation bias. The third and fourth columns attempt to alleviate this measurement error by instrumenting for log income or log expenditures, respectively, using the years of schooling attained by the head of household. Instrumenting for income in this fashion increases the coefficient roughly three-fold to 0.029. Likewise, instrumenting for log total expenditures increases the coefficient by about 50 percent to 0.045.

The last column uses education as a direct regressor, replacing log income or log expenditures with a dummy for whether the head of household is high skilled or not. Here high skill is defined as having exactly 16 years of education, while low skill is defined as having exactly 12 years. (The rest of the households are dropped, leading to the smaller sample size.) The coefficient indicates that the share of value-added embodied in expenditures is 2.3 percentage points higher in households with a high-skilled head.

We have examined the robustness of the results in Table 1 along various dimensions. Table 1 uses “quarterly” expenditures of the household across the three months they are surveyed, but if we use the monthly data directly, we find nearly identical results. By defining high skill as those with at least 16 years of education, and low skill as those with less than 16 years of education, we expand the sample somewhat, but the raw estimates are similar (0.032 rather than 0.023). Dropping demographic controls increases the sample by about 15 percent and lowers the coefficients on income by roughly 25 percent and the coefficient on expenditures by roughly one-third, but the coefficients remain highly significant. Dropping the controls has essentially no impact on the high-skilled head of household coefficient. The main effect of dropping the controls is substantially lower R^2 values.

Quantitatively, even the larger, instrumented, expenditure coefficient of 0.045 is substantially smaller than the aggregate time series value of 0.17 for value-added in Figure 1, but not negligible in comparison. We therefore take this as suggestive evidence that, in addition to relative prices, non-homotheticities may also play a role in accounting for the observed pattern of skill-biased structural change.

Lastly, we note an important limitation in directly applying the micro elasticity as an income effect. Because the CEX captures only out-of-pocket expenditures, it underestimates the true consumption of certain goods like insurance premiums (a substantial share of which is paid by employers) and higher education (a substantial share of which is paid by government).[10]

2.3 Summary

In summary, we have documented a robust relationship in the time series data for advanced economies regarding the movement of activity into high-skill services and the process of development. We refer to this process as skill-biased structural change, so as to emphasize both its connection to the traditional characterization of structural change and the special role of skill intensity. This relationship is remarkably stable across advanced economies, thus suggesting that it is explained by some economic forces that are robustly associated with development, with country specific tax and financing systems not playing a central role in explaining the time series changes.

In documenting this relationship we have used a two-way split into high and low skill intensive sectors. This masks important within sector heterogeneity. Indeed, within the low skill intensive sector, a pattern emerges that the relatively more skill intensive sectors within this category, e.g., manufacturing industries like electrical equipment and chemicals, expand relative to the less skill intensive sectors like agri-

[10]The estimated income semi-elasticity of the share of out-of-pocket insurance is actually significantly negative in the CEX data although overall insurance consumption is certainly positive. Similarly, although the expenditure share-income semi-elasticity of higher education is positive, it is likely understated. Finally, the lack of primary and tertiary expenditures may actually be overstated in the CEX data because it neglects public expenditures, but we conjecture that this relationship is small relative to the higher education relationship.

culture or textiles.[11] In principle, our simple dichotomy may understate the true extent of skill-biased structural change.[12] However, the relative price patterns, use patterns (consumption and investment), and trade patterns make the analysis at a more disaggregated level more difficult to interpret and much less directly tied to traditional structural change forces.

The traditional structural transformation literature emphasizes the role of both non-homotheticities and relative price changes as drivers of structural change, and we have also presented evidence that both of these effects seem relevant in the context of skill-biased structural change as well. Specifically, we documented a strong positive correlation between the relative price of high skill services and GDP per capita in a cross-country panel as well as a positive correlation between household value added expenditure shares on high skill services and income in the US cross-section. These relationships are not only highly statistically significant, but they are also economically significant in a quantitative sense.

3 Model and Equilibrium

Our analysis emphasizes how intratemporal equilibrium allocations are affected by changes in the economic environment that operate through changes in income and relative prices. To capture these interactions in the simplest possible setting, we adopt a static closed economy model with labor as the only factor of production.[13] Our model is essentially a two-sector version of a standard structural transformation model extended to allow for two labor inputs that are distinguished by skill. In this section, we describe the economy and its equilibrium at a point in time; later we describe the features that we will allow to change over time to generate skill-biased structural change as described in the previous section.

[11] Katz and Murphy (1992) give a detailed analysis across 150 2-digit industry-occupation cells for the period, 1963-1987. Autor and Dorn (2013) present a recent account focusing on detailed occupation categories.

[12] Our own empirical analysis summarized in Section 5.4 did not find that aggregation was quantitatively important, however.

[13] We later carry out an exercise to assess how changes in net trade flows by sector affect our key findings.

3.1 Model

There is a unit measure of households. A fraction f_L are low-skill, and a fraction f_H are high skill, where $f_L + f_H = 1$. All households have identical preferences defined over two commodities. In our empirical analysis these two commodities will be connected to the low and high skill intensive aggregates studied in the previous section. As a practical matter, all of our high skill intensive sectors are services and all goods sectors are in the low skill intensive sector. It is notationally convenient to label the two commodities as goods and services even though what we label as goods includes low-skill services.

We assume preferences take the form:

$$U_i = a_G c_{Gi}^{\frac{\varepsilon-1}{\varepsilon}} + (1 - a_G)\left(c_{Si} + \bar{c}_S\right)^{\frac{\varepsilon-1}{\varepsilon}}$$

where c_{Gi} and c_{Si} are consumption of goods and services by an individual of skill level i, $0 < a_G < 1$, $\bar{c}_S \geq 0$ and $\varepsilon > 0$. Note that if $\bar{c}_S > 0$, preferences are non-homothetic and, holding prices constant, the expenditure share on services will be increasing in income.[14] This non-homotheticity is motivated by the cross-sectional analysis in the previous section. Note that households are assumed to not value leisure, since our focus will be on the relative prices of labor given observed supplies.

Each of the two production sectors has a constant returns to scale production function that uses low- and high-skilled labor as inputs. We assume that each of these production functions is CES:

$$Y_j = A_j \left[\alpha_j H_j^{\frac{\rho-1}{\rho}} + (1 - \alpha_j)\, L_j^{\frac{\rho-1}{\rho}}\right]^{\frac{\rho}{\rho-1}} \quad j = G, S$$

where L_j and H_j are inputs of low- and high-skilled labor in sector j, respectively. The parameter α_j will dictate the importance of low- versus high-skilled labor in each sector. While one could imagine that the elasticity of substitution between these two

[14] This is a simple and common way to create differential income effects across the two consumption categories. One can also generate non-homothetic demands in other ways. For example, Hall and Jones (2007) generate an income elasticity for medical spending that exceeds unity through the implied demand for longevity. Boppart (2014), Swiecki (2014) and Comin et al. (2015) all consider more general preferences with the common feature being that income effects associated with non-homotheticities do not vanish asymptotically. This property is likely to be relevant when considering a sample with countries at very different stages of development. Because we focus on a sample of predominantly rich countries, we have chosen to work with the simpler preference structure in order to facilitate transparency of the economic forces at work.

factors also differs across sectors, our benchmark specification will assume that this value is the same for both sectors. We consider the effects of cross-sectional variation in this parameter in our sensitivity analysis.

Before proceeding to analyze the equilibrium for our model we want to comment on the significance of abstracting from capital and trade. By excluding capital we implicitly adopt a somewhat reduced form view of skill-biased technological change. For example, changes in relative demand for skilled labor due to capital-skill complementarity and changes in the price of equipment (as in (Krusell et al., 2000), for example), will show up in our model as skill-biased technological change. While it is obviously of interest to understand the underlying mechanics of skill-biased technological change, for our purposes we believe our results are strengthened by adopting a more expansive notion of skill-biased technological change rather than focusing on a specific mechanism.

Although we abstract from trade in our benchmark analysis, we view our analysis as complementary to those that emphasize the potential role of trade in shaping the evolution of the skill premium. In particular, our analysis focuses on the extent to which compositional changes between goods and high-skill services diminish the role of skill-biased technological change in accounting for changes in the skill premium. To the extent that trade is dominated by trade in goods, it could diminish the role of skill-biased technical change by potentially affecting compositions within the goods sector. That is, if the US increasingly exported high skill-intensive manufactured goods and imported low skill-intensive manufactured goods, the composition of production within the goods sector would shift, and in our analysis would be interpreted as skill-biased technological change within the goods sector. Put somewhat differently, trade may serve to generate what appears as a process of skill biased structural change within the goods sector. As trade in services have increased over time, it is also possible that trade contributes to the changing composition of US production across sectors. In Section 5.2 we carry out an exercise to assess the importance of this aspect.

3.2 Equilibrium

We focus on a competitive equilibrium for the above economy. The competitive equilibrium will feature four markets: two factor markets (low- and high-skilled labor) and two output markets (goods and services), with prices denoted as w_L, w_H, p_G and p_S. We will later normalize the price of low-skilled labor to unity so that the price of high-skilled labor will also represent the skill premium.

The definition of competitive equilibrium for this model is completely standard and straightforward, so here we focus on characterizing the equilibrium. Individuals of skill $i = L, H$ solve

$$\max_{c_{Gi}, c_{Si}} a_G c_{Gi}^{\frac{\varepsilon-1}{\varepsilon}} + (1 - a_G)\left(c_{Si} + \bar{c}_S\right)^{\frac{\varepsilon-1}{\varepsilon}}$$

subject to

$$p_G c_{Gi} + p_S c_{Si} = w_i. \tag{1}$$

Using the first order conditions of this problem and normalizing w_L to unity, the aggregate expenditure share for services is:

$$\frac{p_S\left[(1-f_H)c_{SL} + f_H c_{SH}\right]}{1 - f_H + f_H w_H} = \frac{1}{\left(\frac{1-a_G}{a_G}\right)^{\varepsilon} + \left(\frac{p_G}{p_S}\right)^{1-\epsilon}} \left[\left(\frac{1-a_G}{a_G}\right)^{\varepsilon} - \frac{p_S \bar{c}_S \left(\frac{p_G}{p_S}\right)^{1-\epsilon}}{1 - f_H + f_H w_H}\right]. \tag{2}$$

This expression serves to illustrate the two forces driving structural change in the model: relative prices and income effects. Provided that $\epsilon < 1$, as p_G/p_S declines, the expenditure share of services increases. And, provided that $\bar{c}_S > 0$, an increase in income measured in units of services, (i.e., $(1 - f_H + f_H w_H)/p_S$) also leads to an increase in the expenditure share of services.

The problem of the firm in sector $j = G, S$ is

$$\max_{H_j, L_j} \; p_j A_j \left[\alpha_j H_j^{\frac{\rho-1}{\rho}} + (1 - \alpha_j) L_j^{\frac{\rho-1}{\rho}}\right]^{\frac{\rho}{\rho-1}} - w_H H_j - L_j.$$

Cost minimization plus the requirement that profits be zero in a competitive equilibrium for a firm with a constant returns to scale production function imply anequation for the price of sector j output in terms of the skill premium w_H :

$$\hat{p}_j\left(w_H\right) = \frac{1}{A_j}\left[\frac{\alpha_j^\rho}{w_H^{\rho-1}} + (1-\alpha_j)^\rho\right]^{\frac{1}{1-\rho}}. \tag{3}$$

The above expression implies that the search for equilibrium prices can be reduced to a single dimension: if we know the equilibrium wage rate for high-skilled labor then all of the remaining prices can be determined.

Finally, we derive an expression for the market-clearing condition for high-skilled labor that contains the single price w_H. Using $H_j/L_j = \left(\frac{\alpha_j}{1-\alpha_j}\frac{1}{w_H}\right)^\rho$, the production function of sector j, and (3), we obtain a sector-specific demand function for high-skilled labor:

$$H_j = \left[\frac{\alpha_j \hat{p}_j(w_H) A_j}{w_H}\right]^\rho \frac{Y_j}{A_j}, \tag{4}$$

which, together with equilibrium in the goods market, yields the market-clearing condition for high-skilled labor solely as a function of w_H:

$$\begin{aligned} &\left[\frac{\alpha_S \hat{p}_S(w_H) A_S}{w_H}\right]^\rho \frac{\sum_{i=L,H} f_i \hat{c}_{Si}\left(w_H\right)}{A_S} \\ +&\left[\frac{\alpha_G \hat{p}_G(w_H) A_G}{w_H}\right]^\rho \frac{\sum_{i=L,H} f_i \hat{c}_{Gi}\left(w_H\right)}{A_G} = f_H. \end{aligned} \tag{5}$$

Here we have used $\hat{c}_{ji}(w_H)$ to denote the demand for output of sector j by a household of skill level i when the high-skilled wage is w_H and prices are given by the functions $\hat{p}_i(w_H)$ defined in (3).

4 Accounting for Growth and Structural Transformation

In this section we calibrate the model of the previous section so as to be consistent with observations on structural transformation, growth, and the skill premium under the assumption that the driving forces are changes in technology (both skill-biased and skill-neutral) and changes in the relative supply of skill.[15] In particular, we will

[15] To the extent that factors such as changes in the minimum wage and unionization affect the skill premium, our analysis will identify them as changes in skill biased technical change. Our estimate of the contribution of skill biased technical change should be understood as including the effects of

use the above model to account for observed outcomes at two different points in time, that we denote as 0 and T for the initial and terminal periods respectively. Consistent with the existing literature on technological change and the skill premium, we do not allow the parameter ρ to change over time. We also assume that preferences are constant over time.

4.1 Targets for Calibration

Calibrating the model in the initial and terminal period requires assigning values for 14 parameters. Nine of these are technology parameters: 4 values of the α_j (two in each period), 4 values of the A_j (two in each period), and ρ. Three are preference parameters: ε, a_G and $\bar{c}_S$. Lastly we have the value of f_H at the initial and terminal dates. The two initial values of the A_j represent a choice of units, reducing the overall number of parameters to be set to twelve. In our benchmark specification we will set the two elasticity parameters ρ and ε based on existing estimates, further reducing this number to ten.

As described below, we will directly measure the initial and final values of f_H from the data. To calibrate the remaining parameters we will target the following values which reflect the salient features of growth, structural transformation and demand for skill: the initial and final values for factor shares in both sectors, the initial and final value added shares for the two sectors, the initial and final value of the skill premium, the change in the relative price of the two sectors, and the overall growth rate of the economy.

In choosing values for these targets we rely on the EUKLEMS data from Section 2. For the U.S., complete data are available for the years 1977 to 2005, so we choose these two years as our initial and terminal year respectively.[16] This period is of interest, since 1977 effectively marks a local minimum in the skill premium (see Acemoglu and Autor, 2011, for earlier data), and it secularly increases after 1977.

Many of the values for targets have direct counterparts in the data and so require no discussion, but the construction of targets for the labor variables does merit some discussion. The data contain total compensation and total hours by industry, skill

these other factors.

[16]BEA data on value added and prices are also available for the period 1977-2007 and line up quite closely with the KLEMS data. The BEA data does not allow consistent aggregation prior to 1977. Data on labor compensation and hours are only available through 2005, which is why we choose 2005 as our terminal date.

level ("low", "medium", and "high", which are effectively, less than secondary completion, secondary completion but less than tertiary completion, and four year college degree or more), gender, and age groupings (15-29, 30-49, and 50 and over). Consistent with our calculations in Section 2, we combine the compensation of EUKLEMS categories of "low" and "medium" educated workers of all genders and ages into our classification of low-skilled, and "high" educated workers into our classification of high-skilled, in order to calculate labor income shares by skill at both the aggregate and sectoral level. We use the same sectoral classification as in Section 2.

Setting targets for the skill premium and the relative supply of skilled workers requires that we decompose factor payments into price and quantity components. If all workers within each skill type were identical then we could simply use total hours as our measure of quantity, but given the large differences in hourly wage rates among subgroups in each skill type this seems ill-advised. Instead, we assume that each subgroup within a skill type offers a different amount of efficiency units per hour of work. We normalize efficiency units within each skill type by assuming one hour supplied by a high school-educated ("medium") prime-aged (i.e., aged 30-49) male is equal to one efficiency unit of low skill labor and that one hour supplied by a college-educated ("high") prime-aged (i.e., aged 30-49) male is equal to one efficiency unit of high skill labor.[17] With this choice of units, the skill premium is defined as the ratio of college-educated ("high") to high school-educated ("medium") prime-aged (i.e., aged 30-49) male wages. This premium rises from 1.41 in 1977 to 1.90 in 2005.[18]

Finally, we infer f_H using the identity that the ratio of labor compensation equals the product of the skill premium and the relative quantity of high- to low-skilled labor (f_H and $f_L = 1 - f_H$, respectively). Equivalently, one could compute efficiency units of each skill type by using relative wages within each skill group to infer efficiency units and directly aggregating efficiency units. Note that our implicit assumption is that differences in wages between different low-skilled (high-skilled) demographic

[17]While one could obviously normalize units by choosing other reference groups, this group seems most natural since its uniformly high rate of participation over time minimizes issues associated with selection.

[18]Comparing earnings of full time workers using CPS data, Figure 1 in Acemoglu and Autor (2011) indicates values of 1.48 and 1.89 for 1977 and 2005 respectively. Our measure indicates a nine percentage point greater increase. This difference basically reflects the fact that whereas they compare workers with 16 years of education to workers with 12 years of education, our groups are somewhat broader. If we redo their analysis with CPS data but using our broader categories we find a 49 percentage point increase in the skill premium, consistent with our measured increase using EU KLEMS data.

groups reflect differences in efficiency units of low-skilled (high-skilled) labor. This procedure implies that high skill labor was 19% of total labor supply in 1977 and rose to 31% in 2005.

Table 2 summarizes the values used for the targets listed above.

Table 2

Values Used to Calibrate Technology Parameters

f_{H0}	f_{HT}	w_{H0}	w_{HT}	$\%\Delta\frac{p_S}{p_G}$	$\%\Delta Y$	θ_{G0}	θ_{GT}	θ_{S0}	θ_{ST}	$\frac{C_{S0}}{Y_0}$	$\frac{C_{ST}}{Y_T}$
0.19	0.31	1.41	1.90	58.9	80.8	0.18	0.35	0.54	0.66	0.19	0.32

4.2 The Calibration Procedure

Having described the targets to be used in the calibration and the data used to determine the values of these targets, we now describe the details of the mapping from targets to parameters. We proceed in two steps. The first step shows how the technology parameters are inferred. In the second step, we describe how to infer values for the preference parameters.

We begin with the determination of technological change. First, we show that given a value for ρ, the four values of the α_{jt} are pinned down by sectoral factor income shares and the skill premium, w_{Ht}. To see this, from equations (3) and (4) note that the share of sector j income going to high skill labor, $\theta_{Hjt} = \frac{w_{Ht}H_{jt}}{\hat{p}_j(w_{Ht})Y_{jt}}$, is

$$\theta_{Hjt} = \frac{\alpha_{jt}^{\rho}}{\alpha_{jt}^{\rho} + (1-\alpha_{jt})^{\rho} w_{Ht}^{\rho-1}}$$

Therefore, given ρ, the skill premium w_{Ht}, and data for θ_{Hjt}, the value of the α_{jt} are given by:

$$\alpha_{jt} = \frac{1}{1 + \frac{1}{w_{Ht}^{(\rho-1)/\rho}} \left(\frac{1-\theta_{Hjt}}{\theta_{Hjt}}\right)^{\frac{1}{\rho}}}.$$

Next we turn to determining the values of the A_{jt}'s. As noted previously, the two values in period 0 basically reflect a choice of units and so can be normalized. We will normalize A_{S0} to equal one, and given the calibrated values for the α_{j0} and the value of w_{H0}, we choose A_{G0} so as to imply $p_{G0}/p_{S0} = 1$. In this case p_{GT}/p_{ST} can be easily identified with the change in the relative sectoral prices. As is well known in the literature, with identical Cobb-Douglas sectoral technologies, relative sectoral prices are simply the inverse of relative sectoral TFPs, so the change in relative prices would therefore determine the values of the two A_{jT}'s up to a scale factor.[19] This precise result does not apply to our setting because of sectoral heterogeneity in the α_{jt}'s. (The skill premium also plays a role in determining relative prices, which we examine in Section 6.) Nonetheless, there is still a close connection between relative sectoral prices and relative sectoral TFPs (i.e., the A_{jt}). In particular, using equation (3) for the two sectors we have:

$$\frac{A_{Gt}}{A_{St}} = \frac{p_{St}}{p_{Gt}} \left[\frac{\frac{\alpha_{Gt}^{\rho}}{w_{Ht}^{\rho-1}} + (1-\alpha_{Gt})^{\rho}}{\frac{\alpha_{St}^{\rho}}{w_{Ht}^{\rho-1}} + (1-\alpha_{St})^{\rho}} \right]^{1/(1-\rho)} . \tag{6}$$

The scale factor will of course influence the overall growth rate of the economy between periods 0 and T, so we choose this scale factor to target the aggregate growth rate of output per worker.[20]

To this point, given a value for ρ, we have identified all of the technology parameters. For our benchmark analysis we set $\rho = 1.42$, which corresponds to the value used in Katz and Murphy (1992), and which is commonly used in the literature. Though this is a commonly used value in the literature, it is worth noting that previous estimates using an aggregate production function do not necessarily apply in our setting. For this reason we will also do sensitivity analysis with regard to ρ over a fairly wide interval, ranging from 0.77 to 2.50. Table 3 below shows the implied values for the technology parameters.

Table 3

Calibrated Technology Parameters ($\rho = 1.42$)

α_{G0}	α_{S0}	α_{GT}	α_{ST}	A_{ST}/A_{S0}	A_{GT}/A_{G0}
0.28	0.55	0.44	0.67	1.30	2.33

[19] This same relation holds more generally, and in particular would also apply if the sectoral production functions are CES with identical parameters.

[20] Note that to compute aggregate output at a point in time (and thus also the growth rate in aggregate output) it is necessary to know the sectoral distribution of output. The relations imposed thus far guarantee that maximum profits will be zero in each sector but do not determine the scale of operation. Intuitively, the split of activity across sectors at given prices will be determined by the relative demands of households for the two outputs. Below we will describe how preference parameters can be chosen to match the sectoral distribution of value added at both the initial and final date. At this stage we simply assume this split is the same as in the data.

A few remarks are in order. Not surprising given the way in which we grouped industries into the two sectors, the weight on low-skilled labor is greater in the goods sector than in the service sector at both dates. More interesting is that in both sectors technological change has an important component that is skill biased. While the level rise in α is greater for the goods sector than the service sector, the changes are of similar magnitude (16pp and 12pp).

However, neutral technological progress is much greater in the goods sector than in the service sector. The TFP term in the goods sector more than doubles between 1977 and 2005, corresponding to an average annual growth rate of 2.97%. In contrast, the growth of the TFP term in the service sector averages only 0.80% per year.

We now turn to the issue of determining the values for the three preference parameters: a_G, $\bar{c}_S$ and ε. While technological change can be inferred without specifying any of the preference parameters, we cannot evaluate some of the counterfactual exercises of interest without knowing how relative demands for the sectoral outputs are affected by changes in prices. As noted above, the calibration of technology parameters used information about sectoral expenditure shares without guaranteeing that observed expenditure shares were consistent with household demands given all of the prices. Requiring that the aggregate expenditure share for goods (or services) is consistent with the observed values in the data for the initial and terminal date would provide two restrictions on the three preference parameters. It follows that we would either need to introduce an additional moment from the data, or perhaps use information from some outside study to determine one of the three preference parameters. As noted earlier, for our benchmark results we will follow the second approach and fix the value of ε, and then use data on aggregate expenditure shares to pin down the values for a_G and $\bar{c}_S$. Our main finding is relatively robust to variation over a large range of values of ε, thereby lessening the need to tightly determine its value. Nonetheless, in Section 5 we will describe how cross-sectional data on expenditure shares could be used as an additional moment and allow us to determine all three preference parameters.

The empirical literature provides estimates of ε that correspond to the categories of "true" goods and "true" services, but not for our definitions of the two sectors that are based purely on skill intensity. The key distinction is that we have grouped low-skill services with goods. However, given that our goods sector does contain all of the industries that produce goods, while our service sector does consist entirely of service sector industries, it seems reasonable that information about the elasticity of substitution between the true goods and services sectors should be informative about the empirically plausible range of values for ε in our model. Recalling that the objects in our utility function reflect the value-added components of sectoral output, the relevant estimates in the literature would include Herrendorf et al. (2013), Buera and Kaboski (2009), and Swiecki (2014). All of these studies suggest very low degrees of substitutability between true goods and true services. For this reason we consider values for ε in the set $\{0.125, 0.20, 0.50\}$, with $\varepsilon = 0.20$ chosen as our benchmark.[21]

Given a value for ε, equation (2) can be used to determine values for a_G and $\bar{c}_S$ if we require that the model match the initial and final sectoral value added shares.

Table 4 shows the values for the preference parameters in the different scenarios.

Table 4
Calibrated Preference Parameters

	ε	a_G	$\bar{c}_S$
Benchmark	0.20	0.97	0.09
High ε	0.50	0.61	0.20
Low ε	0.125	0.99	0.08

The qualitative patterns in this table are intuitive. Note that in each case the changes in income, relative prices and the aggregate expenditure shares are the same. As we move from $\varepsilon = 0.20$ to $\varepsilon = 0.125$ we decrease the elasticity of substitution between the two goods, implying a smaller response in relative quantities but a larger response in relative expenditure shares. In order to compensate for this larger effect, we need to decrease the impact of income changes on relative expenditure shares, implying a lower value for $\bar{c}_S$. The lower value for $\bar{c}_S$ will in turn lead to a higher expenditure share on services in the initial period, since the non-homotheticity is now less important. Hence, in order to match the expenditure shares for the initial period we need to attach a lower weight, a_G, to consumption of goods. As we move from $\varepsilon = 0.20$ to $\varepsilon = 0.50$ we see the reverse pattern.

[21] Comin et al. (2015) redo the exercise in Herrendorf et al. (2013) for a more general class of preferences and find an elasticity of substitution that is somewhat higher, around 0.50, which is our upper range.

5 Decomposing Changes in the Skill Premium

Our model is calibrated so as to account for the observed change in the skill premium between 1977 and 2005. In this section we use the calibrated model to perform counterfactuals that allow us to attribute changes in the skill premium to the various exogenous driving forces in the model. Our primary objective is to decompose the effect of changes in technology on the skill premium into a piece due to skill biased technological change and a residual piece that is due to other forms of technological change. The residual piece affects the relative demand for skilled individuals indirectly, through its impact on the relative consumption of services.

Table 5 reports the results of our counterfactual exercises for each of the three specifications that differ with respect to the value of ε. As we will see, the key results are very similar across the three specifications, so to better focus our discussion we will concentrate on the ε=.20 case and later summarize the other cases.

Table 5

Decomposing Changes in the Skill Premium

US, 1977-2005

		$\varepsilon = 0.50$	$\varepsilon = 0.20$	$\varepsilon = 0.125$
(i)	w_{H0}	1.41	1.41	1.41
(ii)	w_{HT}	1.90	1.90	1.90
(iii)	w_{HT} – changes in f_i only	0.91	0.88	0.88
(iv)	Total Change in Demand: $((ii) - (iii))$	0.99	1.02	1.02
(v)	w_{HT} – changes in f_i and A_j only	1.10	1.09	1.09
(vi)	SBSC Share at $\alpha_{j,0}$: $\left(\frac{(v)-(iii)}{(iv)}\right)$	19%	22%	21%
(vii)	w_{HT} – changes in f_i and α_j only	1.64	1.63	1.63
(viii)	SBSC Share at $\alpha_{j,T}$: $\left(\frac{(ii)-(vii)}{(iv)}\right)$	26%	27%	27%

The first two rows of the table report the starting and ending values for the skill premium, which are the same in our model as they are in the data. The rest of the table decomposes this change into several pieces by considering several counterfactual exercises in our model. The first counterfactual assesses the role of "supply" versus "demand" factors. Specifically, the share of labor supply coming from high-skilled workers increases between 1977 and 2005, and in the absence of any other changes exerts downward pressure on the skill premium. As noted above, focusing on the $\varepsilon = .20$ case for now, Row (iii) of Table 5 shows that if the change in relative supply of skill (i.e., the f_i's) had been the only change between 1977 and 2005 the skill premium would have decreased from 1.41 to 0.88, a 53 percentage point fall. Given that we in fact observe an increase in the skill premium of 49 percentage points, it follows that the overall effect of technological change is to increase the skill premium by 102 percentage points, as shown in Row (iv).

Our next goal is to decompose the 102 percentage point increase in the skill premium due to the overall effect of technological change into one part that is due to skill biased technological change (i.e., changes in the α_{jt}'s) and a second part due to other dimensions of technical change (i.e., changes in the A_{jt}'s).

There are two natural calculations that one can perform to assess the contribution of changes in the A_{jt}'s to changes in the skill premium. In both calculations we start from the previous counterfactual in which we change only the supply of skill. In the first calculation we add in the change in the A_{jt}'s and compute the fraction of the overall 102 percentage point increase that they account for. This counterfactual keeps the α_{jt}'s at their initial value. In the second calculation we instead add in the changes in the α_{jt}'s and compute the fraction of the 102 percentage point increase that is not accounted for. That is, we calculate the contribution of skill-biased structural change at the final α_{jt}s values. In a linear model these two calculations would give the same answer, but to the extent that nonlinearities are present they may differ. It will turn out that the answers do indeed differ, with the latter being larger.

Rows (v)-(viii) in Table 5 present the results of these two calculations. Specifically, moving from row (iii) to row (v) we see that the change in the A_{jt}'s increases the skill premium from 0.88 to 1.09, an increase of 21 percentage points. This represents roughly 20 percent of the overall 102 percentage point increase accounted for all technical change, as shown in row (vi). Moving from the row (iii) to row (vii), we see that the changes in the α_{jt}'s cause the skill premium to increase from 0.88 to 1.63. The residual (row (vii) minus row (ii)) is 27 percentage points, which represents approximately 27 percent of the 102 percentage point increase due to all changes in technology, as shown in row (viii). Based on this we conclude that non-skill biased technical change accounts for between 20 and 27 percent of the overall change in the skill premium due to technical change. Put somewhat differently, according to our calibrated model, if skill biased technical change had been the only force affecting the relative demand for skill then the skill premium would have increased by only 22 percentage points instead over the period 1977 to 2005 instead of increasing by 49 percentage points.

If we redo these calculations for the other two values of ε the answers are similar. For $\varepsilon = 0.50$ the two methods imply that changes in the A_{jt}'s account for 19% and 26% of the overall change in the skill premium due to technical change, whereas for $\varepsilon = 0.125$ the two values are effectively identical to those for the $\varepsilon = 0.20$ case, being equal to 20% and 27%. From this we conclude that our finding of a significant contribution of changes in the A_{jt}'s is robust to a large variation in the value of ε.

5.1 Sources of Structural Change

In the introduction we stressed the fact that aggregate production function analyses abstract from compositional changes, and that our main objective was to assess the quantitative importance of the compositional changes that are associated with the process of structural transformation during development. The previous calculations decomposed the overall changes in the skill premium into parts due to skill-biased technological change and skill-neutral technological change. In order to make the connection between this decomposition and compositional changes it is of interest to examine the connection between technological change and changes in sectoral value added shares. Table 6 reports the results for each of the three values of ε.

Table 6
Technical Change and Value Added Share of Skill-Intensive Services
US, 1977-2005

	$\varepsilon = 0.50$	$\varepsilon = 0.20$	$\varepsilon = 0.125$
Model 1977	0.19	0.19	0.19
Model 2005	0.32	0.32	0.32
Model 2005 with fixed A_j	0.17	0.16	0.16
Model 2005 with fixed α_j	0.35	0.34	0.34

The first two rows of the table remind us that the (skill-intensive) service sector grew significantly between 1977 and 2005, increasing its share of value added from 19 percent to 32 percent. Recall that our calibrated model perfectly replicates the change in the data. The last two rows provide two different ways of assessing the role of changes in the A_j's and the α_j's in accounting for this compositional change. The third row reports the service sector value added share that would have resulted if the changes in the change in the α_{jt}'s had been the only source of technological change, whereas the fourth row reports the service sector value added share that would have resulted if the change in the A_{jt}'s had been the only source of technological change. Both calculations lead to the same conclusion: effectively all of the compositional change is accounted for by changes in the sectoral TFPs. It follows that our previous decomposition of changes in the skill premium due to the two different sources of technical change can effectively be interpreted as statements about the importance of structural change.

Non-skill biased technological change in our model still has two distinct dimensions: one which increases the overall level of TFP in the economy and the other of which increases relative TFP in the goods sector. As we noted above, both of these changes tend to reallocate activity from the goods sector to the service sector, thereby indirectly increasing the relative demand for skill. Next we examine the relative magnitude of these two effects.

Note that for given changes in the A_{jt}'s the relative magnitude of these two effects is dictated by the preference parameters ε and $\bar{c}_s$: as ε becomes smaller, relative TFP changes have larger effects, and as $\bar{c}_S$ becomes larger then sector neutral changes in the A_{jt}'s have larger effects. Because our calibration procedure implies that as ε becomes smaller the value of $\bar{c}_S$ decreases, we expect to find that sector neutral change plays a larger role for smaller values of ε.[22]

To evaluate this we consider the counterfactual in which we hold all parameters fixed from the original calibration, allow the f_{it}'s and the α_{jt}'s to change as before, but counterfactually force the A_{jt}'s to grow at the same rate, with this rate chosen so as to yield the same overall change in aggregate output as in the data. When we do this, the implied values of the skill premium are 1.83, 1.72, and 1.69 for the cases of $\varepsilon = 0.50$, 0.20, and 0.125 respectively. It follows that when $\varepsilon = 0.50$ it is income effects that dominate the overall impact of the A_{jt}'s on the skill premium, whereas for the smaller values of ε the sector biased nature of TFP growth is somewhat more important than the income effect. So while the three different specifications offer very similar decompositions regarding the overall effect of changes in the A_{jt}'s on the skill

[22]Although the exact values of $\bar{c}_S$ and ε are not important to our overall results, one might be tempted to use the measured cross-sectional relationship estimated in Table 1 to identify them. Recall, however, that we argued that this relationship is likely to have underestimated the true importance of income effects in the time series. Indeed, the contributions of relative prices are limited by the Leontieff case of $\varepsilon = 0$. Even in this case, matching the structural change facts requires too strong of an income effect, i.e., too large of a $\bar{c}_S$, to simultaneously match the measured cross-sectional relationship.

premium, they have distinct implications for the mechanics through which changes in the A_{jt} lead to changes in the skill premium.

The preceding discussion has focused on the role of technological change in bringing about changes in the composition of final demand. But one may also ask to what extent increases in the supply of skill can act as a driving force behind structural change? To assess our model's predictions for this we compute the change in the expenditure share for services that would result if the change in the relative supply of skill had been the only driving force. The result is that instead of increasing from .19 to .32, the expenditure share for services actually decreases modestly to .17. Intuitively, there are two effects at work. First, the increase in the relative supply of skill serves to decrease the skill premium and hence the relative price of services. With $\varepsilon < 1$ this leads to a decrease in the services expenditure share. Second, the changes in the skill premium and the price of services lead to a change in income measured in units of services. In our calibrated economy this change in income is positive (i.e., the decrease in the price of services dominates the effect of a decrease in the skill premium), leading to an increase in the services expenditure share. As noted above, the net quantitative effect is a modest decrease. The main message is that increases in the supply of skill do not serve to expand the size of the high skill service sector.

5.2 Allowing for Trade

Our benchmark analysis considers a closed economy and so abstracted from changes in trade as a potential driving force. As we noted earlier, to the extent that much of trade takes place within the goods producing sector, it is possible that some of the skill biased technological change that we infer reflects changes in the composition of trade within our goods sector. This alone would not affect our estimate of the contribution of skill biased structural change to the overall change in the skill premium, though by diminishing the contribution of skill biased technical change it would increase the importance of skill biased structural change relative to skill biased technical change.

More generally, lower trade costs can lead to greater specialization and hence higher productivity, so part of the productivity increases that we measure may result from trade. Our procedure aims to assess the contribution of productivity increases to the skill premium, but does not seek to understand the underlying source of the productivity increase. While we think it is of interest to assess the role of trade as a source of productivity growth, this issue is separate from the one we address. We refer the reader to the paper by Cravino and Sotelo (2018) for an analysis of the effects of lower trade costs on the skill premium in a framework similar to ours.

But not all trade takes place within the goods sector and the share of trade accounted for by trade in services is increasing over time. It is therefore possible that changes in trade patterns may also contribute to changes in the relative size of the high skill service sector. In this subsection we carry out a simple exercise to assess the potential magnitude of this effect. In particular, we will take sectoral net trade flows as given and solve for the equilibrium of our model given these flows.

Net sectoral trade flows create a wedge between production and consumption in each sector. If net exports from the high skill service sector are increasing over time, this would imply a decrease in consumption of high skill services holding labor allocations constant. Hence, this would create an incentive to increase the share of labor allocated to the high skill service sector in order to increase consumption from that sector. Similarly, if the imports of goods are increasing over time, then this would increase the relative consumption of low skill goods holding labor allocations fixed, and again create an incentive to reallocate labor to the high skill sector. It follows that part of the movement of resources to the high skill service sector could be the result of changes in trade and not necessarily technology.

To estimate net trade flows for our two sector breakdown we do the following. From the Balance of Payments Accounts we obtain data on net trade flows for the "true" goods sector and the "true" services sector in the US economy. Disaggregated net trade flows in services are obtained from the BEA that can be split into low and high skill services components using our previous definitions. We then aggregate net trade flows to correspond to our model defined sectors. Between 1977 and 2005 the US ran a trade deficit in trade in "true" goods, and the deficit increased from around 1.4 percent of GDP to around 6 percent of GDP. Over the same time period the US ran a small trade surplus in trade in "true" services, increasing from around 0.2 percent of GDP to around 0.5 percent of GDP. This trade surplus in services is to first approximation a trade surplus in high skill services, as there is a small and relatively constant trade deficit in low skill services, so that the overall change in the trade deficit in what we label the low skill sector (consisting of both goods and low skill services) is to first approximation the same as the trade deficit coming purely from goods.[23]

Taking net sectoral trade flows as given we implement the same calibration procedure as before and carry out the same counterfactuals to decompose the effects of technology. Intuitively, if net exports of the high skill service sector are increasing over time, our calibration procedure would imply a lower value of $\bar{c}_s$, since the needed income effect from changes in technology would be reduced. Accordingly, the implied amount of skill biased structural change would also be reduced.

The key message is that we find that incorporating the effect of changes in trade on our results is relatively small. In the interest of space we only report results for the case of $\varepsilon = .20$. Whereas our earlier results implied that changes in the A_{jt}'s accounted for between 20 and 27 percent of the overall change in the skill premium due to technological change, we now find that the range is between 18 and 24 percent. While the changing net sectoral trade balance does account for some of the movement of resources into the high skill service sector, we find this effect to be relatively small.

5.3 Sensitivity Exercises

For the results in the previous section we assumed that $\rho = 1.42$, which we noted was a standard value in the literature, and the value implied by the analysis in Katz and Murphy (1992). However, we also noted that the aggregate analyses that have supported this estimate are not necessarily appropriate in our multi-sector economy. For this reason we also consider a wider range of values for ρ to assess the extent to which the above conclusions are robust to variation in this parameter.

We consider two alternative values of ρ, corresponding to higher and lower elasticities of substitution. Specifically, we consider $\rho = 0.77$ and $\rho = 2.5$. In each case we redo the calibration procedure as before. While the value of ρ does affect the quantitative findings, it leaves our main message largely unchanged. For example, focusing on the case of $\varepsilon = 0.20$ we find that when $\rho = 0.77$, the share of changes in the skill premium due to technical change that are accounted for by changes in the A_{jt} is 23% and 38% from the two methods. When $\rho = 2.50$ the corresponding values are 15% and 18%. We conclude that our main finding of a significant role for changes in demand composition induced by technical change in accounting for changes in the

[23] Our net export figure for the goods sector is based on total value and is likely an overestimate of the deficit measured in terms of value added. For this reason we think our estimates for the effect of trade are likely an upper bound.

skill premium is robust to considering a wide range of values for ρ, though higher values of this elasticity parameter do lead to modest declines in the estimated role played by demand composition.

Our analysis has assumed that the value of ρ is the same in both sectors. Absent any empirical evidence on the extent of heterogeneity in ρ across sectors, this seemed a natural benchmark. However, Reshef (2013) suggests that the elasticity of substitution between high and low-skilled workers may be lower in services. It is therefore important to assess whether our results are sensitive to the assumption of ρ being constant across sectors. To do this we redo our exercise for several specifications in which we allow the two values of ρ to vary across sectors, allowing for the ratio ρ_G/ρ_S to be both larger and smaller than one. In all cases we assume that the weighted average of the two elasticities–$(H_G/H)\rho_G + (H_S/H)\rho_S$–is equal to 1.42 when evaluated at the initial factor shares, so that our analysis can be interpreted as assessing the effect of heterogeneity holding the aggregate elasticity of substitution constant. We consider values for ρ_S of 0.77, 0.91, 1.11, and 2.00, which lead to implied values for ρ_G of 2.23, 2.06, 1.82, and 0.73. Table 7 reports the same statistics as in Table 5, focusing on the case of $\varepsilon = 0.20$.

Table 7

The Effect of Sectoral Variation in ρ

US, 1977-2005

	$\frac{\rho_S}{\rho_G} = 0.35$	$\frac{\rho_S}{\rho_G} = 0.44$	$\frac{\rho_S}{\rho_G} = 0.61$	$\frac{\rho_S}{\rho_G} = 1.00$	$\frac{\rho_S}{\rho_G} = 2.73$
w_{H0}	1.41	1.41	1.41	1.41	1.41
w_{HT}	1.90	1.90	1.90	1.90	1.90
	Counterfactual w_{HT}				
changes in: f_i only	0.99	0.97	0.94	0.88	0.74
f_i and A_j only	1.11	1.11	1.10	1.09	1.08
f_i and α_j only	1.71	1.70	1.68	1.63	1.48

For ease of comparison, the fourth column repeats the results from our benchmark specification. For values of $\rho_S/\rho_G < 1$ the implications are affected very little, and to the extent that a very large value of ρ_S/ρ_G influences the quantitative results, it yields a larger role for the demand effects that we focus on (between 29% and 36%). Noting that we are considering a very wide range of variation in the relative values of ρ, we conclude that our results are quite robust to variation in ρ across sectors.

Lastly, we consider the extent to which mismeasurement of relative prices might influence our results. Our quantitative analysis utilized information about changes in the relative price of the high skill intensive sector. Between 1977 and 2005 this relative price increased by more than sixty percent. One possible concern is that price inflation in the high skill intensive sector might be upward biased because of the failure to properly account for quality improvements.

Here we report the results of a simple exercise to assess the extent to which our conclusions are affected by this possibility. In particular, consider the case in which the true increase in the relative price of the high skill intensive sector was only half as much as indicated by the official data. This means that real value added in this sector increased by roughly 30% more than indicated by the official data, and aggregate GDP grew by roughly 15 additional percentage points. We set $\rho = 1.42$ and $\varepsilon = 0.20$ and carry out the same calibration procedure as previously. Not surprisingly, given that we are holding ε fixed and decreasing the role of relative price changes, the calibration procedure yields a larger value for $\bar{c}_S$, indicating a larger role for nonhomotheticities. However, we find that the contribution of demand factors is virtually identical to what we found in our benchmark calculation. So while mismeasurement of relative price changes has implications for relative magnitudes of preference parameters, it has virtually no effect on our assessment of the role of demand factors.

5.4 Comparison with Earlier Literature

The increase in the relative demand for high-skilled labor that we attribute to structural change is substantially higher than the overall effects of relative demand shifts found in the earlier literature on the topic. For example, in the overlapping years of our samples, 1979-1987, using a shift-share analysis, Katz and Murphy (1992) (KM hereafter) attributed 4.6 percentage points of increase in relative demand for high-skilled labor to changes in industrial composition (i.e., their "between industry" analysis, see Table VIII). Given their estimated elasticity of substitution, this accounts for only 11 percent of the increase in the skill premium over their period of study. Bound and Johnson (1992) estimate a small but slightly *negative* contribution of industrial composition. In contrast, when we restrict attention to the overlapping years 1979-1987, our simulations attribute between 25 and 28 percent of the increase in the skill premium to the increase in the relative demand of high-skilled labor associated with skill-biased structural change. Why do we find an effects that are between two and three times larger than KM? This is the question that we take up in this subsection.

One obvious difference between the analysis in KM and ours is that they use shift share analysis and we carry out explicit model based counterfactuals. As we show below, this is quantitatively significant. But there are also many other differences, including different data sources (CPS versus EU KLEMS), different measures of payments to workers (wages versus compensation), different sample periods (1963-1987 versus 1977-2005), different measures of skill intensity (relative employment versus relative compensation), different measures of industry size (compensation versus value added), and different degrees of disaggregation (50 sectors versus 2 sectors).[24] Each of these could be important and our goal here is to assess which factor or factors are behind the very different conclusions.

To explore this we have carried out a sequence of exercises that change one element at a time and which cumulatively will take us from the KM shift share analysis to our model based counterfactuals. The sequence of results is presented in Table 8, with each row corresponding to one additional departure as we move from the KM results to our results. In each case the focus of our attention is on the implied percentage of the overall demand for skilled labor that is accounted for by changes in the composition of demand across sectors.

[24] In addition, Katz and Murphy use experience, while we use age, and our demographic cells are slightly different as well. These differences turn out to be of second order. These and other details are available in the online appendix.

Table 8

Comparison With Katz-Murphy (1992)

	Years	Data	Skill Intensity	# Sectors	Method	Weights	Contribution
(i)	1979-87	CPS	Hours	50	Shift-share	Wages	11%
(ii)	1979-89	IPUMS	Hours	31	Shift-share	Wages	10%
(iii)	1980-90	WK	Hours	31	Shift-share	Wages	10%
(iv)	1980-90	WK	Factor Shares	31	Shift-share	Wages	19%
(v)	1980-90	WK	Factor Shares	2	Shift-share	Wages	23%
(vi)	1977-05	WK	Factor Shares	2	Shift-share	Wages	19%
(vii)	1977-05	WK	Factor Shares	2	Model-based	Wages	$24-33\%$
(viii)	1977-05	WK	Factor Shares	2	Model-based	VA	$18-25\%$
(ix)	1977-05	EUK	Factor Shares	2	Model-based	VA	$20-27\%$

The first row of Table 8 displays the results as reported in KM for the period 1979-1987 using the CPS data and disaggregating the data into 50 different industries. A key feature of the analysis in KM is that it is based on an analysis of micro data. In contrast, the EU KLEMS data that we use only reports statistics at various levels of aggregation. The underlying micro data that serves as the source for the various aggregates reported in the EU KLEMS is IPUMS. The first departure that we consider from the KM benchmark is to redo their analysis using the IPUMS micro data rather than the CPS. Data availability forces us to also consider the period 1979-1989 instead of 1979-1987. As the Table indicates, we implement this exercise using only 31 industries. Although the IPUMS would allow us to us the same 50 industry breakdown as KM, this is not possible when we move to World KLEMS, so at this stage we adopt the finest breakdown that will be permitted in World KLEMS. Despite a few differences in details, the key message from row (ii) is that the effect of using IPUMS rather than the CPS is effectively negligible.

As we move from row (ii) to row (iii) we now switch from using a micro data set to a data set that only reports outcomes at various levels of aggregation. However, instead of moving directly to the EU KLEMS data set, in this step we move to the World KLEMS data set. IPUMS is also the underlying micro data used to construct the aggregates in World KLEMS in Census years. The reason that we move first to the World KLEMS data set rather than EU KLEMS is that the concordance between industry categories in IPUMS and World KLEMS is much stronger than between

IPUMS and EU KLEMS and we do not want to introduce an additional variation at this step. Importantly, using the aggregated data in World KLEMS yields the same result as using the micro data in IPUMS.

To this point, the key message is that we are effectively reproducing the results from KM. Moving to row (iv), however, leads to roughly a doubling of the role for changes in the composition of demand. The key change here is the method used to measure differences in skill intensity across sectors. In our analysis, we use relative wage payments by skill as a measure of skill intensity. Assuming a given wage per efficiency unit of labor of each skill type, our measure of relative skill intensity across sectors is equivalent to the relative ratio of quantities of efficiency units of the two skill types across sectors. Importantly, we allow for efficiency units to vary across workers within a given education/age/gender cell, since this is how we account for wage differences within a given cell. In contrast, KM assume that all workers within a given cell supply the same number of efficiency units and measure relative quantities of skilled and less skilled labor without using data on compensation. This turns out to have very significant implications. For example, when we later consolidate sectors to yield only two sectors, our method implies a much larger increase in the efficiency units demanded by the skill intensive sector of 8 percentage points whereas KM's method implies an increase of only 4.5 percentage points. Intuitively, demand shifts will have much larger effects if the growth of the skill intensive sector is larger, and row (iv) reflects the quantitative significance of this, as the contribution of demand shifts increases from 10 percent to 19 percent.

Row 5 decreases the level of sectoral disaggregation. Consistent with our analysis, we now carry out the shift share analysis based on a two sector decomposition. This results in a modest increase for the role of demand shifts. Apparently there are demand shifts within our two sector aggregates that serve to offset these changes. As we move to row (vI) we now change the sample period to correspond to the sample that we use in our analysis: 1977-2005. The effect of this is to shift the contribution of demand shifts back to 19 percent. Note, of course, that as we change the sample period we are changing both the numerator and denominator that goes into this calculation, since both demand shifts are different and the overall change in the demand for skill has changed. Notably, the combined effect of rows (v) and (vi) is to bring us back to the same value as shown in row (iv).

Row (vii) introduces the second important difference in our results: moving from

KM's local approximation of endogenous movement in industry to our fully solved general equilibrium evaluation of exogenous shifts in technology parameters. As KM acknowledge, their linear approximation underestimates the true contribution of demand shifts because the skill premium rose during the period of analysis. A rising skill premium disproportionately increases the price of the skill-intensive output (see our equation (8)), reducing the movement of resources into that sector relative to what would be observed with perfectly elastic labor supply (i.e., the full shift in demand).[25] Whereas they are able to analytically sign the bias, the added structure of our model enables us to actually quantify this bias. In addition, our analysis uses a global solution of the model, instead of a local approximation. Moreover, since we map industrial shifts into exogenous technology parameters, the interpretation of our effects are slightly different as well, and they depend on the exact counterfactual. We measure the impact of sectoral productivity changes as demand shifters. The impact of these changes depends on whether they happen alongside our skill-biased technical change or on their own. Moving from the local approximation to our global method attributes an increase of 24 percent to our SBSC parameters in a counterfactual world with the initial values for the skill-bias parameters α_j (which corresponds to the SBSC contribution in row (vi) of Table 5) and 33 percent in a world with the final values of α_j (which correspond to the SBSC contribution in row (viii) of Table 5). The fact that the latter are higher indicate that SBSC and SBTC reinforce one another.

To this point, the analysis in Table 8 has used relative wage shares to measure the sizes of the sectors, as this is what KM did. However, our results were based on a calibration exercise in which we targeted the value added shares of the two sectors. Recall that we only have sector-specific relative price movements for value-added, so this model has a clearer mapping to the data. Row 8 shows that the contribution of SBSC is somewhat smaller when we use value added instead of wages to measure the change in relative sector sizes. When using value-added, the contributions for the two counterfactuals fall from 24 and 33 percent to 18 and 25 percent, respectively.

The final step in our analysis is to move from World KLEMS to EU KLEMS. The reason that EU KLEMS is of interest is that it allows for greater comparability in terms of cross-country analysis. Row (ix) shows that using the more internationally

[25] Bound and Johnson adjust for the increase in relative supply of high-skilled labor without accounting for the fact that the relative wage nevertheless rose. This appears to account for their much lower estimate than KM.

comparable EU KLEMS data increases these contributions slightly to 20 and 27 percent. This last row also uses data on compensation as opposed to wages in carrying out the exercise. The Table indicates that the effect of this change is not of first order importance for our results.

In summary, while there are many small variations, there are two important factors that explain why we find a substantially larger role for skill-biased structural change in accounting for increases in the skill premium relative to what the earlier literature attributed to industrial composition. The first is that we use wage data to control for unobservable differences among workers within a cell. This implies a larger increase in the demand of efficiency units by the skill intensive sector, thereby increasing the potential impact of compositional changes on the relative demand for skill. The second is that our structural approach allows us to precisely disentangle the role of different driving forces by solving an explicit model-based, globally-solved counterfactual from exogenous technology parameters.

6 Decomposing Changes in Relative Prices

While our main focus has been to understand the relative importance of different factors in generating the observed changes in the skill premium, our model also allows us to assess the importance of different factors in generating the change in the relative price of skill intensive services over time. In particular, our model suggests two distinct channels at work. As is standard in the literature on structural change with uneven technological progress across sectors, differential growth in sectoral TFP will lead to changes in relative sectoral prices. But our model also features an additional channel: because the sectors have different factor shares, changes in the relative price of factors will also lead to changes in relative sectoral prices. In particular, since the high-skill intensive sector uses skilled labor more intensively, any increase in the relative price of skilled labor will lead to a higher relative price for this sector. This effect was previously documented in equation (3).[26]

Here we perform some counterfactuals in our benchmark specification (i.e., $\rho = 1.42$ and $\varepsilon = 0.20$) to assess the relative importance of these two forces. In the data, the relative price of high-skill intensive services increases by 62 percentage

[26]Buera and Kaboski (2012) highlight this effect in a theoretical model in which the difference in skill-intensity across the goods and service sectors arises endogenously.

points between 1977 and 2005, and by virtue of our calibration procedure, our model perfectly accounts for this increase. To assess the pure role played by the increase in the skill premium, we compute the implied relative price from equation (3) assuming that all technology parameters remain fixed at their 1977 values, but letting the skill premium increase from 1.41 to 1.90, as in the data. The result is an increase in the relative price of skill intensive services of 11 percentage points, or roughly 18% of the overall increase. In interpreting this magnitude it is important to recall our earlier discussion of the possibility that estimates of the change in relative prices are biased upward due to a failure to properly control for quality increases in the service sector. If the true change in relative prices was indeed only half as large as in the data, then the change in the skill premium would account for 36% of the overall change. While still not the dominant factor, this suggests that changes in the skill premium may well be a significant factor behind changes in relative prices.

The issue of price mismeasurement notwithstanding, the direct effects of technological change are the dominant force behind the increase in the relative price of skill intensive services in our benchmark calibrated model. Moreover, it is the difference in sectoral TFP growth rates that drives this direct effect. To see this, take equation (3), hold the skill premium and sectoral TFPs constant and consider the pure effect of skill biased technological change. The result is that the relative price of skill intensive services would have *decreased* by 19 percentage points.

This last calculation examined the direct effect of changes in skill-biased technological change, but without incorporating the general equilibrium effect on wages. Our previous counterfactuals (see row 5 in Table 5) argued that if we eliminated changes in sectoral TFP, so that skill-biased technical change was the only source of technological change, the skill premium would have increased from 1.41 to 1.63. If we include this effect in combination with the direct effect of skill biased technological change, the result is that the relative price of skill intensive services decreases by 15 percentage points. We conclude that skill-biased technological change is not a source of increases in the relative price of services.

In summary, we conclude that although increases in the skill premium may directly account for a non-trivial share of the increase in the relative price of high-skill intensive services, the dominant factor behind this increase is the relatively slow sectoral TFP growth in this sector.

7 Cross Country Analysis

In this section we extend our analysis to ten other OECD countries for which the available data exists and thereby address two distinct issues. The first issue concerns model validation, and the second issue is to assess the importance of skill-biased structural change for a larger set of countries.

7.1 Model Validation Using Cross-Country Data

Our calibration procedure assigned parameter values by targeting the same number of moments as there were parameters. While both the production structure and our method for inferring technological change are very standard, we inferred values for utility function parameters by requiring that the model match the beginning and final values for sectoral valued added shares. If our utility function were misspecified in an important way, this procedure would still allow us to fit the initial and final sectoral value added shares, but in this case we might be wary of using our calibrated specification for the counterfactual exercises.

One simple test of the specification is to consider its ability to fit not only the two endpoints of our sample, but also the entire time series. Unfortunately this is not a very stringent test for the period we are studying, since the key series in our analysis are fairly linear, and the model is able to match them fairly well.

As a somewhat more stringent test, we turn to cross country data. For this exercise we use data from the following ten countries: Australia, Austria, Belgium, Denmark, Germany, Italy, Japan, the Netherlands, Spain and the United Kingdom.[27] We assume that the utility function for each country is the same as the one implied by our benchmark calibration with $\rho = 1.42$ and $\varepsilon = 0.20$, i.e., we impose the implied values for a_G and $\bar{c}_S$. Additionally, we assume that ρ is the same for all countries. However, using the same procedures as earlier, for each country we measure the relative supply of skilled labor from the data and we use our model to infer the time series for technological change. Because preference parameters are imported from the calibration using US data, we have not imposed that the model will fit the time series of interest for each country. Nonetheless, Figure 3 shows that this specification provides a reasonably good fit to the actual data for this set of countries. Because the

[27] The set of countries that we use in this exercise is smaller than the sample in Section 2 as some of the countries do not have all of the data required for the exercise carried out in this section.

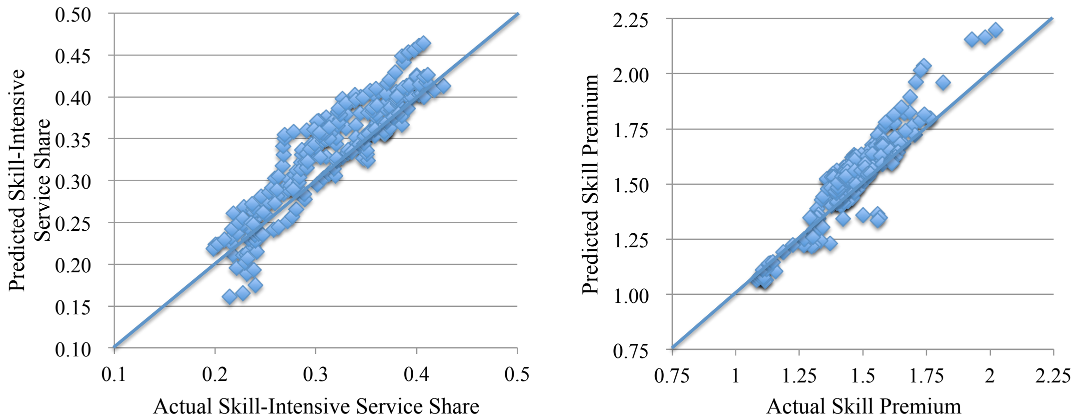

Figure 3: Model Fit in a Panel of Countries: Structural Change (left panel) and the Skill Premium (right panel).

behavior of the skilled labor share and the skill premium do differ across countries, we believe that this finding is supportive of our parsimonious structure.

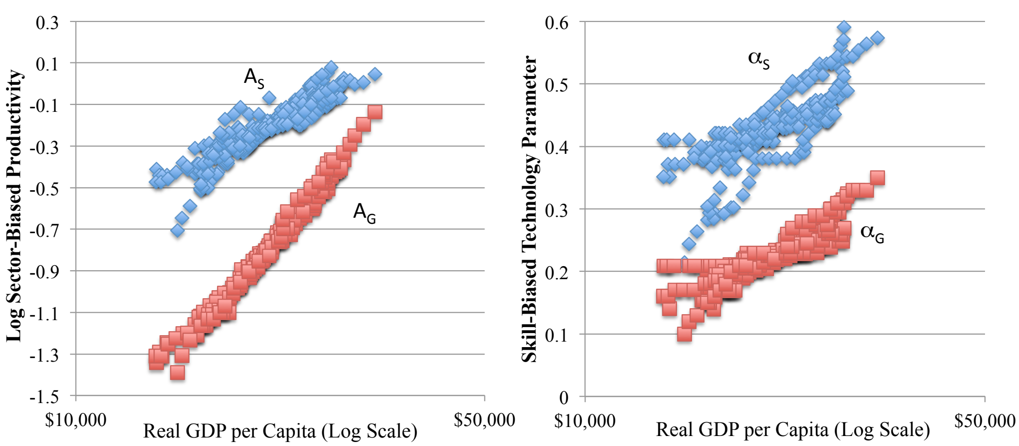

Figure 4: Calibrated Technological Processes: Sector-Biased (left panel) and Skill-Biased (right panel) Technologies. The diamonds (squares) correspond to the high (low) -skill intensive sector.

It is of interest to note that the above procedure implies processes for technological change that are broadly similar across countries, as shown in Figure 4.[28] To the extent that we believe the process of technology adoption and diffusion are at least generally similar across rich countries, we would view it is as somewhat problematic if our procedure indicated dramatically different processes across these countries.

7.2 Skill-Biased Structural Change and the Skill Premium in Cross Country Data

In this subsection we assess the extent to which skill biased structural change has influenced the skill premium in each of the countries studied in the previous subsection. We could carry out this calculation for the specifications in the last subsection, i.e., assuming the same preference parameters for these countries as in the US. A potential disadvantage of this method is that although the model with common preference parameters across countries offers a good fit to the cross country time series data, it does not necessarily account for all of the changes in the skill premium for each of the countries. Alternatively, we could assume country specific values for a_G and $\bar{c}_S$ and simply repeat the analysis that we have carried out for the US for each of the additional economies. These two methods provide fairly similar answers, and in the interest of space we only report the results of the second exercise, which are shown in Table 8.

To compute the values in Table 9 we first calculate the contribution of all forms of technological change by computing the difference between the actual skill premium in 2005 versus the skill premium that would have existed in 2005 if there had been no technological change relative to 1977 but allowing for the observed change in the supply of skill. We then isolate the fraction of this overall contribution of technological change that is due to skill biased structural change by computing the fraction of this change that is accounted for by changes in the A_j's. As in our previous analysis, we compute this in two ways. The column labelled "initial α_j" column gives the impact at the initial level of α_j (which corresponds to the change moving from row 3 to row 4 in Table 5). The column labelled "final α_j" is the impact at the final level of α_j (which correspond to the difference between row 2 and row 5 of Table 5).

[28]The plots in Figure 4 have removed country fixed effects in order to focus on the changes in technology over time rather than the cross-sectional differences.

Table 9

Contribution of SBSC Across Countries		
	Initial α_j	Final α_j
Australia	4%	15%
Austria	21%	28%
Belgium	14%	16%
Denmark	9%	14%
Spain	20%	25%
Germany	23%	24%
Italy	20%	47%
Japan	11%	17%
Netherlands	18%	21%
UK	5%	32%
US	20%	27%
Median	18%	24%

Again, we see that the magnitudes are larger given the final values of α_j,which again indicates that SBTC and SBSC reinforce each other. The magnitude of the contribution of SBSC varies significantly, from a low of 4% in Australia (14% in Denmark) to a high of 23% in Germany (47% in Italy). Nevertheless, the median values of 18% and 24% are very much in line with our estimates from the US. We conclude that the demand side forces associated with skill biased structural change seem to be quantitatively significant in a broad group of advanced economies.

8 Conclusion

Using a broad panel of advanced economies, we have documented a systematic tendency for development to be associated with a shift in value added to high-skill intensive sectors. It follows that development is associated with an increase in the relative demand for high skill workers. We coined the term skill-biased structural change to describe this process. We have built a simple two-sector model of structural transformation and calibrated it to US data over the period 1977 to 2005 in order to assess the quantitative importance of this mechanism for understanding the large increase in the skill premium during this period. We find that technological change overall increased the skill premium by roughly 100 percentage points, and that between 20 and 27 percent of this change is due to technological change which operated through compositional changes.

Our findings have important implications for predicting the future evolution of the skill premium, since the continued growth of the value added share of the high-skill intensive sector will exert upward pressure on this premium even in the absence of skill-biased technological change.

In order to best articulate the mechanism of skill-biased structural change we have purposefully focused on a simple two-sector model. As we noted in Section 2, there is good reason to think that the mechanism we have highlighted is also at work at a more disaggregated level, so it is of interest to explore this mechanism in a richer model.

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