Skill-Biased Technological Change and the Business Cycle*

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Abstract

Over the past two decades, technological progress in the United States has been biased towards making skilled labor more productive. What does skill-biased technological change imply for business cycles? To answer this question, we construct a quarterly series for the skill premium from the CPS and use it to identify skill-biased technology shocks in a VAR with long run restrictions. We find that hours fall in response to skill-biased technology shocks, indicating that at least part of the fall in total hours in response to improvements in technology is due to a compositional shift in labor demand towards skilled workers. Skill-biased technology shocks have no effect on the relative price of investment, suggesting that capital and skill are not complementary in aggregate production.

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1 Introduction

Over the past two decades, technological progress has been biased towards making skilled labor more productive. The evidence for this finding is based on the marked increase in the skill premium in the US and many other industrialized countries starting in the early 1980s, which coincided with a substantial rise in the average education level of the workforce. This parallel increase in the price and quantity of skill points towards an increase in the demand for skilled workers that exceeded the increase in their supply, suggesting that newly developed production technologies require relatively more educated and fewer uneducated workers (Katz and Murphy (1992); Autor et al. (1998); Acemoglu (2002); Autor et al. (2005) and Autor et al. (2008)).

This paper documents a set of stylized facts about the implications of skill-biased technological change for business cycle fluctuations. To our knowledge, this paper is the first to undertake this task. The lack of interest in skill-biased technology in the business cycle literature is surprising given the large number of studies dedicated to the effect of this type of technological progress on growth and inequality. Our results show that allowing for skill bias in technological change is important to understand business cycles and in particular speak to two important debates in the macroeconomics literature. First, traditional identifying restrictions, which are justified in models with homogeneous labor, may give a misleading picture of the effect of technology shocks on the economy. In particular, we show that skill-biased improvements in technology lead to a fall in total hours worked. Second, we show that the response of the economy to skill biased technology shocks implies restrictions on the production technology that are of interest to macroeconomists studying growth as well as business cycles. In particular, we find that skill-biased technological change, unlike skill-neutral technological progress, does not affect the relative price of investment goods. These results reject the hypothesis that there is an economically meaningful degree of capital-skill complementarity in the aggregate production function.

Following previous studies on skill-biased technological progress, we identify skill-biased technology shocks from their effect on the skill premium. To this end, we construct a time series for the skill premium, which was so far not available at a quarterly frequency. Using the Current Population Survey (CPS) outgoing rotation groups, we calculate the skill premium as the log ratio of wages of college graduate equivalent workers over high school graduate equivalents, controlling for experience and other observable worker characteristics. In combination with comparable measures for the relative supply and employment of skilled workers, these series give a good picture of the high frequency movements in the price and quantity of skill in the US over the 1979:I-2006:II period.

We use a structural vector autoregression (VAR) to estimate the response of the economy to technology shocks, identifying technology shocks using long-run restrictions as in Blanchard and Quah (1989) and Galí (1999). We find that improvements in technology significantly increase the skill premium, providing strong evidence for skill bias in technological change at business cycle frequencies. This finding is novel and somewhat surprising, given that the skill premium is roughly acyclical over our sample period, which seems to suggest that skill-biased technological change is not relevant for business cycle fluctuations.[1] However, in the presence of multiple shocks, unconditional correlations are the result of a mixture of responses, which obscures the effects of changes in technology.[2] The structural VAR allows us to estimate the response of the economy conditional on technology shocks. This exercise delivers two sets of results.

For our first set of results, described in more detail in section 3, we propose a long-run restriction to separately identify skill-biased technology shocks. We argue that skill-biased technology shocks are the only shocks that affect the skill premium in the long run.[3] Following Galí (1999), we identify skill-neutral technology shocks as all remaining shocks that permanently

[1]This interpretation seems to be supported by the fact that the skill premium is negatively correlated with the relative supply of skilled labor at business cycle frequencies. For example, Acemoglu (2002) and Autor et al. (2005) argue this observation indicates that fluctuations in the skill premium are driven by fluctuations in the supply of skill rather than its demand.

[2]Lindquist (2004) reaches a similar conclusion, although from a completely different exercise. Lindquist argues that skill bias in technology shocks, generated by investment-specific technology shocks and capital-skill complementarity in the aggregate production function, explains the cyclical behavior of the skill premium. We discuss his argument in more detail in section 4.3.

[3]If there are exogenous, permanent changes in the supply of skilled labor, then this restriction is not valid, because increases in the supply of skill would also affect the skill premium in the long run. However, we separately identify skill supply shocks using a short run restriction, assuming that the supply of skilled workers is predetermined, and find that there are no exogenous changes in the supply of skill: skill supply shocks explain a negligible and insignificant fraction of fluctuations in all variables considered.

change labor productivity. We find that skill-biased technology shocks, like skill-neutral technology shocks, increase labor productivity. Skill-biased improvements in technology shocks also cause a large decline in total hours worked. This finding suggests that the fall in hours in response to technology shocks, which has been interpreted as evidence for price rigidities, is due at least in part to a compositional shift in labor demand towards skilled workers. This result is robust to the precise way to estimate the VAR. We also find very similar results if we construct skill-biased technological changes directly from data on the skill premium and the relative hours worked of skill using assumptions on the production function rather than a structural VAR.

Our second set of results, described in section 4, concerns the following question: What kind of changes in the aggregate production function best describe the skill-biased improvements in technology we observe over the past two decades? In a production function that takes capital, skilled and unskilled labor as inputs, a change in productivity must be either a change in total factor productivity (TFP) or capital or skilled labor augmenting technological change.[4] Whereas changes in TFP are always skill-neutral, both capital and skilled labor augmenting technological change may increase the relative demand for skilled labor, depending on the elasticities of substitution between the different inputs. Krusell et al. (2000) argue that capital and skill are complements in the aggregate production function, and that skill-biased technological change is the result of an increase in the relative productivity of the investment-goods producing sector.[5] Our results cast doubt on this hypothesis.

In order to explore the issue of capital-skill substitutability, we include both the skill premium and the relative price of investment goods in the VAR. We use the latter to identify investment-specific technology shocks,

[4] A change in the productivity of the third input, unskilled labor, cannot be separately identified. For example, a change in technology that makes unskilled labor more productive relative to capital and skilled labor would be the combination of an increase in total TFP and a decrease in capital and skilled labor augmenting productivity.

[5] It is a well-documented fact that, over the same period that the skill premium has risen, the relative price of investment goods (software, equipment structures) has fallen substantially, providing evidence for investment-specific technological change (Gordon (1990); Greenwood et al. (1997); Cummins and Violante (2002)). Krusell et al. (2000) show that if capital and skilled labor are sufficiently complementary, investment-specific technological progress can explain the increasing trend in the skill premium, because the increase in the capital-labor ratio makes skilled labor relatively more productive.

following Fisher (2006), as the only shocks that affect the relative price of investment in the long run. An investment-specific improvement in technology lowers the relative price of investment goods. The remaining shocks that affect labor productivity in the long run, are then investment-neutral technology shocks. We find that investment-specific technology shocks do not affect the skill premium, while investment-neutral technology shocks have a positive effect on this variable. Conversely, skill-biased technology shocks, identified as described above, do not affect the relative price of investment goods, whereas skill-neutral shocks do. Using a simple two-sector real business cycle model that is consistent with our identifying restrictions, we explore what value of the elasticity of substitution between capital and high skilled labor corresponds to these estimates. For different values of the elasticity of substitution, we simulate data from the model and use those to estimate our structural VAR. We obtain the best match of the response of the skill premium to investment-specific shocks in the model-simulated data to the response estimated from actual data, if we assume capital and skill are mildly substitutable.

The remainder of this paper is organized as follows. Section 2 describes our empirical approach. We define the different shocks to the production technology that we consider and discuss how to identify the effects of these shocks using long-run restrictions. We also describe the data that are necessary to estimate these effects and present some descriptive statistics on the cyclicality of our quarterly series for the skill premium and the relative supply and employment of skill. In section 3 we describe the properties of skill biased technology shocks using the structural VAR analysis as well as a decomposition using the production function. Section 4 discusses our evidence against capital-skill complementarity in aggregate production. Section 5 concludes.

2 Empirical Approach

In this section, we outline our approach to estimate the implications of skill-biased technological progress for the business cycle. We start by defining different types of of technological change, discussing various specifications for the aggregate production function. Next, we explain how to identify these different technology shocks from the data using either the functional form of the production function or a VAR with long-run restrictions. Finally, we describe the data needed for the identification, including quarterly series for the skill premium and the relative supply and employment of skilled labor, which we construct from micro data.

2.1 Shocks to the production technology

Consider an aggregate production function for output Y_t that takes capital K_t, high skilled labor H_t and low skilled labor L_t as inputs. The production function satisfies the standard conditions: it is increasing and concave in all its arguments and homogenous of degree one so that there are constant returns to scale. Shocks to total factor productivity are neutral technology shocks, in the sense that they affect the productivity of all inputs in the same proportion. To allow for skill-biased technological change, the literature has typically assumed an aggregate production function of the following form (see e.g. Katz and Murphy (1992), Katz and Autor (1999), Autor et al. (2008)).

$$Y_t = A_t K_t^{\alpha} \left[\beta \left(B_t H_t \right)^{\frac{\sigma-1}{\sigma}} + \left(1 - \beta \right) L_t^{\frac{\sigma-1}{\sigma}} \right]^{\frac{(1-\alpha)\sigma}{\sigma-1}} \tag{1}$$

Here, A_t is total factor productivity and B_t is skilled labor augmenting technology. An increase in B_t can be skill or unskill biased, depending on the elasticity of substitution between skilled and unskilled labor $\sigma > 0$. If high and low skilled labor are substitutes rather than complements ($\sigma > 1$), the substitution effect of improvements in skilled labor augmenting technology dominates the income effect so that an increase in B_t increases the demand for skill and therefore the skill premium (assuming the supply curve for skill is downward sloping). The consensus estimate for σ is around 1.5 (see Katz and Murphy (1992), Ciccone and Peri (2006), Teulings and van Rens (2008)), so that we can think of skill-biased technology shocks as increases in B_t.

There are two ways to interpret skill-biased technology shocks to an aggregate production function as in (1). If the production function for all goods in the economy is the same, then we can think of an increase in B_t as a technological development that makes skilled labor more productive in all sectors. Alternatively, we may think that the production in different sectors i requires skilled labor in different proportions β_i of total labor input.

In this case, even if skilled and unskilled labor are neither substitutes nor complements within each sector,[6] a sector-specific technology shock to a skill-intensive sector would still increase the skill premium.

A particularly interesting case is an economy that consists of a consumption goods producing sector and an investment goods producing sector. In this economy there are two mechanisms, by which sector-specific shocks may affect the skill premium. First, the input shares for skill might be different across the two sectors as explained above. Because investment goods are used to build up capital, which is an input in the production process, sector-specific shocks may also affect the capital-labor ratio used in production. If capital and skill are complements, as argued by Krusell et al. (2000), then a higher capital labor ratio increases the relative demand for skilled labor and therefore the skill premium.

Suppose the two sectors have identical production functions except for a difference in total factor productivity. In this case, as shown among others by Fisher (2006) and Krusell et al. (2000), the economy can be aggregated to a one-sector economy, where total output is divided between consumption and investment,

$$Y_t = C_t + p_t I_t \tag{2}$$

where the relative price of investment goods p_t reflects technological improvements in the investment goods producing sector. An aggregate production function that allows for capital-skill complementarity is a slightly generalized version of (1).

$$Y_t = A_t \left[\beta \left(\gamma K_t^{\frac{\rho-1}{\rho}} + (1-\gamma)(B_t H_t)^{\frac{\rho-1}{\rho}} \right)^{\frac{\rho}{\rho-1}\frac{\sigma-1}{\sigma}} + (1-\beta) L_t^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \tag{3}$$

where σ is the elasticity of substitution between skilled and unskilled labor as before, which now also measures the elasticity of substitution between capital and unskilled labor, ρ is the elasticity of substitution between capital and skilled labor and β and γ are share parameters. As shown by Krusell et al. (2000), improvements in investment-specific technology increase the skill premium if and only if the elasticity of substitution between capital and skilled labor ρ is lower than the elasticity of substitution between capital and

[6]This is the case where $\sigma_i = 1$ for all i. In the limit for $\sigma \to 1$, production function (1) becomes Cobb-Douglas, so that changes in B_t are indistinguishable from changes in A_t.

unskilled labor σ, i.e. if there is capital-skill complementarity in production.

2.2 Identification and estimation

Under the assumption that workers' wages are proportional to their marginal product, we can calculate the skill premium directly from the production function. Using aggregate production function (1), we get the following expression,

$$\log\left(\frac{w_{H,t}}{w_{L,t}}\right) = \log\left(\frac{\beta}{1-\beta}\right) - \frac{1}{\sigma}\log\left(\frac{H_t}{L_t}\right) + \frac{\sigma-1}{\sigma}\log B_t \tag{4}$$

where $w_{H,t}$ and $w_{L,t}$ are the wages of high and low skilled workers respectively. This equation can be interpreted as a demand curve for skill. The skill premium is decreasing in the relative demand for high skilled workers, $\log(H_t/L_t)$, where the elasticity of demand depends on the elasticity of substitution between high and low skilled workers.

Changes in skill-biased technology B_t represent shifts of the skill demand curve or skill demand shocks. Since the skill premium and the relative quantity of skill are observable, these shocks can be directly retrieved from equation (4), using an estimate for the elasticity of substitution between low and high skilled workers σ.[7] The estimates for the skill-biased technology shocks obtained this way are identified from the assumption that wages are proportional to marginal products. A sufficient condition for this assumption is that labor markets are perfectly competitive, in which case the wage of all workers equals their marginal product. If there are frictions in the labor market, the weaker assumption that wages are proportional to marginal products still holds approximately. However, if there are frictions in the wage determination process, then wages may deviate from marginal products in the short run. Therefore, we will use long-run effects in order to identify skill-biased technological progress.

We estimate technology shocks using a structural VAR with long-run restrictions on labor productivity as suggested by Galí (1999). Consistent with equation (4), we identify skill-biased technology shocks as the only shocks that affect the skill premium in the long run, conditional on the

[7] An estimate for the share parameter β is unnecessary since this parameter affects only the level of B_t and we normalize the mean and variance of the shocks to zero and one respectively.

supply of skill. Since the identifying restriction is an assumption on the long-run effects of the structural shocks on the variables in the VAR, it is a weaker assumption than assuming that (4) holds in each period and makes the estimates robust to, for example, wage rigidities. In addition, the long run identification does not depend on the exact functional form of the production function and we no longer need to use an estimate for σ.[8] In section 3.3, we compare the results from the long-run restrictions to a direct decomposition using equation (4) and find that for the simplest estimates the differences are not large.[9]

The estimation of structural shocks using long run restrictions is implemented in two steps. First, we estimate a reduced form VAR in the variables labor productivity, hours worked, the skill premium and in some specifications also the relative price of investment goods. Second, we map the reduced form coefficients and residuals into structural coefficients and shocks by normalizing the variance of all structural shocks to one, assuming orthogonality between these shocks and imposing the identifying restrictions. The long-run identifying restrictions are incorporated using a Cholesky decomposition of the infinite horizon forecast error variance.[10]

We estimate various different types of technology shocks with specific restrictions depending on the type of shock we are interested in. Skill-biased technology shocks are shocks to the production technology that affect the skill premium, investment-specific technology shocks change the relative price of investment goods and in the presence of capital-skill complementarity technology shocks may be both investment-specific and skill-biased. Neutral technology shocks increase productivity but do not affect either the relative price or the skill premium. We discuss the specific identifying restrictions used to identify neutral, skill-biased and investment-specific technology shocks as we describe our results in section 3. The identifica-

[8] Of course the assumption is not valid for all production functions. For example, with capital-skill complementarity, as in (3), any shocks that affect the capital stock also affect the skill premium in the long run. However, the restriction can easily be modified to incorporate this case, see section 4.

[9] An alternative approach that allows to identify skill-biased technology shocks without assuming a specific model, would be to use sign restrictions as in Uhlig (2005) and Dedola and Neri (2007). We opt for long-run zero restrictions because we believe that any assumption on the short run behavior of the skill premium would be more problematic than the assumption that only skill-biased technology shocks affect the premium in the long run.

[10] Please refer to the Web Appendix for details on the estimation and identification.

tion of different types of shocks using the Cholesky decomposition is then implemented by simply reordering the variables in the VAR.

Our baseline VAR includes 8 lags and is estimated on quarterly data from 1979:I to 2006:II. All variables are used in first differences in order to allow for unit roots.[11] The baseline specification includes labor productivity, hours worked and the skill premium. We further include the relative supply of skill if we want to account for supply shocks, see Section 3.2. In Section 3.4, we show that our results are robust to adding other variables, such as consumption and investment. In order to identify investment-specific technology shocks, we further include the relative price of investment goods into the VAR in Section 4.

We use a Bayesian VAR to estimate the reduced form and employ a Minnesota prior, similar to Canova et al. (2010). This prior reflects the belief that the true data generating process is a univariate unit root in each variable. It is implemented as a joint prior that the coefficient matrix of the first lag in the VAR is close to the identity matrix and the coefficients on further lags are close to zero, where the strength of the prior increases with the lag order.[12] The Minnesota prior makes our estimation results more stable in the presence of high frequency variation in the skill premium that is due to measurement error. The prior does not affect the long-run restrictions in any way and we show that our results are robust to the strength of the prior and to estimating the reduced form VAR using ordinary least squares.

We control for low frequency fluctuations in the data by filtering the data with a low-pass filter excluding frequencies above 52 quarters in line with Canova et al. (2010). Note that the trend is removed from the first differences of the data series, not the levels. Removing a trend from levels would take away the unit root that the long-run restriction is based on. We show that the results are robust to various trend specifications, such as a

[11] In the context of the identification of neutral technology shocks, there has been a debate in the literature whether hours worked should be included in levels (Christiano et al. (2003)) or in first differences (Galí and Rabanal (2004)). Canova et al. (2010) show that once the very low frequencies are purged out from the data, the results of Galí (1999) are robust to using hours worked in levels. We control for these low frequency fluctuations as described below.

[12] The strength of the Minnesota prior increases with lag length to reflect the belief that the higher order lags are less likely to matter. This is imposed in form of a harmonic decay of the prior variance on the lag coefficients. Apart from the decay, the Minnesota prior employed is quite loose. The Web Appendix provides more information on the specification.

dummy broken at 1997:I as advocated by Fernald (2007) or a deterministic polynomial trend, see Section 3.4 and Table 4.

2.3 Data

We construct quarterly series for the skill premium and the relative hours worked and supply of skill using individual-level wage and education data from the CPS outgoing rotation groups. This survey has been administered every month since 1979 so that our series runs from 1979:I to 2006:II.[13] Wages are usual hourly earnings (weekly earnings divided by usual weekly hours for weekly workers) and are corrected for top-coding and outliers. We limit our sample to wage and salary workers between 16 and 64 years old in the private, non-farm business sector and weight average wages by the CPS-ORG sampling weights as well hours worked in order to replicate aggregate wages as close as possible. Education is measured in five categories (less than high school, high school degree, some college, college degree, more than college) and made consistent over the full sample period following Jaeger (1997). In an average quarter, we have wage and education data for about 35,000 workers.

Our measure for the skill premium is the log wage differential between college graduates and high school graduates. The relative hours worked and supply of skill are defined as the log ratio of the number of college graduates over the number of high school graduates in the population and the workforce respectively. Following Autor et al. (2005), we map the five education levels in the data to college and high school graduate equivalents and control for changes in experience, gender, race, ethnicity and marital status. To do this, we first estimate a standard Mincerian earnings function for log wages. The predicted values from this regression for males and females at 5 education levels in 5 ten-year experience groups yield average wages for 50 education-gender-experience cohorts keeping constant the other control variables. We then calculate the number of workers in each cell as a fraction of the workforce or population. Dividing by a reference category, this procedure gives us relative the prices and quantities of skill for 50 skill

[13]The BLS started asking questions about earnings in the outgoing rotation group (ORG) surveys in 1979. The March supplement goes back much further (till 1963), but does not allow to construct wage series at higher frequencies than annual. The same is true for the May supplement, the predecessor of the earnings questions in the ORG survey.

categories. Finally, we aggregate to two skill types by averaging relative prices using average quantity weights and averaging quantities using average price weights.[14] The resulting series are adjusted for seasonality using the X-12-ARIMA algorithm of the Census Bureau.

The way we measure the skill premium and the relative hours and supply of skill allows easy comparison to models with workers of only two skill levels. Yet, the measures do justice to the greater degree of heterogeneity in the data. This is necessary to ensure that changes in the price of skill are correctly attributed to changes in the skill premium and changes in the quantity of skill to the relative hours worked or supply of skill. Suppose, for example, that there is an increase in the number of workers with a masters degree. This represents an increase in the supply of skill. However, a naive measure of the relative supply, which just counts the number of workers with at least a college degree, would not reflect this increase. Moreover, if workers with a masters degree earn on average higher wages than workers with a bachelors degree only, then a naive measure of the skill premium would increase. In our measures, this increase in the supply of skill would leave the skill premium unchanged and increase the relative supply measure. Our data show a pronounced increase in the skill premium since 1980, which seems to slow down mildly towards the end of the 1990s, as documented in previous studies, e.g. Autor et al. (2005). The trend and fluctuations in our measure of the skill premium are similar to those in the Mincerian return to schooling, indicating we have adequately controlled for heterogeneity beyond two skill types.

The other data series we use in our analysis are the following. Output is non-farm business output of all persons from the national income and product accounts (NIPA). Hours are total hours of non-supervisory workers in the non-farm business sector from the Current Employment Statistics establishment survey, corrected to be representative for the entire workforce including supervisors. Labor productivity is output per hour. All three series are available from the Bureau of Labor Statistics (BLS) productivity and cost program. As the relative price of investment goods, we use a quarterly intrapolation of the quality adjusted NIPA deflator for producer

[14]For the skill premium and relative hours series, we calculate average prices and quantities weighting individual workers in each cell by hours worked. For the relative supply series this is not possible since we do not observe hours worked for non-employed workers. For this series, we weight averages only by the CPS-ORG sample weights.

durable equipment over the consumption deflator. These data were constructed by DiCecio (2009), extending the series by Fisher (2006) and based on the annual data constructed by Gordon (1990) and Cummins and Violante (2002).[15]

Table 1 shows business cycle statistics for the skill premium, the relative hours worked and supply of skill, output, hours, productivity and the relative price of investment goods for our estimation sample 1979:I to 2006:II. The skill premium is basically acyclical: it is only very mildly positively correlated with output and even less with hours worked. This finding is consistent with previous studies (Keane and Prasad (1993); Lindquist (2004)). The relative supply of skill is acyclical as well, but the relative hours of skill are higher in recessions than in booms, indicating the presence of a composition bias in employment as argued by Solon et al. (1994). The correlation of the skill premium with the relative investment-price is negative and insignificant. This is a first indication that capital-skill complementarity does not seem an important feature of the data at business cycle frequencies. Note that the correlations of the naive measure of the skill premium are quite different than the ones of the baseline measure. Accounting for heterogeneity is important for the cyclical behavior of the skill premium.

3 Skill-biased technology shocks

In this section, we present our results for the effects of technology shocks on aggregate variables. We start by assessing the degree of skill bias in 'traditional' shocks to total factor productivity. We then assess to what extent these estimates are biased due to the presence of shocks to the supply of skill and find that this bias is negligible. Next, in section 3.3, we propose an identification strategy to separate skill-biased from skill-neutral technology shocks and estimate the response of the economy to each type of shock.

3.1 Skill bias in technology

Galí (1999) identifies permanent technology shocks as the only source of long-run movements in labor productivity. In a wide range of models, closed-

[15] We thank Ricardo DiCecio for making these data available to us. The Web Appendix describes the time-series properties of the data that are relevant for the specification of the VAR such as autocorrelations, integration and cointegration properties.

economy, stationary, one-sector RBC models as well as models of the new Keynesian variety, shocks to total factor productivity are the only shocks that satisfy this identifying restriction. The remaining disturbances in the structural VAR are non-technology or 'demand' shocks, an amalgum of other possible shocks in the model: government expenditure shocks, preference shocks, or shocks to price or wage markups. As a first pass at our data, we evaluate the skill bias in technology shocks identified in this manner.

Figure 1 presents impulse response functions to technology shocks, identified as in Galí (1999). The first row of responses replicates the estimates in Galí (1999), using data on labor productivity and hours worked over the period 1948:I-1994:IV (postwar sample). These responses are estimated using a VAR with 4 lags and a 'flat' prior with median equal to the OLS point estimate. Here, as in all graphs that will follow, we present the median as well as the 16th and 84th percentiles of the posterior distribution of the structural impulse-response coefficients, following Uhlig (2004). A positive innovation in technology leads to an almost immediate increase in labor productivity equal to the long run effect, and a reduction in hours worked. The first finding is supportive of the interpretation of the identified shock as a permanent improvement in technology. The second finding has typically been interpreted as evidence in favor of price rigidities, which dampen the substitution effect on impact and thus make the income effect of higher productivity that increases the demand for leisure dominant in the short run.[16]

The second row shows the responses from the same sample, now estimated with the Minnesota prior and 8 lags as in our baseline specification. Compared to the responses in the first row, the response of hours worked is shifted up slightly in this specification, so that the initial drop in hours is no longer significant. The third row again estimates the same specification, but using data for the 1979:I-2006:II (recent) sample and controlling for low frequency movements in the data, see the final paragraph in Section 2.2. Over this time period, the fall in hours worked is significant and more persistent than in the postwar sample, although the differences are not significant.[17]

In the fourth row of Figure 1, we add the skill premium to the VAR,

[16] An alternative explanation is the combination of habit formation in consumption and adjustment costs in investment, see Francis and Ramey (2005).

[17] We obtain similar results if we estimate the VAR on the recent sample without controlling for the low frequency fluctuations or with OLS and 4 lags.

obtaining our baseline specification discussed in section 2.2. Introducing this additional regressor leaves the responses of labor productivity and total hours worked virtually unchanged. The skill premium increases in response to a permanent improvement in technology. The effect is permanent and fully realized on impact. This finding is consistent with the hypothesis of skill-biased technological change, suggesting that the improved technology increased the demand for high-skilled labor.

3.2 Shocks to the supply of skill

In the identification of technology shocks used above, we assumed that technology shocks are the only shocks that drive productivity in the long run. We showed that these shocks have asymmetric effects on the demand for high and low skilled labor. Thus, production does not use a standard Cobb-Douglas technology, but either requires high and low skilled labor as separate and imperfectly substitutable inputs, as in equation (1), or output to be produced in multiple sectors with different input shares of skilled labor. In these cases, the identifying assumption of Galí (1999) is no longer valid in the presence of exogenous changes in the supply of skill, because such changes may affect labor productivity in the long run.

Suppose a preference shock causes college enrollment to increase permanently. When the new, larger cohort of college graduates enters the labor market, the supply of skill exogenously increases. The resulting lower skill premium leads firms to employ relatively more skilled workers. Since skilled workers are more productive, this raises average labor productivity. Thus, this shock to the supply of skill satisfies the identifying restriction for a technology shock, even though technology has not changed at all.

To assess the importance of this bias, we separately identify shocks to the supply of skill and compare the results from the estimation with and without skill supply shocks. For this purpose, we include a measure of the relative supply of skilled workers in the VAR. We use a short-run restriction to identify shocks to the supply of skill: only skill supply shocks affect the supply of skill in the short run. This restriction is equivalent to assuming that the supply of skill is predetermined. Of course there are many other shocks that may increase the supply of skill endogenously, through an increase in the skill premium. Skill-biased technology shocks are just one example. However, the intuition for the identifying restriction is that in order to increase the supply of skill in response to an increase in its price, workers need to obtain more education, which lasts at least a year. It seems unlikely therefore, that other shocks would affect the supply of skill within the quarter.

There is substantial measurement error in our time series for the relative supply of skill because each observation is based on a relatively small cross-section of individual workers. By construction, this measurement error is independently distributed over time, because the same individual is never in the outgoing rotation group in two subsequent quarters. In order to prevent that measurement error is identified as a skill supply shock, we implement the short-run restriction after one quarter rather than on the impact effect.

It is crucial for our identification that we use a measure of the relative *supply* of skill, not the relative employment as measured by hours worked. It is reasonable to assume that the supply of skill is predetermined, but the same is not true for the employment of skill. If low and high skilled workers are imperfect substitutes, then firms may hire relatively more skilled workers in recessions, when the unemployment pool is larger and these workers are more abundantly available. This composition bias has been documented by Solon et al. (1994). We measure the relative supply of skill as the ratio of skilled workers to low skilled workers in the workforce, whereas the relative hours worked correspond to the equivalent ratio among employed workers, see section 2.3.

The strategy to identify technology shocks conditional on skill supply shocks is recursive. We first identify skill supply shocks with the short-run restriction and then use the same long run restriction discussed in the previous subsection to identify technology shocks. Thus, skill supply shocks are allowed to have a long run effect on productivity.[18] Having identified fluctuations in productivity (as well as other variables in our VAR) that are due to skill supply shocks, technology shocks are the only *remaining* shocks that affect labor productivity in the long run. The details on the implementation of this combination of short and long run restrictions are provided in the Web Appendix.

The fifth row of Figure 1 documents that controlling for skill supply changes the impulse responses to identified technology shocks very little.

[18]They are also allowed to have a long-run effect on all other variables such as the skill premium or the relative price of investment, which is important in later specifications.

The responses of productivity, hours and the skill premium are all very similar to those in the baseline specification in the fourth row of the Figure. In addition, Table 2 compares the variance decomposition for the identification with and without supply shocks. Supply shocks matter very little for business cycle fluctuations in output, hours and even the skill premium. Moreover, controlling for skill supply shocks does not significantly alter the importance of technology shocks for fluctuations in these three variables. We conclude that the size of the bias induced by supply shocks is small. Since this is true for all of our specifications, we do not report the results controlling for supply shocks in the remainder of the paper.

3.3 Identified skill-biased technology shocks

Our evidence for skill bias in technological change at business cycle frequencies casts doubt on the traditional interpretation of identified technology shocks. If these were truly shocks to total factor productivity, as in equation (1), the demand for skilled and unskilled labor should increase in equal proportions and the relative demand should be unaffected. Here, we propose an alternative identification strategy to directly identify skill-biased technology shocks in addition to skill-neutral shocks to productivity.

In sections 3.1 and 3.2 above, we interpreted the increase in the skill premium in response to a technology shock as a measure of skill bias in technology. Here, we formalize that interpretation as an identifying restriction, identifying skill-biased technology shocks as those shocks that affect the relative price of skill in the long run, see equation (4). This restriction is similar in spirit to the identification of investment-specific technology shocks as shocks that affect the relative price of investment goods proposed by Fisher (2006). Precisely, the identifying assumptions are now as follows. We identify skill-biased technology shocks as the only shocks that affect the relative price of skill in the long run. These shocks may or may not affect labor productivity. Skill-neutral technology shocks are all remaining shocks that affect labor productivity in the long run. We implement these assumptions by ordering the respective variables subsequently in the VAR.

This identification scheme strictly speaking is not a *decomposition* of technology shocks as in Galí (1999) into skill-biased and skill-neutral shocks. In principle, there might be shocks that affect the skill premium but not labor productivity in the long run. However, as explained in section 2.1, it is hard to imagine non-technology shocks other than skill supply shocks to affect the skill premium in the long run. Moreover, our estimates indicate that the shocks we identify as skill-biased technology shocks increase labor productivity, supporting our interpretation of these shocks as a specific type of technology shock.

Figure 2 shows the responses of the skill premium, labor productivity and total hours worked to a one-standard deviation skill-biased technology (SBT) shock and skill-neutral technology shock. By assumption, a positive SBT shock drives the skill premium up in the long run. The estimates indicate that this effect is realized immediately on impact. A skill-neutral technology shock has no significant effect on the wage premium on impact and by assumption there is no long run effect either.

In response to a positive SBT shock, hours worked and persistently fall. The response of hours to skill-neutral technology shocks is also negative, but the fall is smaller in size. This finding suggests that at least part of the fall in hours worked in response to technology shocks, as in Galí (1999) and in Section 3.1, is related to the skill bias in these shocks. If high skilled workers are much more productive than low skilled workers, then it is possible that by substituting low skilled for high skilled workers in response to an SBT shock, firms may increase effective labor input in their production process, while reducing total hours or employment. In section 3.6, we explore this mechanism in more detail.

Table 3 shows a decomposition of the forecast error variance of the VAR at business cycle frequencies with periodicities from 8 to 32 quarters. Separating out skill-biased and skill-neutral technology shocks increases slightly the overall contribution of technology shocks to fluctuations. Skill-neutral and skill-biased technology shocks together explain about 9% of the business cycle variance of output, compared to 5% than the estimated contribution of technology shocks in the specification of Table 2. Technology shocks explain about 9% of the volatility in hours worked, compared to about 6% in Table 2. Skill-neutral technology shocks are relatively more important for output fluctuations, but skill-biased shocks explain a larger fraction of fluctuations in hours worked that are driven by technology shocks. Fluctuations in the skill premium are almost exclusively due to SBT shocks.

3.4 Robustness

We now explore the robustness of our estimates to changes in the estimation specification and the construction of the data. The results of this exercise are summarized in Table 4. The fall in hours after a SBT shock is robust across specifications. In response to skill-neutral technology shocks hours worked may fall or rise depending on the specification.

First, we check whether the finding that skill supply shocks are not important carries over to our specification with identified SBT shocks. In this specification, these shocks potentially matter more because of the standard simultaneity problem in estimating demand and supply equations. An exogenous, permanent increase in the supply of skill would permanently reduce the price of skill and thus satisfies our identifying restriction for skill-biased technology shocks. We find, however, that controlling for shocks to skill supply as described in section 3.2 does not affect our estimates, although it reduces the effect of skill-neutral shocks on hours.

In order to allow for low frequency movements, we filter the data with a low-pass filter excluding frequencies above 52 quarters in our baseline specification. As suggested by Fernald (2007), we further employ a dummy broken at 1997:I and include a deterministic polynomial trend into the specification. In the latter case, the results hardly changed varying this trend up to a third order polynomial. We also check significance to a shorter sample ending in 2000:IV. Older studies on investment-specific technology shocks considered time range due to data availability. In the short sample, hours worked increase after a skill-neutral shock.

In our baseline estimates, we impose a Minnesota (Litterman) prior on the decay of the lag coefficients in order to be able to allow for a large number of lags. However, our results are not driven by this prior. The responses of productivity and the skill premium to skill-biased technology shocks are virtually unaltered when we vary the strength of the prior or when we estimate the VAR using ordinary least squares (OLS). If we vary the lags in the specification, hours worked increase in response to a neutral technology shock.

Next we explore to what extent the way we constructed our measure for the skill premium matters for the results. Using a 'naive' measure of the skill premium that does not take into account the heterogeneity over and above two skill types, we would not have observed the fall in hours in response to an SBT shock. As we found in the unconditional moments in Section 2.3, accounting for heterogeneity is important for the cyclical behavior of the skill premium. We also re-estimated the VAR using total hours per capita calculated from the CPS rather than the usual series from the establishment survey. The CPS series is much noisier than the baseline series because the underlying micro-data sample is much smaller, but it is more consistent with our skill premium series. All results are robust to this alternative hours series.

As shown by Fernandez-Villaverde et al. (2007), it is important to include a proper set of variables in order to have a mapping between the VAR and the underlying DSGE model.[19] Therefore, we include additional and potentially omitted variables in the VAR: the relative price of investment goods; consumption, measured as real personal consumption expenditures from the NIPA; investment, measured consistent with the series for the relative price; and the interest rate, measured as the return on a 3-month T-bill as in Fisher (2006). Including these variables does not significantly alter any of our results.

3.5 Production function decomposition

As a final robustness check, we compare the properties of our identified SBT shocks to a simple decomposition using the production function, see section 2.2. This decomposition is similar in spirit to a Solow residual and requires a value for the elasticity of substitution between high and low skilled workers σ. We use $\sigma = 1.5$, which is the consensus estimate from the literature based on several different data sources (Katz and Murphy (1992), Ciccone and Peri (2006), Teulings and van Rens (2008)). With this value, we can use equation (4) to retrieve changes in skill-biased technology B_t from our data on the skill premium and the relative hours of skill. After demeaning these changes and normalizing their variance to unity, they are comparable to the identified SBT shocks from the structural VAR. The difference is in the identification. Whereas the identified shocks require assumptions only on the long run behavior of the skill premium, the decomposition requires equation (4) to hold in each period.

We compare the response of productivity, hours worked and the skill

[19] The inclusion of additional variables may also alleviate the problem of finite lag length, see Erceg et al. (2005).

premium to the identified SBT shocks and the estimated shocks using the decomposition. We regress these variables on lags of the shocks, estimated either from the decomposition using equation (4) or as the residuals from our structural VAR, as suggested by Basu et al. (2006). This is a direct estimate of the moving average representation of the impulse response functions and the results are comparable to the impulse responses in Figure 2. Since the impulse responses in Figure 2 seem to flatten out after about 6 quarters, we use 6 lags of the shocks. The results are presented in the first row of Figure 3. The responses to identified SBT shocks estimated in this way are very similar to those directly calculated from the VAR estimates. We now discuss how the responses to SBT shocks obtained from the decomposition compare to these. The second row of Figure 3 shows the responses to SBT shocks estimated using the decomposition. Generally, the responses are very similar to the responses to the VAR residuals and never significantly different.

3.6 Wages and hours of high and low skilled workers

Regressing on the estimated shocks from the production function decomposition, we can evaluate the response of other variables to SBT shocks. Here, we explore the response of the wages of high and low skilled workers, as well as the relative hours and the hours of each skill group, in order to provide supportive evidence for our interpretation for the fall in total hours worked in response to skill-biased technology shocks as a compositional shift in labor demand. Figure 4 presents these responses.

The first row in Figure 4 replicates the increase in the skill premium to skill-biased improvements in technology from the production function decomposition, as in the second row of Figure 3, and decomposes this increase into the responses of wages of high and low skilled workers. These estimates are consistent with our interpretation of a compositional shift in labor demand. In response to an SBT shock, the wage of high skilled workers increases substantially, while the wage of low skilled workers falls.

In the second row of Figure 4, we look directly at the quantity of labor of each type that is employed in equilibrium. As expected, relative hours of skilled workers increase in response to skill-biased improvements in technology. This increase is driven by a strong fall in hours of unskilled workers. Hours of skilled workers respond very little in response to a positive SBT shock. To understand this result, we argue that skill-biased improvements in technology lead to a shift in the composition of labor demand towards skilled workers. This compositional shift tends to increase hours of skilled workers and decrease hours of unskilled workers. In addition, skill-biased technology shocks have the same effect as skill-neutral improvements in technology, which is a mild decrease in hours worked. The combination of the two effects is a sharp drop in hours of unskilled workers, and virtually no effect on hours of skilled workers.

4 Capital-skill substitutability

Over our sample period the relative price of investment goods fell substantially. This finding has been interpreted to mean that technological progress has been faster in investment goods producing sectors than in consumption goods producing sectors (Greenwood et al. (1997), Cummins and Violante (2002)). Fisher (2006) has argued that such investment-specific technological change is important not only for long run trends, but also for business cycle fluctuations. Because the increase in the skill premium roughly coincided with the decrease in the relative price of investment goods, Krusell et al. (2000) argue that investment-specific and skill-biased technological change might be one and the same. If capital and skill are complements in the aggregate production function, technological innovation in the investment-sector will necessarily lead to an increase in the demand for skill. If this is the case, then investment-specific technology shocks should lead to business cycle fluctuations in the skill premium. In this section, we explore this hypothesis and do not find evidence for it.

4.1 Skill bias in investment-specific shocks

Consider the alternative aggregate production function (3), as in Krusell et al. (2000), which allows for complementarity or substitutability between capital and skill. Assuming as before that wages are proportional to marginal products in the long run, expression (4) for the skill premium changes to the following.

$$\log\left(\frac{w_{H,t}}{w_{L,t}}\right) = \log\left(\frac{\beta\left(1-\gamma\right)}{1-\beta}\right) - \frac{1}{\rho}\log\left(\frac{H_t}{L_t}\right) + \frac{\rho-1}{\rho}B_t + \frac{\sigma-\rho}{\sigma\left(\rho-1\right)}\log\left(\gamma K_t^{\frac{\rho-1}{\rho}} + \left(1-\gamma\right)\left(B_t H_t\right)^{\frac{\rho-1}{\rho}}\right) \quad (5)$$

Since investment-specific technological progress raises the long run capital-labor ratio, it is clear that such technological change will also raise the skill premium if $\rho < \sigma$, i.e. if capital and skill are complements rather than substitutes in production. As a result, our identifying restriction that skill-biased technology shocks are the only shocks that affect the skill premium in the long run is no longer valid, and we need to separately control for investment-specific shocks. In addition, it is interesting in itself to assess the skill bias in investment-specific shocks, because it will allow us to assess the degree of capital-skill complementarity in aggregate production.

We follow Fisher (2006) in identifying investment-specific and investment-neutral technology shocks using the relative price of investment goods. We estimate the effect of these shocks on the skill premium in order to evaluate the hypothesis of capital-skill complementarity. We identify investment-specific technology shocks as the only shocks that affect the relative price of investment goods in the long run. Finally, investment-neutral technology shocks are all remaining shocks that drive labor productivity in the long run. For implementation, we include the relative price of investment, ordering it first, before labor productivity in the VAR.[20]

Figure 5 shows the responses of the the skill premium, labor productivity, hours worked and the relative price of investment goods to investment-specific and investment-neutral technology shocks.[21] After an improvement in investment-specific technology, the relative price of investment falls, productivity rises and hours worked increase. An investment-neutral technology shock, has no effect on the relative price of investment, increases productivity and leads to a fall in hours worked.[22]

The skill premium does not respond to an improvement in investment-

[20]Note that including the relative price of investment in the estimation of technology shocks in Section 3.1 or in the estimation of skill-biased technology shocks in Section 3.3 does not change the results documented there.

[21]Note that again controlling for skill supply shocks changes the results very little.

[22]Since productivity increases after an investment-specific technology shock in our specification, we do not need to use an additional assumption on this effect as in Fisher (2006).

specific technology. Thus, we find no evidence for a relation between skill bias and investment-specific technical change: investment-specific shocks do not affect the demand for unskilled labor. Because we have already documented that technology shocks are skill biased, it should not be surprising that investment-neutral technology shocks increase the skill premium, suggesting these shocks increase the demand for skilled labor.

The same finding can be documented in an alternative way. In Figure 6, we present impulse responses of the relative price of investment goods to skill-biased and skill-neutral technology shocks, identified as in section 3.3. The graphs provide the mirror image to those in Figure 5: skill-biased technology shocks do not affect the relative price of investment goods, suggesting these shocks not are not investment-specific and there is no evidence that capital and skill are complements in production.

4.2 Relation to previous literature

Our findings are in striking contradiction with the argument in Krusell et al. (2000). What explains the difference is that Krusell et al. (2000) base their argument on a correlation in the long run trends in the skill premium and the relative price of investment goods. In our approach, we control for deterministic trends in the variables, which are captured by the constant term in the VAR, and use only the stochastic trends to identify skill-biased from skill-neutral changes in technology. It is possible that the comovement in the trends in both relative prices is a spurious correlation between two integrated series. It is also possible that the model needed to explain long run growth trends is different from the model that describes higher frequency fluctuations. In any case, our findings reject the hypothesis that there is a stable aggregate production function with capital-skill complementarity.

Lindquist (2004) argues that capital-skill complementarity explains not only the trends, but also the business cycle fluctuations in the skill premium. He develops a business cycle model with neutral and investment-specific technology shocks and evaluates this model by comparing its predictions for the (unconditional) moments to the data, in particular the fact that the skill premium is volatile but acyclical. Lindquist argues that strong capital-skill complementarity is necessary to explain these facts. In his model, investment-specific technological improvements increase the skill premium whereas neutral improvements in technology decrease the skill premium, in both cases because of capital-skill complementarity. Since business cycles are driven by both types of shocks in the model, this makes the skill premium volatile, but roughly acyclical.

It is crucial for Lindquist's argument that the model has at least two shocks, the effects of which on the skill premium roughly cancel out against each other. If business cycles were driven exclusively by investment-specific shocks, the skill premium would be strongly procyclical in his model. Although Lindquist presents impulse responses of the premium to each shock separately from the model, he does not compare the conditional moments to the data. Our estimated impulse responses show that his model implies the wrong response of the skill premium to investment-specific shocks. Another way to say that is that although the model with capital-skill complementarity captures the volatility of the skill premium, the implied correlation of the premium with the relative price of investment goods has the wrong sign. In section 4.3, we show that Lindquist's model can replicate the empirical response of the skill premium to investment-specific shocks if we recalibrate the model such that capital and skill are strong substitutes rather than strong complements in the production function.

4.3 A model with capital-skill substitutability

Our findings that the skill premium does not respond to investment-specific shocks, and the relative price of investment is not affected by skill-biased technology shocks suggest that capital and skill are not complements (nor substitutes) in the aggregate production function. But these responses are measured with error. This raises the question what range of parameters of production function (3) are consistent with our estimates. To answer this question, we simulate a simple business cycle model with a production function as in (3) and compare the estimated impulse response functions from the actual data to those from simulated data for different values of the substitution parameters.[23] This procedure also allows us to see whether

[23]Alternatively we could estimate the model, which would provide a more precise estimate of the degree of complementarity or substitutability between capital and skill in the production function. However, in order to do this we would have to make additional assumption about parts of the economy that are unrelated to the production function. Our test for capital-skill complementarity would then be a joint test together with these auxiliary assumptions. Therefore, we prefer to focus on the impulse response that is likely to be most informative about the degree of capital-skill complementarity and estimate this response with minimal assumptions on the structure of the rest of the economy.

the structural VAR performs well in capturing the conditional moments of the variables in a model that is consistent with our interpretation of the results.[24]

The model is a simple real business cycle model with high and low skilled workers. The model is taken from Lindquist (2004) and combines the two sector model of Greenwood et al. (1997), in which output can be used for consumption or accumulation of capital equipment, with the model of Krusell et al. (2000) with two skill types and capital-skill complementarity. Business cycle fluctuations in the model are driven by shocks to total factor productivity and the relative price of investment goods.

For the calibration of the structural parameters of the model we also follow Lindquist (2004), but we assume that the two technology shocks are highly persistent and uncorrelated with each other.[25] The substitution parameters in the aggregate production function (3) are $\sigma = 1.67$ and $\rho = 0.67$. These values were estimated by Krusell et al. (2000) to be consistent with the trends in the relative price of investment goods and the skill premium. Since $\rho < \sigma$ in this calibration the aggregate production function exhibits capital-skill complementarity. In alternative calibrations, we keep σ constant, because the value of the elasticity of substitution between high and low skilled workers is well documented, and change ρ to vary the degree of capital skill complementarity. We consider the cases of capital-skill complementarity ($\rho = 0.67$), weak complementarity ($\rho = 1.17$), neither complementarity nor substitutability ($\rho = \sigma = 1.67$), weak substitutability ($\rho = 2.17$), substitutability ($\rho = 2.67$), strong substitutability ($\rho = 3.17$) and very strong substitutability ($\rho = 5$). In each case, we recalibrate the other model parameters to keep the calibration targets constant.

We simulate the model 1000 times for 110 quarters, the same sample length as in our data. In each simulation, the model is first simulated for

[24]In particular, it allows us to check whether our VAR includes sufficiently many lags to properly identify the true model impulse responses, addressing the potential problem with the VAR approach pointed out by Chari et al. (2008).

[25]We assume shocks in the model are uncorrelated in order to be consistent with the identifying assumptions of our VAR. In addition, we are not sure how to interpret the predictions of a structural model with correlated shocks, which introduce comovement outside of the model. Similar to Uhlig (2004) we assume persistent, but not permanent, autoregressive processes for the shocks because the production function does not imply balanced growth. These changes in the calibration with respect to Lindquist change the simulated data very little, and none of the results change if we follow Lindquist's calibration exactly.

200 periods, which are then discarded, in order to remove dependence on the initial conditions. We add measurement error to the simulated variables as we seek to identify two shocks out of four variables in the VAR. We then estimate the VAR for each sample of 88 quarters and average the impulse responses across the 1000 simulations. Figure 7 illustrates this for the calibration, in which capital and skill are neither complements nor substitutes. For better comparison, the responses are normalized such that they match the responses in the actual data of the investment price and labor productivity to the two technology shocks respectively 10 quarters after the shock has hit. The estimated responses from the simulated data closely match the theoretical ones from the model. This is also the case for other degrees of substitutability of complementarity between capital and high-skilled labor. Most importantly for our purposes, the estimated response of the skill premium to investment-specific shocks is positive if capital and skill are complements, negative if they are substitutes and zero when they are neither substitutes nor complements.

Figure 8 shows the impulse responses of the skill premium to an investment-specific shock according to the model for different degrees of capital-skill complementarity or substitutability, as well as our estimated response. Comparing the response of the skill premium to investment-specific shocks in the actual data to that in the model, our estimates reject both strong capital-skill complementarity and substitutability in the data. In the long run, our point estimate suggests an elasticity of substitution between capital and high skilled labor of around $\rho = 2.67$, which corresponds to mild substitutability between the two production inputs.

4.4 Contribution to business cycle fluctuations

When we allow for investment-specific technology shocks, our estimates replicate the finding in Fisher (2006) that investment-specific shocks are an important source of business cycle fluctuations, whereas investment-neutral technology shocks contribute only a small fraction of fluctuations in output and hours, see Table 6. However, our results suggest that there are at least four different types of technology shocks with distinct implications for the comovement of aggregate variables: skill-neutral, investment-neutral; skill-neutral, investment-specific; skill-biased, investment-neutral; and unskill-biased, investment-specific (or skill-biased, consumption-specific) technology shocks.

With the identifying restrictions discussed above, it is not possible to separately identify all four different shocks simultaneously. Recall that both investment-specific and investment-neutral technology shocks affect the skill premium. Conversely, both skill-biased and skill-neutral technology shocks affect the relative price of investment goods. Hence, if we use a recursive identification scheme, identifying first investment-specific technology shocks, then these shocks will include the unskill-biased, investment-specific shocks. In this case, skill-biased technology shocks will be identified as all *remaining* shocks that affect the skill premium in the long run and will exclude shocks that affect both the relative price of investment and the skill premium. Similarly, if we identify first the skill-biased shocks, then these shocks will include the skill-biased, consumption-specific shocks.

Our solution to this problem is to estimate both orderings and use the estimates as a lower and upper bound for the contribution of the various shocks. To be more precise, in ordering I, we identify investment-specific technology shocks as all shocks that affect the relative price of investment goods. These shocks are allowed to affect the skill premium. Skill-biased technology shocks are identified as all remaining shocks that affect the skill premium in the long run. The estimates of this VAR provide an upper bound for the contribution of investment-specific shocks and a lower bound for the contribution of skill-biased technology shocks. In ordering II, we identify skill-biased technology shocks as all shocks that affect the skill premium in the long run and investment-specific shocks as the remaining shocks that affect the relative price in the long run. This ordering provides an upper bound for the contribution of skill-biased shocks and a lower bound for the contribution of investment-specific shocks. In both cases, the remaining shocks affecting labor productivity are neutral technology shocks.

Table 7 shows the variance decomposition of the forecast error variance in output, hours and the skill premium. The contribution of skill- and investment-neutral technology shocks is very similar in both orderings of the identifying restrictions. Neutral technology shocks explain between 10 and 12% of business cycle fluctuations in hours worked and play virtually no role for fluctuations in output and the skill premium. Investment-specific technology shocks explain up to 40% of the volatility in output at business cycle frequencies, and up to 25% of the variation in hours. This finding is consistent with earlier findings in the literature (Fisher (2006), Canova et al. (2010)).

Skill-biased technology shocks explain almost all of business cycle variation in the skill premium. These shocks also explain about 6% of fluctuations in hours worked. Comparing the variance decomposition in Table 7 to that in Table 6, we find that about one third of the technology shocks that drive fluctuations in hours worked are skill-biased, whereas neither skill-biased nor skill-neutral technology is important for output fluctuations. These results suggest that shocks that drive fluctuations in the skill premium are largely unrelated to other variables in the economy. This finding is consistent with the unconditional moments in Table 1, which show the skill premium to be largely uncorrelated with output.

5 Conclusion

In this paper, we explored the implications of skill bias in technological changes for business cycle fluctuations. We constructed a quarterly time series for the skill premium using micro-data from the Current Population Survey (CPS) outgoing rotation groups, and used it to identify skill-biased technology shocks in a structural VAR with long run restrictions. We showed that technology shocks are biased towards skilled labor at all frequencies and documented two main differences between skill-biased and skill-neutral technology shocks. First, the fall in hours in response to improvements in productivity is driven in part by skill-biased technology shocks. Second, the relative price of investment does not respond to skill-biased improvements in technology, indicating that capital and skill are not complements in the aggregate production process. Both findings have important implications for the interpretation of well-known results in the literature.

The fall in hours worked in response to technology shocks, as documented by Galí (1999), has typically been interpreted as evidence for price rigidities. Having access to an improved production technology, which reduces marginal costs, a firm would like to reduce prices in order to increase sales. If prices are rigid however, the firm adjusts labor input in order to produce the amount it can sell. Our results cast doubt on this interpretation. We document a sharp drop in hours worked in response to skill-biased technological improvements. This finding suggests that at least part of the fall in hours is driven by a compositional change in labor demand. In response to a skill-biased improvement in technology, firms increase their relative demand for skilled labor. Since high skilled workers are on average more productive than low skilled workers, effective labor input may increase even if total hours worked fall.

Our conclusion that capital and skill are not complements (nor substitutes) in the aggregate production function, is based on our finding that the relative price of investment goods does not respond to skill-biased technology shocks, or, vice versa, that the skill premium does not respond to investment-specific technology shocks. If capital and skill are complements, as Krusell et al. (2000) argue, we would expect the relative price to fall in response to skill-biased improvements in technology. Is it reasonable to think that capital and skill are complements, substitutes or neither? Clearly, the answer depends on the type of capital and therefore the time period under consideration. In the industrial revolution, new production technologies often involved machines that could be operated by unskilled workers and replaced skilled laborers.[26] Regarding more recent technological developments, Autor et al. (2003) make the point that computer capital complements workers performing nonroutine problem-solving tasks, but substitutes labor in "cognitive and manual tasks that can be accomplished by following explicit rules." Since both nonroutine and routine tasks may be performed by either skilled or unskilled workers, the aggregate elasticity of substitution between capital and skill may vary with the task composition of the workforce. Our results indicate that over the last 20 years, technological improvements in capital substituted skilled and unskilled workers roughly equally. The reason that the skill premium nevertheless increased over this period, is due to investment-neutral technological progress, in which there was strong skill bias.

[26]For example, hand weavers, a skilled profession, opposed the adoption of weaving machinery, going so far as destroying these machines, because many of them lost their jobs and the others were forced to accept lower wages (Noble et al. (2002), p.701).

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Table 1: Unconditional business cycle correlations

	Std	Correlation with			
		Output	Hours	Productivity	Price
Baseline measure					
Skill premium	.0067	0.1131	0.0222	0.1763*	-0.1533
Relative hours	.0184	-0.4124*	-0.2999*	-0.2591*	0.5837*
Naive measure					
Skill premium	.0072	0.0962	0.2102	-0.1853*	0.0851
Relative hours	.0161	-0.4242*	-0.3642*	-0.1688*	0.5418*
Relative supply	.1883	-0.0051	-0.0022	-0.0059	0.0227

Notes: Data series are constructed as explained in section 2.3 and seasonally adjusted using X-12-ARIMA. The series are HP-filtered with λ=1600. The * indicates significance of at least 10%.

Table 2: Variance decomposition with identified technology shocks

	without supply shocks			with supply shocks		
Horizon	8	16	32	8	16	32
output						
techn. shock	5.45	5.39	5.48	4.16	4.02	4.01
	(1.1,17.6)	(0.9,17.7)	(0.7,17.6)	(0.8,15.3)	(0.7,15.3)	(0.6,15.6)
supply shock				5.18	4.21	3.69
				(1.3,12.3)	(1.0,12.2)	(0.8,12.2)
hours						
techn. shock	7.01	6.24	5.81	6.89	5.99	5.77
	(1.3,21.0)	(0.9,20.4)	(0.7,20.0)	(1.3,19.9)	(1.0,19.2)	(0.8,18.5)
supply shock				2.51	2.25	2.14
				(0.4,7.8)	(0.4,8.2)	(0.4,8.8)
premium						
techn. shock	7.48	8.02	8.21	4.11	4.56	4.77
	(2.7,14.7)	(2.4,16.3)	(2.3,17.3)	(1.1,9.5)	(1.0,10.9)	(0.9,11.6)
supply shock				2.88	2.41	2.08
				(1.4,5.8)	(1.0,6.2)	(0.7,6.9)

Notes: Numbers are in percents; the contribution of all shocks, including the (omitted) residual shock, adds up to 100% at each horizon. We report posterior medians and 68% Bayesian confidence bands from the posterior distribution.

Table 3: Variance decomposition with identified skill-biased technology shocks

Horizon	8	16	32
output			
SBT shock	2.72	2.86	2.93
	(0.4,10.2)	(0.3,10.9)	(0.3,11.1)
neutral shock	7.24	6.70	6.36
	(1.2,20.0)	(1.1,19.3)	(1.0,18.9)
hours			
SBT shock	5.59	5.59	5.72
	(0.6,18.0)	(0.6,18.3)	(0.6,18.8)
neutral shock	4.15	3.66	3.40
	(1.0,14.5)	(0.7,13.7)	(0.5,13.4)
premium			
SBT shock	97.74	98.73	99.33
	(94.4,98.9)	(97.0,99.4)	(98.4,99.7)
neutral shock	0.62	0.34	0.18
	(0.2,1.5)	(0.1,0.8)	(0.1,0.4)

Notes: Numbers are in percents; the contribution of all shocks, including the (omitted) residual shock, adds up to 100% at each horizon. We report posterior medians and 68% Bayesian confidence bands from the posterior distribution.

Table 4: Robustness of the response of hours to skill-biased and skill-neutral technology shocks

	SBT shock	skill-neutral shock
Baseline specification		
	-, sign. at all horizons	-, insign. after 3rd quarter
with supply shocks	-, insignificant	-, insign. after 3rd quarter
Variation of the baseline specification with baseline wage premium		
Taking into account low frequencies		
dummy[1]	-, insignificant	+, insignificant
polyn. trend	-, insignificant	-, insign. after 3rd quarter
no trend	-, insignificant	-, insign. after 3rd quarter
subsample stability		
1979:I-2000:IV	-, sign. at all horizons	+, insignificant
Minnesota prior with 8 lags changed to		
2 lags	-, insignificant	-, insignificant
4 lags	-, sign. on impact	+, insign. after 3rd quarter
12 lags	-, sign. at all horizons	+, significant
weaker prior[2]	-, sign. at all horizons	-, insign. after 3rd quarter
Flat prior (OLS equivalent)		
2 lags	-, insignificant	-, insign. after 3rd quarter
4 lags	-, sign. qtr 2-5	-, insign. after 3rd quarter
Alternative and additional variables		
CPS hours	-, sign. qtr 1-3	-, insign. after 3rd quarter
Naive wage premium	+, insignificant[3]	-, insign. after 3rd quarter
Baseline + invest. price	-, sign. at all horizons	-, insign. after 3rd quarter
the above + investment	-, sign. at all horizons	-, insign. after 3rd quarter
the above + consumption	-, sign. at all horizons	-, insign. after 3rd quarter
the above + interest rate	-, insignificant	-, insign. after 3rd quarter

Notes: 1) dummy break at 1997:I; 2) Decay parameter $d = 1$ instead of $d = 3$ as in the baseline; 3) Here, productivity falls after an SBT shock.

Table 5: Variance decomposition with identified
skill-biased and investment-specific technology shocks

Horizon	8		16		32	
	I	II	I	II	I	II
output						
i-shock (ul,lb)	39.76	37.96	40.16	38.19	40.33	37.6
	(21.9,57.7)	(21.8,52.9)	(21.8,58.5)	(21.2,54.0)	(20.9,58.7)	(20.1,54.4)
SBT shock (lb,ub)	1.53	2.79	1.55	3.09	1.56	3.2
	(0.3,5.7)	(0.4,11.7)	(0.2,6.3)	(0.4,12.6)	(0.2,6.7)	(0.4,13.3)
neutral shock	1.36	1.26	1.26	1.22	1.25	1.26
	(0.4,5.1)	(0.3,4.6)	(0.3,5.2)	(0.2,4.8)	(0.2,5.6)	(0.2,4.9)
hours						
i-shock (ul,lb)	24.95	22.54	25.74	23.31	25.11	23.1
	(8.7,43.7)	(8.3,38.4)	(8.6,45.2)	(8.2,40.7)	(7.6,45.2)	(7.6,41.1)
SBT shock (lb,ub)	5.21	6.04	5.33	6.21	5.39	6.38
	(0.6,14.7)	(0.7,20.6)	(0.6,15.4)	(0.7,21.5)	(0.7,15.5)	(0.7,22.1)
neutral shock	11.43	12.65	10.23	11.25	9.98	10.77
	(4.0,23.8)	(4.6,24.3)	(3.0,22.0)	(3.6,22.7)	(2.7,22.0)	(3.3,22.6)
premium						
i-shock (ul,lb)	1.90	1.56	2.14	0.90	2.21	0.5
	(0.7,5.5)	(0.6,4.1)	(0.7,7.3)	(0.3,2.3)	(0.5,8.4)	(0.2,1.2)
SBT shock (lb,ub)	95.56	96.02	96.25	97.76	96.93	98.8312
	(90.8,97.7)	(92.2,97.9)	(91.2,98.3)	(95.8,98.8)	(90.9,98.8)	(97.8,99.4)
neutral shock	0.54	0.56	0.31	0.31	0.16	0.1656
	(0.2,1.4)	(0.2,1.4)	(0.1,0.8)	(0.1,0.8)	(0.1,0.4)	(0.1,0.4)

Notes: Numbers are in percents; the contribution of all shocks, including the (omitted) residual shock, adds up to 100% at each horizon. We report posterior medians and 68% Bayesian confidence bands from the posterior distribution.

Table 6: Variance decomposition with
investment-specific technology shocks

Horizon	8	16	32
output			
i-specific shock	40.78	41.09	40.53
	(23.9,57.5)	(22.9,59.5)	(21.8,60.1)
neutral shock	1.27	1.31	1.28
	(0.3,5.2)	(0.3,5.2)	(0.2,5.5)
hours			
i-specific shock	25.12	25.71	25.35
	(9.6,42.7)	(9.2,45.8)	(8.1,46.2)
neutral shock	17.13	15.89	15.49
	(7.2,31.5)	(6.1,29.5)	(5.6,29.5)
premium			
i-specific shock	1.97	2.47	2.62
	(0.7,5.8)	(0.7,8.1)	(0.5,9.0)
neutral shock	10.52	11.35	11.88
	(5.2,18.1)	(5.1,19.8)	(5.0,21.0)

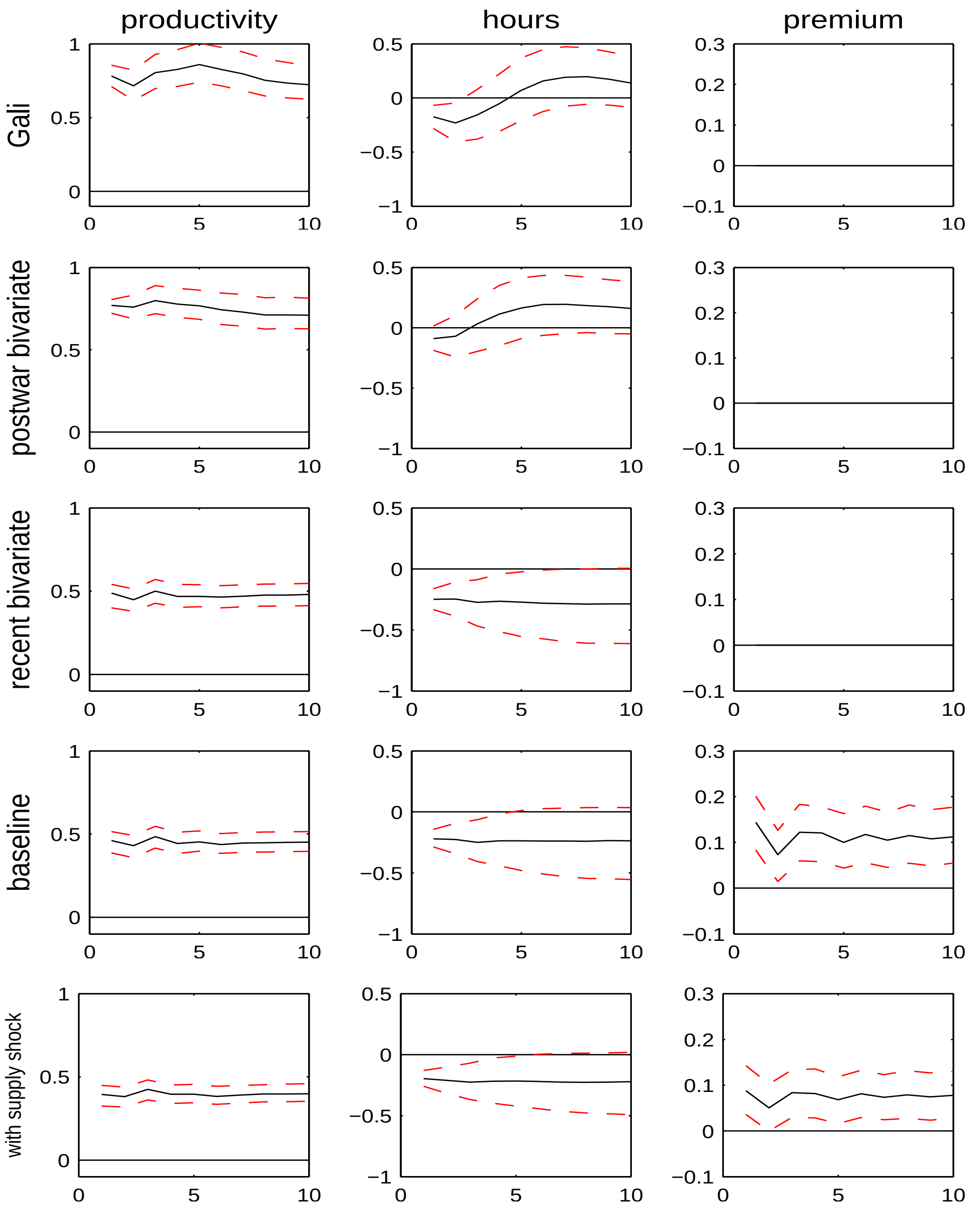
Notes: Numbers are in percents; the contribution of all shocks, including the (omitted) residual shock, adds up to 100% at each horizon. We report posterior medians and 68% Bayesian confidence bands from the posterior distribution.

Table 7: Variance decomposition with identified
skill-biased and investment-specific technology shocks

Horizon	8		16		32	
	I	II	I	II	I	II
output						
i-shock (ul,lb)	39.76	37.96	40.16	38.19	40.33	37.6
	(21.9,57.7)	(21.8,52.9)	(21.8,58.5)	(21.2,54.0)	(20.9,58.7)	(20.1,54.4)
SBT shock (lb,ub)	1.53	2.79	1.55	3.09	1.56	3.2
	(0.3,5.7)	(0.4,11.7)	(0.2,6.3)	(0.4,12.6)	(0.2,6.7)	(0.4,13.3)
neutral shock	1.36	1.26	1.26	1.22	1.25	1.26
	(0.4,5.1)	(0.3,4.6)	(0.3,5.2)	(0.2,4.8)	(0.2,5.6)	(0.2,4.9)
hours						
i-shock (ul,lb)	24.95	22.54	25.74	23.31	25.11	23.1
	(8.7,43.7)	(8.3,38.4)	(8.6,45.2)	(8.2,40.7)	(7.6,45.2)	(7.6,41.1)
SBT shock (lb,ub)	5.21	6.04	5.33	6.21	5.39	6.38
	(0.6,14.7)	(0.7,20.6)	(0.6,15.4)	(0.7,21.5)	(0.7,15.5)	(0.7,22.1)
neutral shock	11.43	12.65	10.23	11.25	9.98	10.77
	(4.0,23.8)	(4.6,24.3)	(3.0,22.0)	(3.6,22.7)	(2.7,22.0)	(3.3,22.6)
premium						
i-shock (ul,lb)	1.90	1.56	2.14	0.90	2.21	0.5
	(0.7,5.5)	(0.6,4.1)	(0.7,7.3)	(0.3,2.3)	(0.5,8.4)	(0.2,1.2)
SBT shock (lb,ub)	95.56	96.02	96.25	97.76	96.93	98.8312
	(90.8,97.7)	(92.2,97.9)	(91.2,98.3)	(95.8,98.8)	(90.9,98.8)	(97.8,99.4)
neutral shock	0.54	0.56	0.31	0.31	0.16	0.1656
	(0.2,1.4)	(0.2,1.4)	(0.1,0.8)	(0.1,0.8)	(0.1,0.4)	(0.1,0.4)

Notes: Numbers are in percents; the contribution of all shocks, including the (omitted) residual shock, adds up to 100% at each horizon. We report posterior medians and 68% Bayesian confidence bands from the posterior distribution.

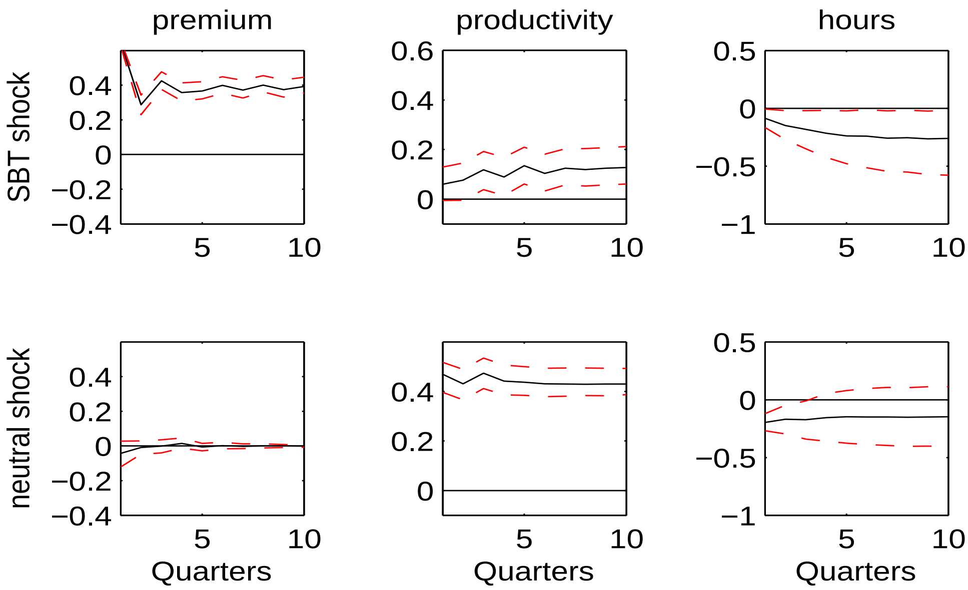
Figure 1: Impulse-responses to identified technology shocks



Notes: Responses in percent and quarters to a positive one-standard-deviation shock. Confidence intervals are 68% Bayesian bands.
First row: Bivariate VAR with labor productivity and hours worked, 1948:I-1994:IV, OLS with 4 lags.
Second row: Bivariate VAR, 1948:I-1994:IV, Minnesota prior with 8 lags.
Third row: Bivariate VAR 1979:I-2006:II, with low-frequency adjustment.
Fourth row: VAR with labor productivity, hours, skill premium, 1979:I-2006:II, with low-frequency adjustment.

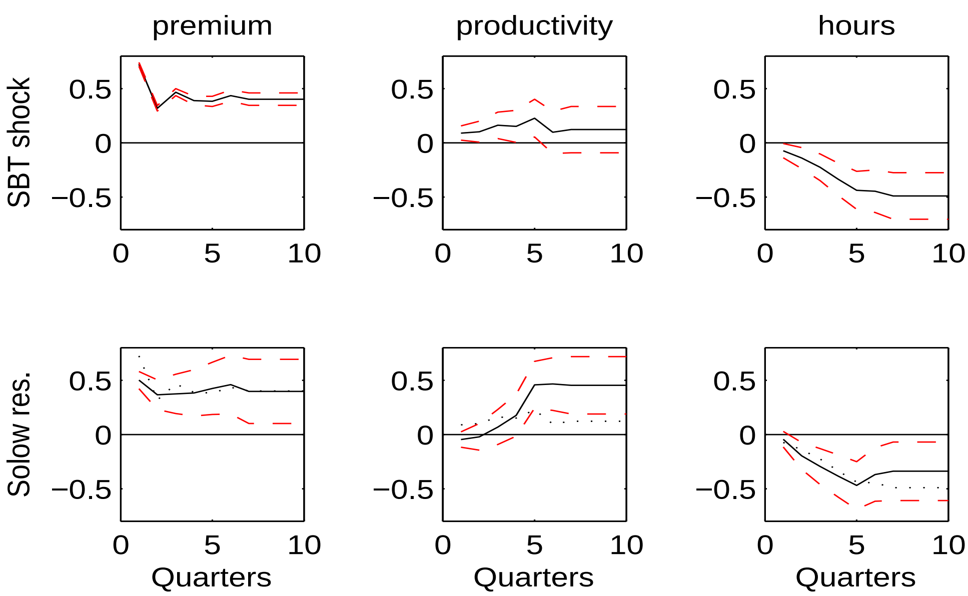
Fifth row: 3 variable VAR adding relative supply of skill and identifying skill supply shocks.

Figure 2: Impulse-responses with identified skill-biased technology shocks



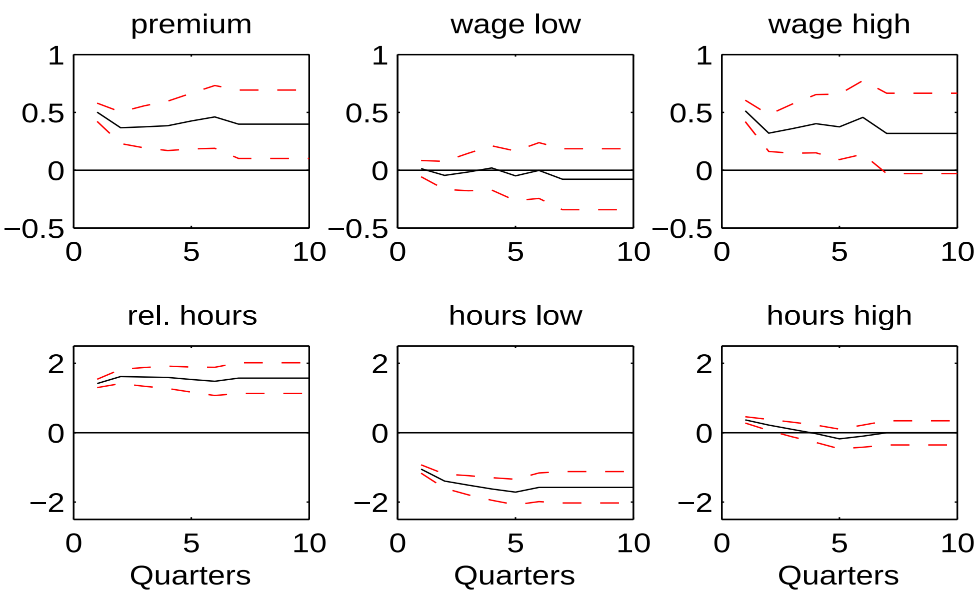
Notes: Percent responses to a positive one-standard-deviation shock.
Confidence intervals are 68% Bayesian bands.

Figure 3: Impulse-responses to SBT shocks from the VAR
and from the production function decomposition



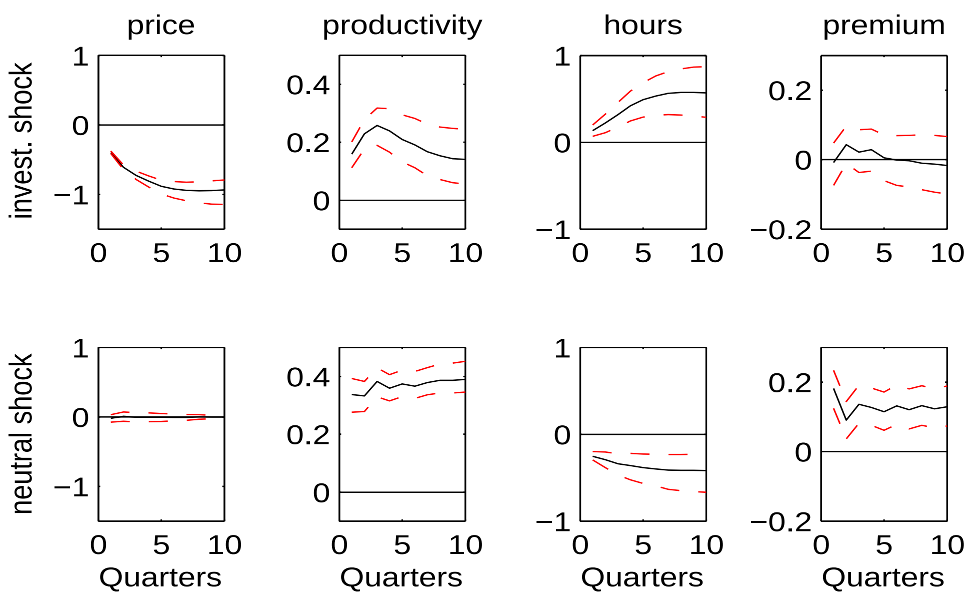
Notes: Impulse-responses from regression on six lags of the identified SBT shock and the production function residual respectively.
Percent responses to a positive one-standard-deviation shock. The black dotted line repeats the estimate from the first row. Confidence intervals are one standard error bands.

Figure 4: Impulse-responses to SBT shocks from the production function decomposition for additional variables



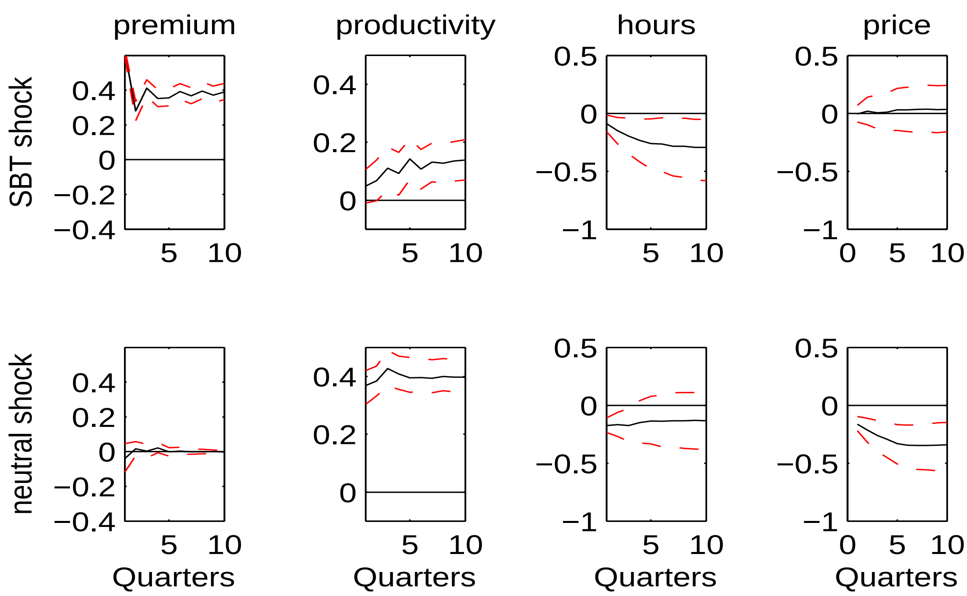
Notes: Impulse-responses from regression on six lags of production function residual.
Percent responses to a positive one-standard-deviation shock.
Confidence intervals are one standard error bands.

Figure 5: Impulse-responses with identified
investment-specific technology shocks



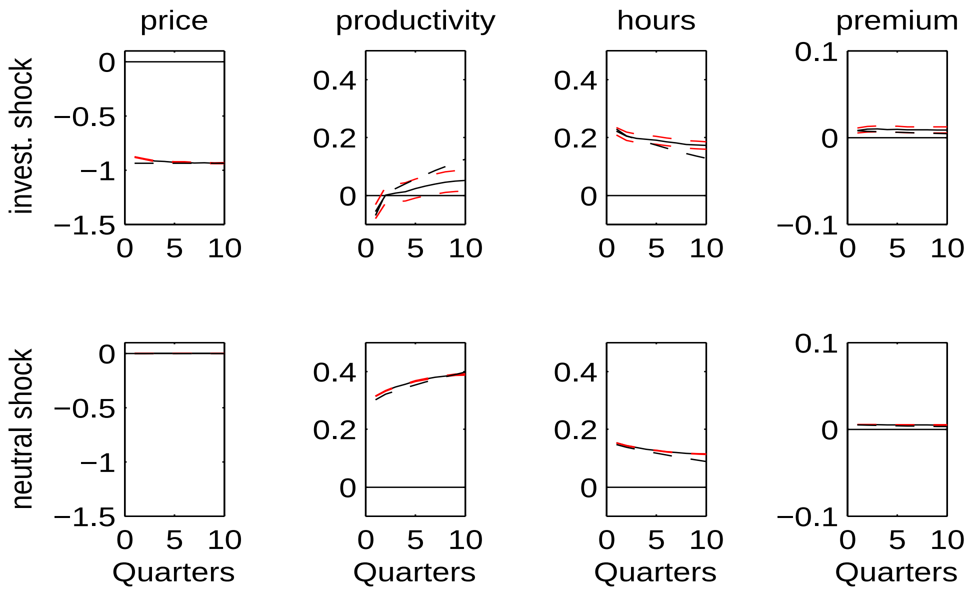
Notes: Percent responses to a positive one-standard-deviation shock.
Confidence intervals are 68% Bayesian bands.

Figure 6: Impulse-responses with identified skill-biased technology shocks including the relative price of investment goods



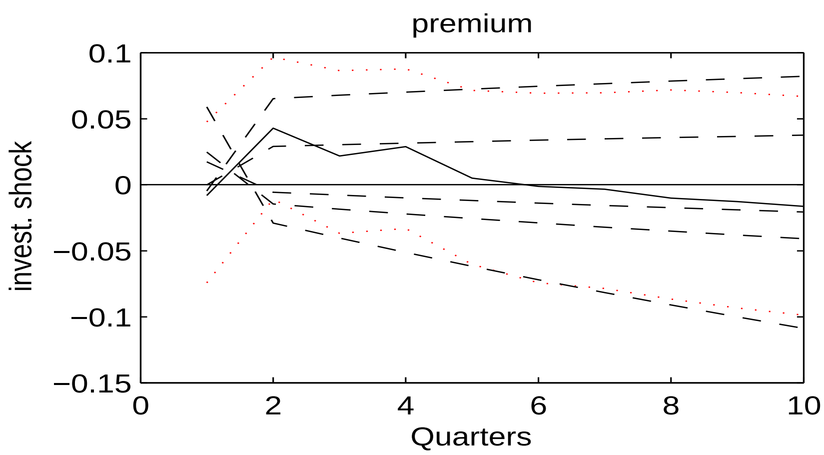
Notes: Percent responses to a positive one-standard-deviation shock.
Confidence intervals are 68% Bayesian bands.

Figure 7: Impulse-responses from a model with investment-specific shocks and shocks to total factor productivity



Percent responses to a positive one-standard-deviation shock. The dashed lines represent the theoretical responses from the model with $\rho = \sigma = 1.67$. The solid lines are the estimated responses from 1000 simulations of 110 quarters each of the same model. The responses are normalized to match the responses of the investment price and labor productivity in the actual data in the longer run (20 quarters).

Figure 8: Capital-skill substitutability



Notes: Black line depicts response of the premium from the estimated structural VAR with actual data together with the Bayesian 68% confidence bands (red dotted lines). The dashed lines show the responses from the model with $\rho = 0.67$, $\rho = 1.17$, $\rho = 2.17$, $\rho = 2.67$ and $\rho = 5$ respectively.