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Labor market effects of technology shocks biased toward the traded sector☆

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ABSTRACT

Our VAR evidence for OECD countries reveals that the non-traded sector alone drives the increase in hours worked following a technology shock that increases permanently traded relative to non-traded TFP. The shock generates a reallocation of labor toward the non-traded sector which contributes to 35% of the rise in non-traded hours worked. Both labor reallocation and variations in labor income shares are found empirically connected with factor-biased technological change. Our quantitative analysis shows that a two-sector open economy model with flexible prices can reproduce the labor market effects we document empirically once we allow for imperfect mobility of labor, a demand for home-produced traded goods which is elastic enough w.r.t. the terms of trade, and factor-biased technological change. When calibrating the model to country-specific data, its ability to account for the cross-country reallocation and redistributive effects we estimate increases once we let factor-biased technological change vary between sectors and countries.

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1. Introduction

The pioneering work of Galí (1999) has sparked a broad literature investigating the labor market effects of technology shocks.[1] This literature commonly identifies technology shocks as shocks that increase permanently aggregate productivity. Because variations in aggregate total factor productivity (TFP thereafter) can be driven by movements that are both common across sectors and sector-specific, shocks to aggregate TFP can be broken down into symmetric and asymmetric technology shocks across sectors. As documented empirically by Foerster et al. (2011) and Garìn et al. (2018) on U.S. data, the contribution of asymmetric shocks has increased dramatically during the great moderation relative to the period before 1984. Despite the growing importance of asymmetric shocks across sectors for economic fluctuations, a systematic exploration of the effects of sector-biased technology shocks in open economy is still lacking.

Building on the evidence documented by Duarte and Restuccia (2010, 2020), and Inklaar and Diewert (2016) who find that productivity grows faster in exporting industries, we make the distinction between a traded vs. a non-traded sector to explore the effects of asymmetric technology shocks in an open economy. By investigating the labor market effects of a technology shock that increases permanently traded relative to non-traded TFP, the purpose of this paper is to address two questions: Is the change in total hours worked uniformly distributed across sectors and if not which sector benefits from labor reallocation? Does the magnitude of labor reallocation vary across OECD countries and which factors are responsible for these international differences?

Answering these questions is important since economic expansions come along with an acceleration in technological change concentrated in traded industries while a fall in the relative productivity of tradables accompanies recessions. As is evident in Fig. 1a, the cyclical component of real GDP (displayed by the red line) co-moves with the detrended (logged) ratio of traded to non-traded TFP (displayed by the blue line) for the seventeen OECD countries of our sample. As traded TFP increases faster than non-traded TFP, non-traded firms set higher prices to compensate for lower productivity gains. Because traded and non-traded goods have low substitutability, see e.g., Kehoe and Ruhl (2009) and Stockman and Tesar (1995), the tradable content of expenditure declines. Labor thus shifts away from the traded sector which leads the traded goods-sector share of total hours worked to be negatively correlated with the relative productivity of tradables. Such a negative correlation should materialize only during the great moderation because the contribution of asymmetric shocks is substantial during this period. On the contrary, when the contribution of asymmetric technology shocks to economic fluctuations is negligible and symmetric technology shocks are predominant, cyclical components of the relative productivity of tradables and the labor share of tradables should be uncorrelated.[2] Since three-fourth of our sample consists of European countries for which the great moderation occurs in the post-1992 period, we choose 1992 as the cutoff year for the whole sample.[3] In Fig. 1b, we plot the detrended (logged) ratio of traded to non-traded TFP (displayed by the blue line) and the detrended labor share of tradables (displayed by the black line). The time series appear to be uncorrelated until 1992 while they move in opposite direction after 1992. More specifically, the correlation between the relative productivity and the labor share of tradables is essentially zero over 1970–1992 and is negative (i.e., at −0.35) in the post-1992 period. Evidence on U.S. data further corroborates the growing importance of asymmetric shifts in sectoral TFPs during the great moderation as the correlation between the labor share and relative productivity of tradables is zero before 1984 and stands at −0.67 from 1984 to 2013.[4]

By adapting the identification scheme of technology shocks proposed by Galí (1999), we document a set of VAR evidence which confirms the empirical facts we describe above. Our estimates reveal that the contribution of identified asymmetric technology shocks across sectors to the forecast error variance of aggregate TFP growth has increased dramatically over time and stands at about 40% in the post-1992 period while asymmetric technology shocks play a negligible role before 1992. When we estimate the effects of technology shocks biased toward the traded sector, we find that real GDP growth originates from the traded sector while the non-traded sector alone drives total hours worked growth.

Our empirical results also show that productive resources, especially labor, shift toward non-traded industries. Labor reallocation contributes to 43% of the rise in non-traded hours worked on impact and 35% on average (over ten years). To rationalize the shift of labor toward the non-traded sector that we document empirically, we put forward a two-sector semi-small open economy model with flexible prices. Likewise Kehoe and Ruhl (2009), we assume that the economy is small in world capital markets so that the world interest rate is given, but large enough in the world goods market to influence the relative price of its export good. We find quantitatively that the model can account for the magnitude of the decline in the traded goods-sector share in total hours worked once it contains a combination of three elements: a demand for home-produced traded goods which is elastic enough w.r.t. the terms of trade, imperfect mobility of labor and factor-biased technological change (FBTC henceforth).

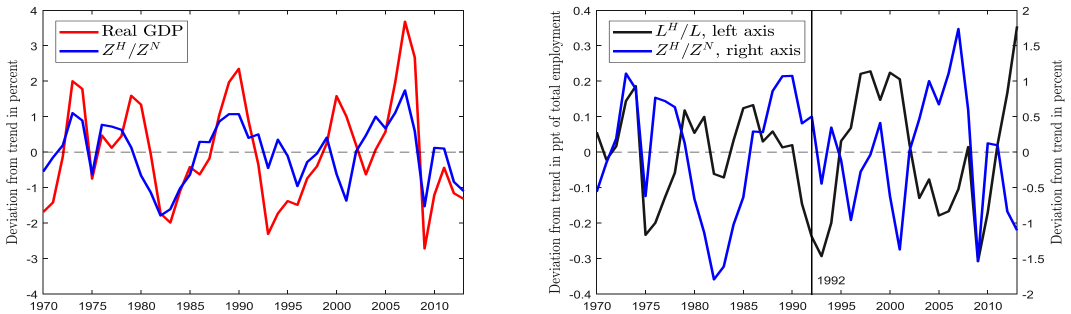
These three specific features are necessary to mitigate the labor reallocation movement caused by the combined effect of financial openness and the low substitutability between traded and non-traded goods. Intuitively, a technology shock biased toward tradables generates an excess demand for non-traded goods which appreciates the relative price of non-tradables. With an elasticity of substitution between traded and non-traded goods smaller than one, the non-tradable content of expenditure rises. Whilst labor shifts away from the traded sector and moves toward the non-traded sector, our quantitative analysis reveals

[1] While Galí (1999) uses labor productivity, like Chang and Hong (2006), we measure technological change with TFP.

[2] In a model with three goods where the substitutability varies across sectoral goods, a symmetric technology shock produces a reallocation of labor across sectors because the variations of sectoral prices have a different impact on sectoral labor demand. When asymmetric technology shocks play a negligible role, the movement in the labor share of tradables should be driven by symmetric technology shocks.

[3] See e.g., Benati (2008) for the U.K. and González Cabanillas and Ruscher (2016) for the euro area.

[4] In the Online Appendix A, we show additional evidence for four OECD countries, including the US.



(a) Real GDP and Relative productivity (b) Labor Share of Tradables and Relative Productivity

Fig. 1. Relative productivity of tradables, real GDP and labor reallocation. *Notes*: TFP of tradables, Z_t^H, and TFP of non-tradables, Z_t^N, are the Solow residuals. The labor share of tradables is calculated as the ratio of hours worked in the traded sector to total hours worked. Detrended relative productivity and real GDP are calculated as the difference between the logarithm of actual series and the trend of logged time series. The trend is obtained by applying a Hodrick-Prescott filter with a smoothing parameter of $\lambda = 100$ (as we use annual data) to the (logged) time series. Detrended labor share of tradables is computed as the difference between actual time series for L_t^H/L_t and the trend of the labor share of tradables, the latter being obtained by applying a Hodrick-Prescott filter with a smoothing parameter of $\lambda = 100$. Sample: 17 OECD countries, 1970–2013, annual data.

that the model considerably overstates the decline in the labor share of tradables. The reason is that we consider an open economy setup where access to foreign borrowing significantly biases labor demand toward the non-traded sector.

To mitigate labor reallocation, we first allow for endogenous terms of trade by assuming that home- and foreign-produced traded goods are imperfect substitutes. As technology improvement is concentrated in the traded sector and puts downward pressure on the marginal cost in this sector, traded firms find it optimal to lower their prices as long as the demand for home-produced traded goods is elastic enough w.r.t. the terms of trade, in line with the evidence (see e.g., Bajzik et al., 2020). By increasing the demand for home-produced traded goods, the depreciation in the terms of trade curbs the demand boom for non-tradables and therefore mitigates the decline in the labor share of tradables. The second key element is imperfect mobility of labor. In line with our evidence indicating that the labor reallocation process is associated with mobility costs, we allow for limited substitutability in hours worked across sectors which further hampers labor reallocation. Even with the two aforementioned ingredients, the model still overstates the shift of labor toward the non-traded sector and does not replicate well the responses of sectoral hours worked.

The third and pivotal element is FBTC which is recovered from our estimation of redistributive effects. More specifically, our evidence reveals that the labor income share (LIS henceforth) increases in both sectors which implies that technological change is not Hicks-neutral but rather biased toward labor. Intuitively, when technological change is Hicks-neutral, the LIS is a function of the capital-labor ratio only. The gross complementarity between capital and labor in production found in the data (see e.g., Klump et al., 2007; Herrendorf et al., 2015; Oberfield and Raval, 2014; Chirinko and Mallick, 2017) and corroborated by our own estimates implies that the LIS and the capital-labor ratio move in the same direction. Because a technology shock biased toward the traded sector drives capital out of the traded sector while labor is subject to mobility costs, the capital-labor ratio falls dramatically, thus driving down the traded LIS under the assumption of Hicks-neutral technological change. Since the non-traded capital-labor ratio is unresponsive to the shock, this assumption also implies that the non-traded LIS should remain unchanged, in contradiction with our evidence. To account for the rise in LISs that we estimate empirically, we assume that capital relative to labor efficiency increases which in turn biases technological change toward labor within each sector.[5] While the model can account for the redistributive effects once we allow for FBTC, the differential in FBTC between sectors increases the performance of the model with imperfect mobility of labor and endogenous terms of trade in reproducing the labor reallocation effects we document empirically.

To assess quantitatively the contribution of each element of our model to the sectoral effects we compute numerically, we consider a simplified version of our setup which collapses to the small open model with tradables and non-tradables developed by Fernández de Córdoba and Kehoe (2000) with no labor mobility costs, and add one ingredient at a time. While the restricted version of the model generates a decline in the labor share of tradables which is almost six times larger to what we estimate empirically on impact, adding labor mobility costs halves the reallocation of labor toward the non-traded sector. When we allow for imperfect mobility of labor and endogenous terms of trade, the model performance improves but the fall in the traded goods-sector share of total hours worked is still 50% larger to what is estimated. Once we allow for technological change biased toward labor varying across sectors, the fall in the labor share of tradables is further mitigated and matches the evidence because technological change is more biased toward labor in the traded than in the non-traded sector which leads traded firms to hire more workers, thus hampering the shift of labor toward the non-traded sector.

[5] Technically, we adapt the methodology by Caselli and Coleman (2006) and make inference about FBTC from the demand for factors of production and a technology frontier which maps sectoral TFP shocks we estimate empirically into factor-augmenting technological shifts.

We further investigate about the role in FBTC in driving international differences in labor market outcomes by taking advantage of the panel data dimension of our sample. When estimating the redistributive effects at a country level, we find that LISs may fall or rise by a magnitude which varies considerably between OECD countries. In the lines of Caselli (2016), we construct time series for sectoral FBTC and detect empirically a strong and positive cross-country relationship between the responses of LISs and FBTC. While the responses of LISs vary between countries as a result of cross-country differences in FBTC, international differences in the labor reallocation effects we estimate empirically are driven by cross-sector differences in FBTC which vary significantly across OECD economies. More specifically, we find that the labor share of tradable falls less in countries where technological change is more biased toward labor in the traded than in the non-traded sector. Once calibrated to country-specific data, numerical results show that the model can account for international differences in the redistributive and reallocation effects we document empirically as long as we let FBTC vary between sectors and across countries.

The remainder of the paper is organized as follows. In Section2, we investigate empirically the labor market effects of a technology shock biased toward the traded sector. In Section3, we develop a two-sector open economy model with flexible prices and FBTC. In Section4, we report the results of our numerical simulations and assess the ability of the model to account for the evidence on the reallocation and redistributive effects of a technology shock which increases permanently traded relative to non-traded TFP. In Section5, we summarize our main results and we conclude with a discussion of some possible avenues for future research. The Online Appendix presents further empirical and numerical results, conducts robustness checks to address the SVAR critique, provides the steps to solve the model, and discusses analytical results from a restricted version of our setup.

Related literature Our paper fits into several different literature strands as we bring several distinct threads in the existing literature together. First, our setup includes several key features which have been put forward by the literature to rationalize the response of aggregate hours worked to a positive productivity shock. Like Collard and Dellas (2007), the open economy dimension of our setup greatly enhances the flexible price model's ability to account for the labor market effects of technology shocks through the terms of trade deterioration. In contrast to Collard and Dellas who generate a decline in total hours worked by assuming that home- and foreign-produced traded goods are gross complements, the ability of our model to account for the dynamics of sectoral hours worked increases when home- and foreign-produced traded goods are gross substitutes. Like Cantore et al. (2014), we put forward FBTC to account for the responses of hours worked to a technology shock. The authors show that technology shocks biased toward capital allow the RBC model to generate a negative response of hours worked while we find that sectoral technological shifts are biased toward labor (for the whole sample and the U.S. as well). The reason for this discrepancy lies in the fact that aggregate technology shocks are a combination of symmetric and asymmetric technology shocks, the former shock being biased toward capital and the latter biased toward labor.

The contribution of asymmetric technology shocks across sectors to economic fluctuations has received attention only very recently. Using U.S. data over 1961–2008 and distinguishing between a consumption and an investment sector, Chen and Wemy (2015) find that technology shocks biased toward the capital-producing sector explain more than 50% of TFP fluctuations. In the same vein, our evidence reveals that the contribution of technology shocks biased toward the traded sector to TFP fluctuations stands at 40% in OECD countries over 1993–2013. Drawing on the pioneering work by Long (1983) and revitalized later by Horvath (2000), Holly and Petrella (2012) quantify the contribution of industry specific shocks to aggregate hours worked by considering input-output linkages. Differently, we explore the sectoral composition effects driven by a shock to TFP taking place at uneven rates across sectors and uncover the key role of heterogenous substitutability across sectoral goods and FBTC in the same spirit as the structural change literature, see e.g., Ngai and Pissarides (2007) and Alvarez-Cuadrado et al. (2018), respectively. Our study differs from the structural change literature because the VAR methodology allows us to quantify empirically the extent of the reallocation of economic activity conditional on a technology shock biased toward the traded sector. Therefore, we are exclusively interested in characterizing the behavior of the economy moving from one initial steady-state to a new steady-state following a permanent increase in traded relative to non-traded TFP rather than studying the convergence of the open economy toward a balanced growth path.

Our work also complements the literature which analyzes sectoral reallocation in open economy within a RBC model, e.g., Fernández de Córdoba and Kehoe (2000), Benigno and Fornaro (2014), Arellano et al. (2018), Fornaro (2018) and Kehoe and Ruhl (2009). The first two works show that capital inflows episodes have contributed to shifting productive resources out of the traded sector. Similarly, in our open economy setup, financial openness amplifies the incentives to shift labor toward the non-traded sector. In contrast to Arellano et al. (2018) and Fornaro (2018) who consider a default risk and a deleveraging shock, respectively, to rationalize the shift of labor toward the traded sector during the sovereign debt crisis in Europe after 2008, this movement of labor is the result of the dramatic decline in the TFP in tradables relative to non-tradables in our setup. Whilst we emphasize the key role of the terms of trade in shaping the labor movement across sectors like Kehoe and Ruhl (2009), none of the aforementioned articles allow for FBTC.

2. Technology shocks biased toward tradables: VAR evidence

To guide our quantitative analysis, we document evidence on the labor market effects driven by a technology shock biased toward the traded sector by estimating a structural VAR model in panel format on annual data. We first present the data and detail our identification strategy, and then we discuss empirical results. We denote below the percentage deviation from initial steady-state (or the rate of change) with a hat.

2.1. Data construction

Before presenting our empirical strategy and VAR evidence, we briefly discuss the dataset we use. Our sample contains annual observations over the period 1970–2013 and consists of a panel of 17 OECD countries. Online Appendix L provides the list of countries. We use the EU KLEMS [2011], [2017] and OECD STAN [2011], [2017] databases which provide domestic currency series of value added in current and constant prices, labor compensation and hours worked at an industry level. All quantities are scaled by the working age population. We use the subscripts i and t to index countries and time periods (years), respectively, and we use the superscript j to index sectors below.

We make the distinction between a traded (indexed by the superscript H) vs. non-traded sector (indexed by the superscript N). Our sample covers eleven 1-digit ISIC-rev.3 industries which are split into traded and non-traded sectors by adopting the classification by De Gregorio et al. (1994). Agriculture, hunting, forestry and fishing; Mining and quarrying; Total manufacturing; Transport, storage and communication are classified as traded industries. Following Jensen and Kletzer (2006), we updated the classification by De Gregorio et al. (1994) by treating Financial intermediation as a traded industry. Electricity, gas and water supply; Construction; Wholesale and retail trade; Hotels and restaurants; Real estate, renting and business services; Community, social and personal services are classified as non-traded industries.[6]

POnce industries have been classified as traded or non-traded, series for sectoral value added in current (constant) prices are constructed by adding value added in current (constant) prices for all sub-industries k in sector $j = H, N$, i.e., $P^j_{\text{it}} Y^j_{\text{it}} = \sum_k P^j_{k,\text{it}} Y^j_{k,\text{it}}$ ($\bar{P}^j_{\text{it}} Y^j_{\text{it}} = \sum_k \bar{P}^j_{k,\text{it}} Y^j_{k,\text{it}}$ where the bar indicates that prices P^j are those of the base year), from which we construct price indices (or sectoral value added deflators), P^j_{it}. Normalizing base year price indices $\bar{P}^j$ to 1, the relative price of non-tradables, P_{it}, is defined as the ratio of the non-traded value added deflator to the traded value added deflator (i.e., $P_{\text{it}} = P^N_{\text{it}} / \mathscr{P}^H_{\text{it}}$). The relative price of home-produced traded goods (or the terms of trade, denoted by P^H_{it}) is constructed as the ratio of the traded value added deflator ($\mathscr{P}^H_{\text{it}}$) to the price deflator of imported goods and services (P^F_{it}). The same logic applies to constructing series for hours worked ($L^j = \sum_k L^j_{k,\text{it}}$) and labor compensation in the traded and the non-traded sectors which allow us to construct sectoral wages, W^j_{it}. The real consumption wage in sector j, $W^j_{C,\text{it}}$, is defined as the sectoral nominal wage, W^j_{it}, divided by the consumption price index, $P_{C,it}$. To construct time series for the aggregate nominal wage, W_{it}, we divide aggregate labor compensation by total hours worked. We also construct hours worked and valued added shares of sector j (at constant prices), denoted by $\nu^{L,j}_{\text{it}}$ and $\nu^{Y,j}_{\text{it}}$, see Online Appendix D.[7] Note that we focus on the change in the value added share at constant prices because as discussed below, it moves in opposite direction to the labor share, the latter being driven by the change in the value added share at current prices. To estimate the redistributive effects, we calculate the LIS for each sector j, denoted by $s^j_{L,\text{it}}$, as the ratio of labor compensation to valued added at current prices in sector j.

Like Chang and Hong (2006), we use sectoral TFPs, Z^j, to approximate technical change. Sectoral TFPs are constructed as Solow residuals from constant-price (domestic currency) series of value added, Y^j_{it}, capital stock, K^j_{it}, and hours worked, L^j_{it}:

$$\hat{Z}^j_{\text{it}} = \hat{Y}^j_{\text{it}} - s^j_{L,i} \hat{L}^j_{\text{it}} - \left(1 - s^j_{L,i}\right) \hat{K}^j_{\text{it}}, \tag{1}$$

where $s^j_{L,i}$ is the LIS in sector j averaged over the period 1970–2013. To obtain series for sectoral capital stock, we first compute the overall capital stock by adopting the perpetual inventory approach, using constant-price investment series taken from the OECD's Annual National Accounts. Following Garofalo and Yamarik (2002), we split the gross capital stock into traded and non-traded industries by using sectoral valued added shares. While in the main text, we measure technology change with the Solow residual, we alternatively constructed time series for utilization-adjusted-sectoral-TFPs, as recommended by Basu et al. (2006), by adapting the methodology proposed by Imbs (1999). As shown in Online Appendix U.5, our results are little sensitive to the correction of sectoral TFPs with the (sectoral) capital utilization rate.

2.2. VAR identification of asymmetric technology shocks

In this subsection, we present our identification strategy of asymmetric technology shocks and document some evidence pointing at their increasing importance over time. Like Galí (1999), permanent productivity shocks are identified by assuming that technology shocks are the only source of movements in long-run productivity. Because we adapt the SVAR approach by Galí (1999) to the identification of asymmetric technology shocks, we first answer to two questions below: Are shocks to

[6] Because "Financial Intermediation" and "Real Estate, Renting and Business Services" are made up of sub-sectors which display a high heterogeneity in terms of tradability and "Hotels and Restaurants" has experienced a large increase in tradability over the last fifty years, we perform a sensitivity analysis with respect to the classification for the three aforementioned sectors in Online Appendix O.3. Treating "Financial Intermediation" as non-tradables or classifying "Hotels and Restaurants" or "Real Estate, Renting and Business Services" as tradables does not affect our main results.

[7] We consider an open economy which produces a traded and a non-traded good while the foreign good is the numeraire and its price is normalized to 1. Real GDP, $Y_{R,t}$, is equal to the sum of traded and non-traded value added at constant prices, i.e., $Y_{R,t} = P^H Y^H_t + P^N Y^N_t$ where prices at the initial steady-state are those at the base year so that real GDP collapses to nominal GDP, Y, initially; the value added share at current and constant prices are thus also equal initially.

aggregate TFP evenly distributed across sectors? If not, what is the contribution of asymmetric technology shocks across sectors to the variance of aggregate TFP growth? Beyond the fact that answering these questions will allow us to gain further insight about the mapping between aggregate and asymmetric technology shocks, it will pave the way for our identification strategy.

2.2.1. Sector distribution of shocks to aggregate TFP

We first write down the sectoral decomposition of the percentage deviation of aggregate TFP relative to its initial steady-state, denoted by $\hat{Z}^A_{it}$ (see Online Appendix C):

$$\hat{Z}^A_{it} = \nu^{Y,H}_i \hat{Z}^H_{it} + \left(1 - \nu^{Y,H}_i\right)\hat{Z}^N_{it}, \tag{2}$$

where $\hat{Z}^H_{it}$ and $\hat{Z}^N_{it}$ are the percentage deviation of TFP relative to initial steady-state in the traded and the non-traded sector, respectively, and $\nu^{Y,j}_i$ is the share of value added of sector $j = H, N$ in GDP.

According to Eq. (2), variations in aggregate TFP, $\hat{Z}^A_{it}$, can be associated with shifts in sectoral TFPs which are common across sectors (i.e., $\hat{Z}^H_{it} = \hat{Z}^N_{it}$ in the long-run) or take place at uneven rates across sectors (i.e., $\hat{Z}^H_{it} \neq \hat{Z}^N_{it}$ in the long-run). To investigate whether a shock to aggregate TFP is evenly or unevenly distributed across sectors, we first identify a shock to aggregate TFP, denoted by ϵ^{ZA}_{it}, by estimating a VAR model with two lags in panel format on annual data that includes aggregate TFP and total hours worked, both in growth rate, i.e., $[\hat{Z}^A_{it}, \hat{L}_{it}]$. To identify aggregate technology shocks, we impose restrictions on the long-run cumulative matrix such that only aggregate technology shocks increase permanently Z^A_{it}. In the second step, we consider a VAR model which includes identified technology shocks, ϵ^{ZA}_{it}, ordered first, the rate of growth of traded, non-traded and aggregate TFP, and adopt a Cholesky decomposition. Next, we plot in Fig. 2a the responses for Z^H_{it} shown in the blue line and Z^N_{it} shown in the black line following a 1% permanent increase in Z^A_{it} in the long-run. Estimates show that aggregate technology shocks are not evenly distributed since traded TFP increases significantly more than non-traded TFP.

Above VAR evidence can be mapped into the sectoral decomposition of aggregate TFP by rearranging eq. (2) as follows:

$$\hat{Z}^A_{it} = \hat{Z}^N_{it} + \nu^{Y,H}_i \left(\hat{Z}^H_{it} - \hat{Z}^N_{it}\right). \tag{3}$$

According to our estimates shown in Fig. 2a, an aggregate technology shock which raises Z^A_{it} by 1% in the long-run gives rise to an increase in Z^N_{it} by 0.8% augmented by a productivity differential between tradables and non-tradables of 0.4% (weighted by $\nu^{Y,H}_i$). The RHS of Eq. (3) paves the way for the identification of symmetric and asymmetric technology shocks across sectors. When the shock is asymmetric, both the ratio Z^H_{it}/Z^N_{it} and Z^A_{it} are permanently increased while Z^H_{it} and Z^N_{it} rise by the same amount when the shock is symmetric so that the last term of eq. (3) vanishes.

2.2.2. Contribution of asymmetric technology shocks to FEV of aggregate TFP growth

To identify symmetric vs. asymmetric technology shocks, we consider the same VAR model as above augmented with the ratio of traded to non-traded TFP, Z^H_{it}/Z^N_{it} (in growth rate), i.e., $[\hat{Z}^H_{it} - \hat{Z}^N_{it}, \hat{Z}^A_{it}, \hat{L}_{it}]$. We impose long-run restrictions such that both symmetric and asymmetric technology shocks increase permanently Z^A_{it} while only asymmetric technology shocks increase permanently Z^H_{it}/Z^N_{it} in the long-run. Once we have identified symmetric and asymmetric technology shocks across sectors, we can gauge their contribution to aggregate TFP growth by computing a forecast error variance decomposition (FEVD). To explore whether the contribution of shocks to Z^H/Z^N has changed over time, we estimate the VAR model over two sub-periods, i.e., 1970-1992 and 1993–2013, respectively. Estimates reveal that the share of the FEV of aggregate TFP growth attributable to the shock to the ratio of sectoral TFPs, Z^H_{it}/Z^N_{it}, is negligible over 1970–1992 and stands at about 40% over 1993-2013. Empirical results are shown in Table 4 relegated to Online Appendix G. In Fig. 2b we re-estimate the same VAR model but for one country at a time by imposing long-run restrictions detailed above and plot the FEV of $\hat{Z}^A_t$ attributable to the shock to Z^H_t/Z^N_t over 1970-1992 (horizontal axis) against the FEV of $\hat{Z}^A_t$ attributable to the asymmetric shock over 1993–2013 (vertical axis). Except for four countries (Australia, Germany, Italy, the Netherlands), all OECD countries are above the bisecting line and thus experience a rise in the contribution of asymmetric technology shocks across sectors to the FEV of aggregate TFP growth over time (i.e., in the post-1992 period).

2.2.3. Construction of sector TFP differential index

As in Galí (1999), we impose long-run restrictions in the VAR model to identify permanent technology shocks as shocks that increase permanently the level of TFP. Differently, we focus on the effects of technology shocks biased toward the traded sector and thus identify technology shocks that increase permanently the ratio of traded to non-traded TFP. The empirical strategy is detailed in Appendix B. In line with the Balassa-Samuelson literature, we construct a weighted productivity differential index

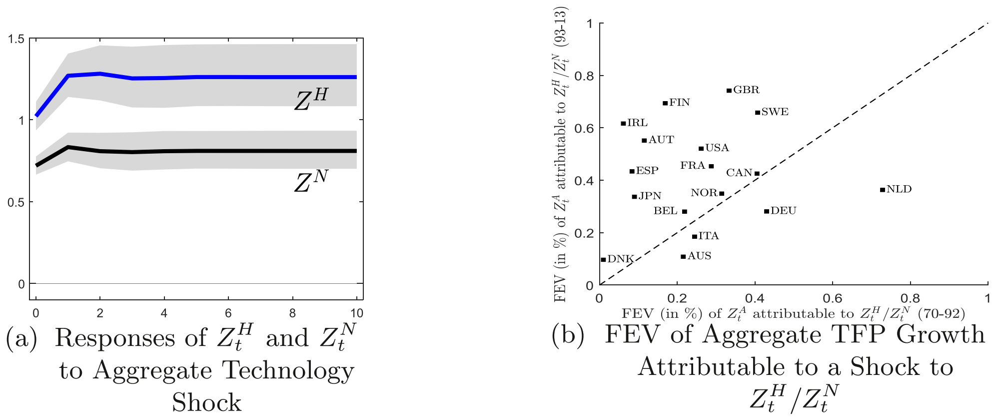


Fig. 2. Symmetric and asymmetric technology shocks across sectors. *Notes*: In (a), we plot the responses of traded TFP, Z_t^H (shown in the blue line), and non-traded TFP, Z_t^N (shown in the black line), to identified shock to aggregate TFP, Z_t^A. Shaded area indicates the 90 percent confidence bounds obtained by bootstrap sampling. (b) The FEV of aggregate TFP growth attributable to shocks to the ratio of sectoral TFPs over 1970-1992 against the FEV of $\hat{Z}_t^A$ attributable to shocks to Z_t^H/Z_t^N over 1993-2013. We compute the FEVD by estimating a VAR model $[\hat{Z}_t^H - \hat{Z}_t^N, \hat{Z}_t^A, \hat{L}_t]$ for one country at a time. To identify symmetric vs. asymmetric technology shocks, we impose long-run restrictions such that both symmetric and asymmetric technology shocks increase permanently Z_t^A while only asymmetric technology shocks increase permanently Z_t^H/Z_t^N in the long-run. Sample: 17 OECD countries, 1970–2013, annual data. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

between tradables and non-tradables by augmenting sectoral TFPs with weights in order to get an economic meaningful normalization (see Online Appendix F):

$$\hat{Z}_{\text{it}} = a_i \hat{Z}_{\text{it}}^H - b_i \hat{Z}_{\text{it}}^N, \tag{4}$$

where $a = \left[(1-\alpha_J) + \alpha_J \frac{s_L^H}{s_L^N}\right]^{-1}$, and $b = a\frac{s_L^H}{s_L^N}$ are country-specific and time-invariant weights which are functions of the labor income share (LIS henceforth) in sector j, s_L^j, and the tradable share in total investment expenditure, α_J, both averaged over 1970–2013. Adding weights a and b 're-scales' sectoral TFP growth so that when the weighted productivity differential increases by 1%, the relative price of non-tradables also appreciates by 1% when terms of trade are exogenous and inputs' mobility costs are absent. Intuitively, higher TFP gains in the traded sector put upward pressure on wages. To compensate for lower productivity gains, non-traded firms increase prices, and all the more so as the production is more intensive in labor, thus explaining why the weighted productivity differential is increasing in s_L^N/s_L^H. In the rest of the paper, for simplicity purposes, we refer to $Z = (Z^H)^a/(Z^N)^b$ as the ratio of traded to non-traded TFP. Note that a and b are close to 1 for the whole sample.

2.3. Labor market effects: VAR evidence

To estimate the sectoral composition effects of a technology shock biased toward tradables, we consider VAR models which include the ratio of traded to non-traded TFP, Z_{it}, and a vector of sectoral variables such as value added at constant prices, Y_{it}^j, hours worked, L_{it}^j, and the real consumption wage, $W_{C,\text{it}}^j$ in sector j or alternatively the value added share, $\nu_{\text{it}}^{Y,j}$, the labor share, $\nu_{\text{it}}^{L,j}$, and the relative wage, $W_{\text{it}}^j/W_{\text{it}}$, in sector j. We also consider a VAR model which includes relative prices to inspect the transmission mechanism. All variables enter the VAR model in rate of growth. We estimate the reduced form of VAR models by panel OLS regression with country and time fixed effects. VAR specifications are detailed in Online Appendix H. While we focus on labor market effects, we also estimate the effects on value added to guide our quantitative analysis as their adjustment allows us to discriminate between models.[8]

We generated impulse response functions which summarize the responses of variables to a 1% permanent increase in traded relative to non-traded TFP (see Eq. (4)). Fig. 3 displays the estimated effects of a technology shock. The horizontal axis measures time after the shock in years and the vertical axis measures percentage deviations from trend. In each case, the solid line represents the point estimate, while the shaded area indicates 90% confidence bounds obtained by bootstrap sampling. In Online Appendix G, Table 5 shows point estimates on impact (i.e., at $t = 0$), and in the long-run (i.e., at a 10-year horizon).

[8] Because we consider alternative VAR models, one might be concerned by the fact that identified technology shocks display substantial differences across VAR specifications. To address this issue, we ran a robustness check by augmenting each VAR model with the same identified technology shock, ordered first. In the quantitative analysis, we take the VAR model which includes the relative productivity of tradables, Z_{it}, real GDP, $Y_{R,it}$, total hours worked, L_{it}, the real consumption wage, $W_{C,it}$, i.e., $x_{\text{it}}^A = \left[\hat{Z}_{\text{it}}, \hat{Y}_{R,\text{it}}, \hat{L}_{\text{it}}, \hat{W}_{C,\text{it}}\right]$, as our benchmark model to calibrate the technology shock. Augmenting each VAR model with the technology shock identified for this benchmark specification, we find that the responses lie within the confidence bounds and thus differences are not statistically significant. Results can be found in Online Appendix O.6.

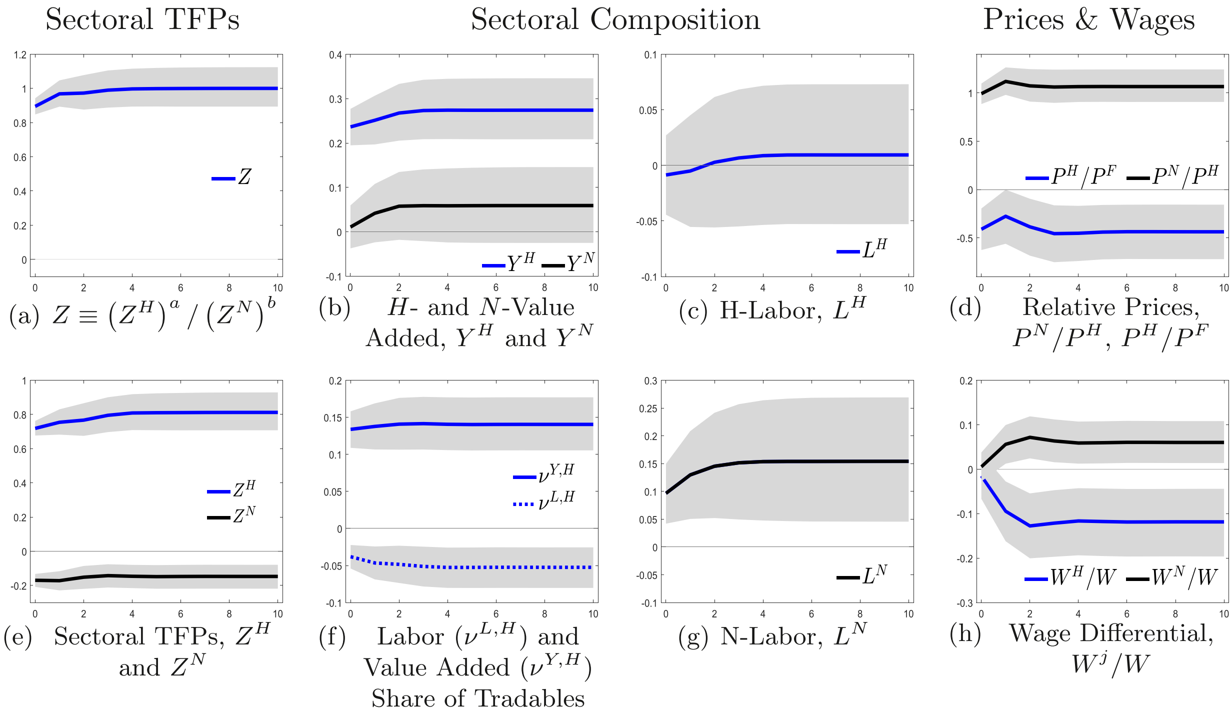


Fig. 3. Sectoral effects of a permanent increase in traded relative to non-traded TFP. *Notes*: Exogenous 1% increase of TFP in tradables relative to non-tradables (as measured by Eq. (4)). Horizontal axes indicate years. Vertical axes measure percentage deviation from trend in GDP units (sectoral value added, sectoral value added share), percentage deviation from trend in total hours worked units (sectoral hours worked, sectoral hours worked share), percentage deviation from trend (sectoral TFPs, relative price of non-tradables, terms of trade, relative wage). Shaded areas indicate the 90% confidence bounds obtained by bootstrap sampling. The blue line shows the response for tradables while the black line shows the response for non-tradables. Sample: 17 OECD countries, 1970–2013, annual data.

2.3.1. Adjustment of sectoral TFPs

As displayed by the solid blue line in Fig. 3a, the relative productivity of tradables rises by 0.9% on impact and increases gradually to reach 1% after 10 years. While TFP of tradables increases by 0.72%, its rise is not large enough to raise Z by 0.9% on impact and thus TFP of non-tradables must decline by 0.17%. Fig. 3b shows that traded TFP grows over time while Z^N remains fairly constant. See Online Appendix M.3 for further details about how we determine empirically the responses of sectoral TFPs.

2.3.2. Sectoral composition effects

The second and third column of Fig. 3 show the output and labor distributional effects of a 1% permanent increase in TFP in tradables relative to non-tradables. The asymmetric technology shock gives rise to an increase in traded value added (at constant prices) by 0.24% of GDP on impact whilst non-traded value added is virtually unchanged. As shown in Fig. 3b, Y^H grows over time while the response of Y^N is not statistically significant, thus indicating that real GDP growth originates from traded industries. The solid blue line of Fig. 3c shows that higher relative productivity of tradables has an expansionary effect on the value added share of tradables at constant prices (i.e., $\nu^{Y,H}$) which stabilizes at 0.14% of GDP.

While higher traded productivity growth relative to average increases the value added share of tradables, $\nu_{it}^{Y,H}$, the reallocation of productive resources lowers it. As can be seen in the dashed blue line in Fig. 3c, the labor share of tradables, $\nu^{L,H}$, declines by about 0.04% of total hours worked on impact. The shift of labor toward the non-traded sector contributes to 43% of the rise in L^N on impact which stands at 0.1% of total hours worked. Labor keeps on shifting toward the non-traded sector over time while the contribution of labor reallocation to the rise in L^N somewhat declines at 34%. On average, 35% of the increase in L^N is attributable to labor movements between sectors.[9] Conversely, as can be seen in the third column of Fig. 3, hours worked do not respond at any horizon in the traded sector. Thus the non-traded sector alone drives the increase in total hours worked. Our empirical findings echo the evidence documented by Hlatshwayo and Spence (2014) on U.S. data who find that during the post-recession

[9] To ensure that $d\nu_{it}^{L,H} + d\nu_{it}^{L,N} = 0$ and compute the contribution of labor reallocation consistently, we reconstructed responses in sectoral labor shares at all horizons by plugging estimated responses of $\hat{L}_{it}^{j}$ and $\hat{L}_{it} = \alpha_{L,i}\hat{L}_{it}^{H} + (1-\alpha_{L,i})\hat{L}_{it}^{N}$ into $d\nu_{it}^{L,j} = \alpha_{L,i}^{j}\left(\hat{L}_{it}^{j} - \hat{L}_{it}\right)$ where $\alpha_{L,i}$ is the labor compensation share of tradables averaged over 1970–2013 in country i, see Online Appendix H for further details. Differences between reconstructed and estimated responses of $d\nu_{it}^{L,N}$ remain very small. Dividing $d\nu_{it}^{L,j}$ by $\alpha_{L,i}^{j}\hat{L}_{it}^{j}$ gives the contribution of labor reallocation to the rise in hours worked in sector j.

period (i.e., 2009–2012), employment growth originates from non-traded industries whilst tradable industries are the drivers of value added growth.

2.3.3. Incentives for labor reallocation

The evidence documented in the last column of Fig. 3 enables us to shed some light on the transmission mechanism. As displayed by the black line in Fig. 3a, a shock to the productivity differential generates an excess demand for non-traded goods which appreciates the relative price of non-tradables by 0.99%. Because the magnitude of the appreciation in P^N/P^H is larger than the productivity differential we estimate on impact (i.e., 0.90%), the share of non-tradables at current prices increases which has an expansionary effect on hiring in the non-traded sector.

2.3.4. Factors hampering labor reallocation

Our VAR evidence in Fig. 3 are in line with the class of neoclassical models such as Ngai and Pissarides (2007) where the sector having greater productivity gains experiences a rise in its value added share at constant prices whilst the sector where productivity growth is smaller, increases its labor share. Loosely speaking, the low substitutability between traded and non-traded goods allows non-traded firms to set higher prices which more than offsets their productivity disadvantage and attracts productive resources. However, the reallocation of productive resources, especially labor, is hampered in an open economy where home- and foreign-produced traded goods are imperfect substitutes and workers experience costs of switching sectors.

As displayed by the blue line in Fig. 3a, a 1% permanent increase in TFP of tradables relative to non-tradables leads to a significant deterioration in the terms of trade which fall by more than 0.4%. Intuitively, by putting downward pressure on the marginal cost, technology improvement concentrated in the traded sector leads traded firms to lower their prices. By stimulating the demand for home-produced traded goods, the depreciation in the terms of trade curbs the demand boom for non-tradables and thereby hampers the outflow of workers (and capital) experienced by the traded sector. Fig. 3d reveals that the shift of labor toward the non-traded sector is further mitigated by the presence of labor mobility costs. Such mobility costs give rise to a positive wage differential for non-tradables by 0.06% in the long-run (see panel E of Table 5), as displayed by the black line, and a fall in the relative wage of tradables by 0.12%, as shown in the blue line.

2.3.5. Capital reallocation and redistributive effects

We now analyze the implications for capital reallocation and sectoral LISs of a permanent increase in the relative productivity of tradables to determine whether sectoral TFP shifts are Hicks-neutral or rather factor-biased. We compute the LIS like Gollin (2002), i.e., labor compensation is defined as the sum of compensation of employees plus compensation of self-employed. We find that our results are robust to alternative constructions of the LIS, see Online Appendix O.5. To explore empirically the redistributive effects, we consider a VAR specification which includes the sector TFP differential index, Z_{it}, the LIS, s_L^j, and the capital-labor ratio in sector j, $k^j \equiv K^j/L^j$, both in rate of growth.

The first and second column of Fig. 4 shows the dynamic responses of capital-labor ratios and LISs, respectively. Our VAR evidence reveals that k^H falls significantly by 0.08% of the aggregate capital stock while k^N is almost unaffected because the rise in non-traded hours worked offsets the capital inflow.[10] If production functions were Cobb-Douglas, the shift of capital would have no impact on sectoral LISs. However, as shown in the second column of Fig. 4, s_L^H increases by more than 0.09% of traded value added on impact while s_L^N increases gradually up to 0.07% of non-traded value added in the long-run. This finding suggests that sectoral goods are produced from CES production functions which is corroborated by our estimates indicating that the elasticity of substitution between capital and labor in production is smaller than one (see Online Appendix M.5).[11]

2.3.6. FBTC hypothesis

The positive and significant response of the LIS in the traded sector together with the fall in k^H calls into question the assumption of Hicks-neutral technological change (HNTC henceforth). The reason is that when capital and labor are gross complements in production, as our evidence and those documented by the existing literature on the subject suggests, see e.g., Klump et al. (2007), Herrendorf et al. (2015), Oberfield and Raval (2014), Chirinko and Mallick (2017), the decline in k^H drives down s_L^H, in contradiction with our empirical findings. A natural candidate to reconcile theory with our evidence is factor-biased technological change (FBTC henceforth). When capital and labor are gross complements, an increase in capital relative to labor efficiency biases technological change toward labor which raises the LIS. To test this hypothesis, we construct time series for FBTC by drawing on Caselli and Coleman (2006) and Caselli (2016) and we estimate a simple VAR model that includes the productivity differential, $\hat{Z}_{\mathrm{it}}$, and $FBTC_{\mathrm{it}}^j$, see Online Appendix I which details the construction of $\mathrm{FBTC}_{\mathrm{it}}^j$. The third column of Fig. 4 shows the responses of FBTC

[10] Due to limited data availability, in the line of Garofalo and Yamarik (2002), we split the aggregate capital stock into tradables and non-tradables in accordance with their value added share. In Online Appendix O.7, we estimate the same VAR model by using databases which provide disaggregated capital stock data (at constant prices) at the 1-digit ISIC-rev.3 level for nine countries of our sample over the entire period 1970–2013. The Garofalo and Yamarik's Garofalo and Yamarik (2002) methodology we adopt in this paper gives very similar results to those obtained when using disaggregated capital stock data.

[11] Variations in the LISs of aggregate sectors could be the result of changes in the value added share of sub-sectors (between-effect) rather than the rise in their LISs (within-effect). We find that on average, 2/3 (80%) of the impact response of the LIS in tradables (non-tradables) can be attributed to the within-effect, see Online Appendix O.4.

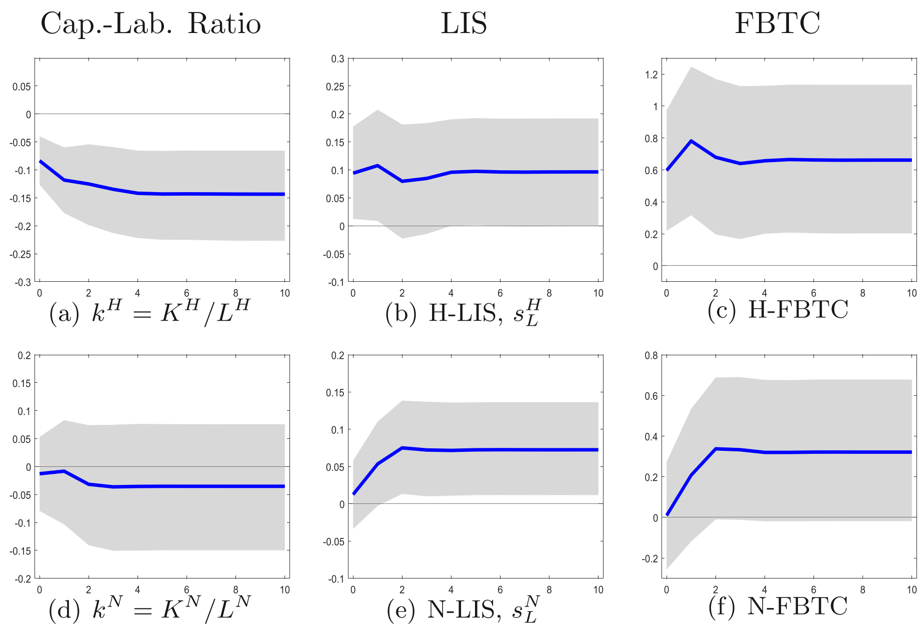


Fig. 4. Redistributive effects of a permanent increase in traded relative to non-traded TFP. *Notes*: Exogenous increase of TFP in tradables relative to non-tradables by 1%. The first two columns show the responses of capital-labor ratios and LISs for tradables and non-tradables. Horizontal axes indicate years. Vertical axes measure deviations from trend in percentage of value added for the LIS, and percentage deviation from trend in capital stock units for the capital-labor ratio. The third column plots the response of FBTC in sector $j = H, N$ which is obtained by running a simple VAR $[\hat{Z}_{it}, \text{FBTC}^j_{it}]$ where details about the construction of time series for FBTC^j_{it} can be found in Online Appendix I. Results for baseline specification are displayed by solid lines with shaded area indicating 90 percent confidence bounds obtained by bootstrap sampling. Sample: 17 OECD countries, 1970-2013, annual data.

following a 1% permanent increase in the relative productivity of tradables. Our estimates reveal that FBTC increases significantly in the traded sector and thus technological change is biased toward labor which is consistent with the rise in s_L^H we estimate empirically. While technological change is also biased toward labor in the non-traded sector, the rise in FBTC^N is not statistically significant. Wide confidence bounds suggest that FBTC varies across countries as corroborated by our evidence documented in the next subsection. Before investigating cross-country effects, we discuss the robustness of our empirical findings below.

2.3.7. SVAR critique: robustness analysis

Because the SVAR estimation allows for a limited number of lags (2 lags on annual data), the SVAR model might face some difficulties to disentangle pure technology shocks from other shocks which have long-lasting effects on productivity when capital adjusts sluggishly. Following the SVAR critique by Faust and Leeper (1997), Erceg et al. (2005) and Chari et al. (2008), we have assessed the robustness of our inference under the long-run scheme in Online Appendix U. In the lines of Francis and Ramey (2005), in Online Appendix U.3, we have run exogeneity tests and find that identified asymmetric technology shocks are not correlated with changes in the labor or capital tax, identified government spending shocks, and variations in the labor wedge while non-technology shocks are strongly correlated with the aforementioned variables. In Online Appendix U.4, in line with the recommendation of Chari et al. (2008), we have increased the number of lags from two to eight to estimate the IRFs and find that dynamic responses remain qualitatively unchanged and quantitatively lie within the initial confidence bounds. Chaudourne et al. (2014) demonstrate that the use of ‘purified’ TFP to measure technological change ensures the robustness of the identification of technology shocks. In Online Appendix U.5, we identify shocks to traded relative to non-traded utilization-adjusted-TFP and find that the dynamic responses are merely affected when we correct sectoral TFPs with a measure of capital utilization. In Online Appendix U.6, we adopt the ingenious idea of Dupaigne and Féve (2009) and replace the country-level sectoral TFP with their ‘world’ counterpart which by construction cannot be contaminated by country-level non-technology shocks. We find that the labor share of tradables declines and the value added share of tradables increases whilst the dynamics lie within the confidence bounds of the baseline VAR model. In the lines of Francis et al. (2014), we conduct an additional robustness check where the Maximum Forecast Error Variance (Max Share) approach extracts the shock that best explains the FEV at a medium (i.e., ten years) horizon of the ratio of traded to non-traded TFP. We find that the median of responses falls within the confidence interval of the baseline VAR model where we adopt a long-run identification approach, see Online Appendix U.7. To conclude, all the robustness checks we have conducted confirm the ability of the long-run identified VAR model to reliably estimate the dynamic responses to an asymmetric technology shock across sectors.

2.4. Cross-country differences in reallocation and redistributive effects

In this subsection, we take advantage of the panel data dimension of our sample to answer two economic questions: Do redistributive (i.e., responses of sectoral LISs) and reallocation (especially labor) effects of a permanent increase in the relative productivity of tradables vary across countries? What are the determinants of these cross-country differences?

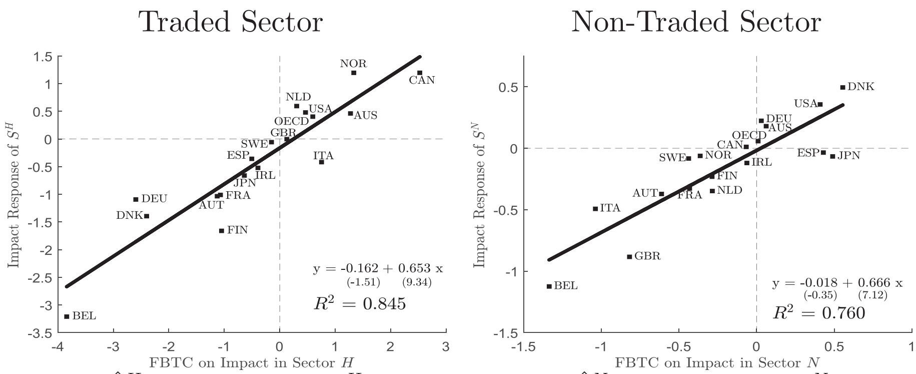
2.4.1. Cross-country redistributive effects and FBTC

As shown in Online Appendix I, the ratio of the demand of labor to the demand of capital implies a direct mapping between $\text{FBTC}^j_{\text{it}}$ and the ratio of labor to capital income share denoted by $S^j_{\text{it}} = s^j_{L,\text{it}}/\left(1 - s^j_{L,\text{it}}\right)$. Since $\hat{S}^j_{\text{it}} = \hat{s}^j_{L,\text{it}}/\left(1 - s^j_{L,i}\right)$ and thus the percentage deviation of the ratio of labor to capital income share relative to its initial steady-state is proportional to the percentage change in the LIS, $\hat{s}^j_{L,t}$, we estimate the responses of s^j_L for one country at a time and scale its response by dividing point estimates by $1 - s^j_{L,i}$ averaged over 1970–2013. Because the responses of S^j and s^j_L differ only by a scaling factor, we refer interchangeably to the LIS or the ratio of factor income share as long as it does not cause confusion.

Fig. 5 plots impact responses of S^j_t on the vertical axis against estimated responses of sectoral FBTC on the horizontal axis. The first conclusion that emerges is that the responses of LISs vary greatly across countries and this dispersion is the result of international differences in FBTC since we detect a positive cross-country relationship between the responses of LISs and FBTC for both the traded and the non-traded sector. More specifically, countries which lie in the north-east experience simultaneously a rise in the LIS and technological change biased toward labor while countries which lie in the south-west experience simultaneously a fall in the LIS and technological change biased toward capital. While FBTC varies greatly across countries, the second conclusion that emerges from Fig. 5 is that FBTC varies significantly across sectors within the same country. We explore its implications for the reallocation of labor across sectors below.

2.4.2. Cross-country labor reallocation effects and differential in FBTC across sectors

Fig. 6a plots the impact response of the labor share of tradables to a 1% permanent increase in traded to non-tradedTFP (on the vertical axis) we estimate for one country at a time against the differential in FBTC between tradables and non-tradables (on the horizontal axis). The difference between traded FBTC and non-traded FBTC displays a significant cross-country dispersion as it varies between -2.9% for Denmark and $+2.6\%$ for Canada. We expect the reallocation of labor toward the non-traded sector and thus the decline in the labor share of tradables to be less pronounced in countries where technological change is more biased toward labor in the traded than in the non-traded sector. Indeed, in Fig. 6a, we detect a positive cross-country relationship indicating that the response of the labor share of tradables to a shock to the relative productivity of tradables is increasing in the differential in FBTC between tradables and non-tradables. Intuitively, when technological change is more biased toward labor in tradables than in non-tradables, it has an expansionary effect on hiring by traded firms which mitigates the fall in $\nu^{L,H}_t$ and may increase it like in Canada. Conversely, in Denmark and Germany, technological change is more biased toward labor in non-tradables which amplifies the decline in $\nu^{L,H}_t$. As we shall see when discussing numerical results, the assumption of FBTC increases the ability of our model to account for the labor reallocation effects we document empirically.



(a) $\hat{S}^H(0)$ against $\text{FBTC}^H(0)$ (b) $\hat{S}^N(0)$ against $\text{FBTC}^N(0)$

Fig. 5. Cross-country redistributive effects of a permanent increase in traded relative to non-traded TFP. *Notes*: Exogenous increase of TFP in tradables relative to non-tradables by 1%. Fig. 5 plots impact responses of the ratio of factor income shares, $\hat{S}^j_t = \hat{s}^j_{L,t}/\left(1 - s^j_L\right)$, on the vertical axis against FBTC in sector $j = H, N$ on the horizontal axis. The response of FBTC in sector $j = H, N$ is obtained by running a simple VAR $[\hat{Z}_t, \text{FBTC}^j_t]$ for one country at a time. Details about the construction of time series for FBTC^j_t can be found in Online Appendix I. Sample: 17 OECD countries, 1970–2013, annual data.

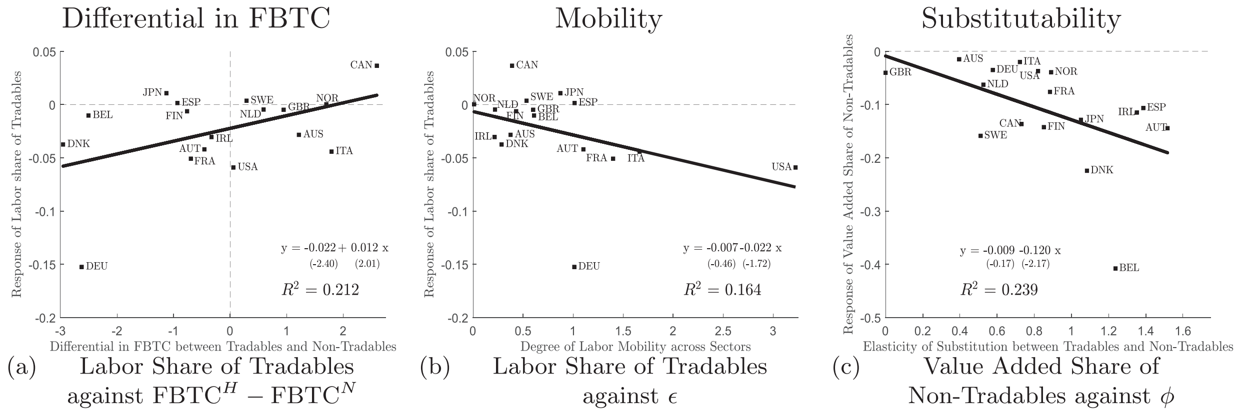


Fig. 6. Cross-country effects of a permanent increase in traded relative to non-traded TFP. *Notes*: Fig. 6 plots impact responses of sectoral labor and sectoral value added shares to a 1% permanent increase in the relative productivity of tradables against four key estimated parameters. Impact responses shown on the vertical axis are obtained by running a VAR model for one country at a time and are expressed in percentage point. Horizontal axis in Fig. 6b, Fig. 6c display the elasticity of labor supply across sectors, ϵ, and the elasticity of substitution between traded and non-traded goods, ϕ, respectively. Panel data estimates for ϵ, ϕ are taken from columns 16 and 15 of Table 8, respectively. The horizontal axis in Fig. 6a displays the differential in FBTC between tradables and non-tradables where estimates are obtained by running the VAR model $[\hat{Z}_t, \text{FBTC}_t^j]$ for one country at a time. Sample: 17 OECD countries, 1970-2013, annual data.

2.4.3. Cross-country labor reallocation effects and labor mobility costs

Besides the differential in FBTC between tradables and non-tradables, labor mobility costs can influence the extent of labor reallocation toward the non-traded sector. We expect countries with a higher degree of labor mobility to experience a greater decline in the labor share of tradables. To explore the cross-country relationship between changes in $\nu_t^{L,H}$ and the magnitude of workers' costs of switching sectors, we need a measure of the degree of labor mobility. In the lines of Horvath (2000), we estimate the elasticity of labor supply across sectors for each country i denoted by ϵ_i; see Online Appendix N.3 for further details about the derivation of the testable equation and the empirical strategy. Higher values of ϵ imply that workers experience lower labor mobility costs caused by sector-specific human capital which may not be perfectly transferable across sectors (see e.g., Lee and Wolpin, 2006; Dix-Carneiro, 2014). In Fig. 6b, we plot impact responses of the labor share of tradables to a 1% permanent increase in the relative productivity of tradables on the vertical axis against our measure of the degree of labor mobility, ϵ_i, on the horizontal axis. In line with our hypothesis, Fig. 6b shows that $\nu_t^{L,H}$ declines more on impact in countries where labor mobility costs are lower (i.e., ϵ takes higher values).

2.4.4. Cross-country reallocation effects and substitutability across goods

While both labor mobility costs and the FBTC differential across sectors determine the extent of the decline in the labor share of tradables, the substitutability between traded and non-traded goods determines the extent of the reallocation of both labor and capital, and thus the extent of the decline in the value added share of non-tradables at constant prices, $\nu_t^{Y,N}$. In a two-sector model with flexible prices, a low elasticity of substitution ϕ between sectoral goods leads to a shift of productive resources to the sector with low TFP growth which in turn mitigates the decline in its value added share at constant prices. Because less productive resources shift toward the non-traded sector as the elasticity of substitution between traded and non-traded goods, ϕ, takes higher values, we should observe a larger decline in $\nu_t^{Y,N}$ in countries where the substitutability between the two goods is higher. In Fig. 6b, we plot impact responses of $\nu_t^{Y,N}$ against ϕ_i we estimate empirically for each country; see Online Appendix N.2 for further details about the empirical strategy to estimate ϕ_i. While all countries experience a fall in $\nu_t^{Y,N}$ on impact, the trend line reveals that the value added share of non-tradables declines more in countries where ϕ is higher. As shown later when discussing numerical results, international capital flows reinforce the reallocation incentives driven by a low value of ϕ.

2.4.5. Summary of evidence motivating the key elements of the model

Our evidence shows that a technology shock biased toward the traded sector leads to a shift of labor toward the non-traded sector which is less pronounced in countries where labor mobility costs are higher or where technological change is more biased toward labor in the traded than in the non-traded sector. As discussed later, although productive resources shift away from the traded sector due to the low substitutability between traded and non-traded goods, the value added share of tradables at constant prices increases and all the more so as the terms of trade depreciate which requires that the substitutability between home- and foreign-produced traded goods (from the point of view of both home and foreign consumers) is not too low. To account for the sectoral composition effects we document empirically, we develop an open economy version of the neoclassical model with tradables and non-tradables which includes the elements uncovered in our cross-country analysis, i.e., imperfect mobility of labor across sectors, imperfect substitutability across goods, CES production functions and sectoral FBTC.

3. A semi-small open economy model with tradables and non-tradables

We consider a semi-small open economy that is populated by a constant number of identical households and firms that have perfect foresight and live forever. The country is assumed to be semi-small in the sense that it is price-taker in international capital markets, and thus faces a given world interest rate, $r^\star$, but is large enough on world good markets to influence the price of its export goods. The open economy produces a traded good which can be exported, consumed or invested and imports consumption and investment goods. Besides the home-produced traded good, denoted by the superscript H, a non-traded sector produces a good, denoted by the superscript N, for domestic absorption only. The foreign good is chosen as the numeraire. We focus on the competitive equilibrium for the open economy because we want to emphasize the role of relative prices in driving the sectoral effects. Time is continuous and indexed by t.

3.1. Households

At each instant the representative household consumes traded and non-traded goods denoted by $C^T(t)$ and $C^N(t)$, respectively, which are aggregated by means of a CES function:

$$C(t) = \left[\varphi^{\frac{1}{\phi}}\left(C^T(t)\right)^{\frac{\phi-1}{\phi}} + (1-\varphi)^{\frac{1}{\phi}}\left(C^N(t)\right)^{\frac{\phi-1}{\phi}}\right]^{\frac{\phi}{\phi-1}}, \tag{5}$$

where $0<\varphi<1$ is the weight of the traded good in the overall consumption bundle and ϕ corresponds to the elasticity of substitution between traded goods and non-traded goods. The traded consumption index $C^T(t)$ is defined as a CES aggregator of home-produced traded goods, $C^H(t)$, and foreign-produced traded goods, $C^F(t)$:

$$C^T(t) = \left[\left(\varphi^H\right)^{\frac{1}{\rho}}\left(C^H(t)\right)^{\frac{\rho-1}{\rho}} + \left(1-\varphi^H\right)^{\frac{1}{\rho}}\left(C^F(t)\right)^{\frac{\rho-1}{\rho}}\right]^{\frac{\rho}{\rho-1}}, \tag{6}$$

where $0<\varphi^H<1$ is the weight of the home-produced traded good and ρ corresponds to the elasticity of substitution between home- and foreign-produced traded goods. The consumption-based price index $P_C(t)$ is a function of traded and non-traded prices, denoted by $P^T(t)$ and $P^N(t)$, respectively:

$$P_C(t) = \left[\varphi\left(P^T(t)\right)^{1-\phi} + (1-\varphi)\left(P^N(t)\right)^{1-\phi}\right]^{\frac{1}{1-\phi}}, \tag{7}$$

where the price index for traded goods is a function of the terms of trade denoted by $P^H(\mathrm{t})$:

$$P^T(t) = \left[\varphi^H\left(P^H(t)\right)^{1-\rho} + \left(1-\varphi^H\right)\right]^{\frac{1}{1-\rho}}. \tag{8}$$

As shall be useful later in the quantitative analysis, we denote the relative price of non-tradables by $P(t) = P^N(t)/P^H(t)$.

The representative household supplies labor to the traded and non-traded sectors, denoted by $L^H(t)$ and $L^N(t)$, respectively. To rationalize the sectoral wage differential which accompanies an asymmetric technology shock across sectors, we assume that hours worked in the traded and the non-traded sectors are imperfect substitutes in the lines of Horvath (2000):

$$L(t) = \left[\vartheta^{-1/\epsilon}\left(L^H(t)\right)^{\frac{\epsilon+1}{\epsilon}} + (1-\vartheta)^{-1/\epsilon}\left(L^N(t)\right)^{\frac{\epsilon+1}{\epsilon}}\right]^{\frac{\epsilon}{\epsilon+1}}, \tag{9}$$

where $0<\vartheta<1$ parametrizes the weight attached to the supply of hours worked in the traded sector and ϵ is the elasticity of substitution between sectoral hours worked. The case of perfect mobility of labor is nested under the assumption that ϵ tends toward infinity which makes our results directly comparable with those obtained in the special case where workers no longer experience switching costs. The aggregate wage index $W(\cdot)$ associated with the above defined labor index (9) is:

$$W(t) = \left[\vartheta\left(W^H(t)\right)^{\epsilon+1} + (1-\vartheta)\left(W^N(t)\right)^{\epsilon+1}\right]^{\frac{1}{\epsilon+1}}, \tag{10}$$

where $W^H(t)$ and $W^N(t)$ are wages paid in the traded and the non-traded sectors.

The representative agent is endowed with one unit of time, supplies a fraction $L(t)$ as labor, and consumes the remainder $1-L(t)$ as leisure. At any instant of time, households derive utility from their consumption and experience disutility from working. Assuming that the felicity function is additively separable in consumption and labor, the representative household maximizes the following objective function:

$$U = \int_0^{\infty} \left\{ \frac{1}{1-\frac{1}{\sigma_C}} C(t)^{1-\frac{1}{\sigma_C}} - \frac{1}{1+\frac{1}{\sigma_L}} L(t)^{1+\frac{1}{\sigma_L}} \right\} e^{-\beta t} dt, \tag{11}$$

where $\beta > 0$ is the discount rate, $\sigma_C > 0$ the intertemporal elasticity of substitution (IES henceforth) for consumption, and $\sigma_L > 0$ the Frisch elasticity of (aggregate) labor supply.

Factor income is derived by supplying labor $L(t)$ at a wage rate $W(t)$, and capital $K(t)$ at a rental rate $R(t)$. In addition, households accumulate internationally traded bonds, $N(t)$, that yield net interest rate earnings of $r^{\star}N(t)$. Households' flow budget constraint states that real disposable income (on the RHS of the equation below) can be saved by accumulating traded bonds, consumed, $P_C(t)C(t)$, or invested, $P_J(t)J(t)$:

$$\dot{N}(t) + P_C(t)C(t) + P_J(t)J(t) = r^{\star}N(t) + R(t)K(t) + W(t)L(t), \tag{12}$$

where $P_J(t)$ is the investment price index defined below and $J(t)$ is total investment.

The investment good is (costlessly) produced using inputs of the traded good and the non-traded good by means of a CES technology:

$$J(t) = \left[\iota^{\frac{1}{\phi_J}} \left(J^T(t) \right)^{\frac{\phi_J - 1}{\phi_J}} + (1-\iota)^{\frac{1}{\phi_J}} \left(J^N(t) \right)^{\frac{\phi_J - 1}{\phi_J}} \right]^{\frac{\phi_J}{\phi_J - 1}}, \tag{13}$$

where $0 < \iota < 1$ is the weight of the investment traded input and ϕ_J corresponds to the elasticity of substitution between investment traded goods and investment non-traded goods. The index $J^T(t)$ is defined as a CES aggregator of home-produced traded inputs, $J^H(t)$, and foreign-produced traded inputs, $J^F(t)$:

$$J^T(t) = \left[\left(\iota^H \right)^{\frac{1}{\rho_J}} \left(J^H(t) \right)^{\frac{\rho_J - 1}{\rho_J}} + \left(1 - \iota^H \right)^{\frac{1}{\rho_J}} \left(J^F(t) \right)^{\frac{\rho_J - 1}{\rho_J}} \right]^{\frac{\rho_J}{\rho_J - 1}}, \tag{14}$$

where $0 < \iota^H < 1$ is the weight of the home-produced traded input and ρ_J corresponds to the elasticity of substitution between home- and foreign-produced traded inputs. The investment-based price index $P_J(t)$ is a function of traded and non-traded prices:

$$P_J(t) = \left[\iota \left(P_J^T(t) \right)^{1-\phi_J} + (1-\iota) \left(P^N(t) \right)^{1-\phi_J} \right]^{\frac{1}{1-\phi_J}}, \tag{15}$$

where the price index for traded investment goods reads:

$$P_J^T(t) = \left[\iota^H \left(P^H(t) \right)^{1-\rho_J} + \left(1 - \iota^H \right) \right]^{\frac{1}{1-\rho_J}}. \tag{16}$$

Installation of new investment goods involves convex costs, assumed quadratic. Thus, total investment $J(t)$ differs from effectively installed new capital:

$$J(t) = I(t) + \frac{\kappa}{2} \left(\frac{I(t)}{K(t)} - \delta_K \right)^2 K(t), \tag{17}$$

where the parameter $\kappa > 0$ governs the magnitude of adjustment costs to capital accumulation. Denoting the fixed capital depreciation rate by $0 \leq \delta_K < 1$, aggregate investment, $I(t)$, gives rise to capital accumulation according to the dynamic equation:

$$\dot{K}(t) = I(t) - \delta_K K(t). \tag{18}$$

Households choose consumption, worked hours and investment in physical capital by maximizing lifetime utility (11) subject to (12) and (18) together with (17). Denoting by λ and Q' the co-state variables associated with (12) and (18), the first-order conditions characterizing the representative household's optimal plans are:

$$C(t) = (P_C(t)\lambda)^{-\sigma_C}, \tag{19a}$$

$$L(t) = (W(t)\lambda)^{\sigma_L}, \tag{19b}$$

$$\frac{I(t)}{K(t)} = \frac{1}{\kappa}\left(\frac{Q(t)}{P_J(t)} - 1\right) + \delta_K, \tag{19c}$$

$$\dot{\lambda}(t) = \lambda(t)\left(\beta - r^\star\right), \tag{19d}$$

$$\dot{Q}(t) = \left(r^\star + \delta_K\right)Q(t) - \left\{R(t) + P_J(t)\frac{\kappa}{2}\left(\frac{I(t)}{K(t)} - \delta_K\right)\left(\frac{I(t)}{K(t)} + \delta_K\right)\right\}, \tag{19e}$$

and the transversality conditions $\lim_{t\to\infty} \lambda N(t)e^{-\beta t} = 0$, $\lim_{t\to\infty} Q(t)K(t)e^{-\beta t} = 0$ where $Q(t) = Q'(t)/\lambda$. In an open economy model with a representative agent having perfect foresight, a constant rate of time preference and perfect access to world capital markets, we impose $\beta = r^\star$ in order to generate an interior solution. Setting $\beta = r^\star$ into (19d) implies that the shadow value of wealth is constant over time, i.e., $\lambda(t) = \lambda$. When new information about the technology shock arrives, λ jumps (to fulfill the intertemporal solvency condition determined later) and remains constant afterwards. For the sake of clarity, we drop the time argument below provided this causes no confusion.

Applying Shephard's lemma (or the envelope theorem) yields the following demand for the home- and the foreign-produced traded good for consumption and investment:

$$C^H = \varphi\left(\frac{P^T}{P_C}\right)^{-\phi}\varphi^H\left(\frac{P^H}{P^T}\right)^{-\rho}C, \qquad C^F = \varphi\left(\frac{P^T}{P_C}\right)^{-\phi}\left(1-\varphi^H\right)\left(\frac{1}{P^T}\right)^{-\rho}C, \tag{20a}$$

$$J^H = \iota\left(\frac{P_J^T}{P_J}\right)^{-\phi_J}\iota^H\left(\frac{P^H}{P_J^T}\right)^{-\rho_J}J, \qquad J^F = \iota\left(\frac{P_J^T}{P_J}\right)^{-\phi_J}\left(1-\iota^H\right)\left(\frac{1}{P_J^T}\right)^{-\rho_J}J, \tag{20b}$$

and the demand for non-traded consumption and investment goods, respectively:

$$C^N = (1-\varphi)\left(P^N/P_C\right)^{-\phi}C, \qquad J^N = (1-\iota)\left(P^N/P_J\right)^{-\phi_J}J. \tag{21}$$

Given the aggregate wage index, we can derive the allocation of aggregate labor supply to the traded and the non-traded sector:

$$L^H = \vartheta\left(W^H/W\right)^{\epsilon}L, \qquad L^N = (1-\vartheta)\left(W^N/W\right)^{\epsilon}L, \tag{22}$$

where the elasticity of labor supply across sectors ϵ captures the degree of labor mobility. As shown in Online Appendix E where we solve for the equilibrium labor share of tradables by combining the labor supply shown above (i.e., the first equation in (22)) and labor demand determined in the next subsection, the movements in L^H/L are only driven by the variations in the value added share of tradables at current prices, $\omega^{Y,H} = P^H Y^H/Y$, when we keep the LISs fixed.

One key determinant of $\omega^{Y,H}(t)$ is the tradable content of consumption expenditure $\alpha_C(t) = \frac{P^T(t)C^T(t)}{P_C(t)C(t)} = \varphi\left(\frac{P^T(t)}{P_C(t)}\right)^{1-\phi}$. Log-linearizing this expression leads to:[12]

$$\hat{\alpha}_C(t) = -(1-\phi)(1-\alpha_C)\left[\hat{P}(t) + \left(1-\alpha^H\right)\hat{P}^H(t)\right] \tag{23}$$

where $P(t) = P^N(t)/P^H(t)$ is the relative price of non-tradables and we used the fact that $\hat{P}^T(t) = \alpha^H\hat{P}^H(t)$. The above expression shows that an appreciation in P caused by a permanent increase in traded relative to non-traded TFP leads to a decline in α_C as long as traded and non-traded goods are gross complements, i.e., if $\phi < 1$, as suggested by our own estimates, see column 15 of Table 8 in Online Appendix M.1. By reducing $\omega^{Y,H}(t)$, the fall in $\alpha_C(t)$ leads labor to shift toward the non-traded sector which lowers $L^H(t)/L(t)$. In a model where home- and foreign-produced traded goods are imperfect substitutes, the terms of trade P^H adjust in response to an increase in the relative productivity of tradables. As traded productivity increases faster than non-traded productivity, traded firms can find it optimal to lower their prices and sell additional units as long as the fall in P^H is not too large. A sufficient condition for this is that

[12] While the change in $\omega^{Y,H}$ is driven by multiple demand components, we emphasize the key role of α_C in determining the change in $\omega^{Y,H}$ and thus the movement in L^H/L because our numerical results in Online Appendix E (see Fig. 10 and Table 3) show that more than 40% of the change in $\omega^{Y,H}(t)$ is driven by the variation in α_C.

ρ and ρ_J take values larger than one, in line with our estimates, see Online Appendix M.6. According to Eq. (23), $\hat{P}^H < 0$ mitigates the decline in α_C and thereby the decrease in the labor share of tradables.

As ρ and ρ_J take larger values, more labor shifts toward the non-traded sector because α_C declines (monotonically) by a larger amount through two channels. First, when the demand for home-produced traded goods turns out to be more price elastic, the terms of trade depreciate less. Formally, the second term in square brackets on the RHS of Eq. (23) (i.e., $\hat{P}^H(t) < 0$) displays a smaller magnitude. Second, a smaller terms of trade depreciation leads households to consume more non-traded goods which further appreciates their relative price as captured by larger values of $\hat{P}(t) > 0$ on the RHS of Eq. (23).

While larger values of ρ and ρ_J lead agents to consume more non-traded goods $C^N(t)$ by mitigating the terms of trade depreciation, a higher substitutability between home- and foreign-produced traded goods also leads households to increase consumption and investment in home-produced traded goods and reduce imports which exerts a positive impact on $\omega^{Y,H}$ and thus on L^H/L by increasing the home content of expenditure in tradable goods, i.e., $\alpha^H(t) = \frac{P^H(t)C^H(t)}{P^T(t)C^T(t)}$ and $\alpha_J^H(t) = \frac{P^H(t)J^H(t)}{P_J^T(t)J^T(t)}$. However, this channel is quantitatively small, see column 8 of Table 3 in Online Appendix E; moreover, the relationship between ρ (ρ_J) and $\alpha^H(t)$ ($\alpha_J^H(t)$) is non-monotonic (i.e., hump-shaped) because the reduction in the terms of trade depreciation dominates over the rise in quantities for high values of ρ (ρ_J).

In the polar case where ρ and ρ_J tend toward infinity, home- and foreign-produced traded goods are perfect substitutes and the case of a small open economy is obtained. Since $\hat{P}^H = 0$, the demand for non-tradables further increases which results in a greater decline in L^H/L. If instead the demand for home-produced traded goods were weakly elastic w.r.t. terms of trade, the decline in P^H that would be necessary to sell additional units would no longer be covered by a reduction in the marginal cost so that traded firms would find it optimal to increase prices (i.e., $\hat{P}^H > 0$) and use less capital and labor (which are more productive) so that L^H/L would fall dramatically.

3.2. Firms

Each sector consists of a large number of identical firms which use labor, L^j, and physical capital, K^j, according to a technology described by a CES production function:

$$Y^j(t) = \left[\gamma^j\left(A^j(t)L^j(t)\right)^{\frac{\sigma^j-1}{\sigma^j}} + \left(1-\gamma^j\right)\left(B^j(t)K^j(t)\right)^{\frac{\sigma^j-1}{\sigma^j}}\right]^{\frac{\sigma^j}{\sigma^j-1}}, \tag{24}$$

where $0 < \gamma^j < 1$ is the weight of labor in the production technology, σ^j is the elasticity of substitution between capital and labor in sector $j = H, N$, and $A^j(t)$ and $B^j(t)$ are labor- and capital-augmenting efficiency.

Firms lease the capital from households and hire workers. They face two cost components: a capital rental cost equal to $R(t)$, and the wage rate equal to $W^j(t)$ in sector $j = H, N$. Both sectors are assumed to be perfectly competitive and thus choose capital and labor by taking prices as given. While capital can move freely between the two sectors, costly labor mobility implies a wage differential across sectors:

$$P^j(t)\gamma^j\left(A^j(t)\right)^{\frac{\sigma^j-1}{\sigma^j}}\left(y^j(t)\right)^{\frac{1}{\sigma^j}} = W^j, \tag{25a}$$

$$P^j(t)\left(1-\gamma^j\right)\left(B^j(t)\right)^{\frac{\sigma^j-1}{\sigma^j}}\left(k^j(t)\right)^{-\frac{1}{\sigma^j}}\left(y^j(t)\right)^{\frac{1}{\sigma^j}} = R, \tag{25b}$$

where we denote by $k^j(t) \equiv K^j(t)/L^j(t)$ the capital-labor ratio for sector $j = H, N$, and $y^j(t) \equiv Y^j(t)/L^j(t)$ refers to value added per hour worked.

Demand for inputs can be rewritten in terms of their respective cost in value added; for labor, we have $s_L^j(t) = \gamma^j\left(A^j(t)/y^j(t)\right)^{\frac{\sigma^j-1}{\sigma^j}}$. Applying the same logic for capital and denoting by $S^j(t) \equiv s_L^j(t)/\left(1-s_L^j(t)\right)$ the ratio of labor to capital income share, we have:

$$S^j(t) \equiv \frac{s_L^j(t)}{1-s_L^j(t)} = \frac{\gamma^j}{1-\gamma^j}\left(\frac{B^j(t)k^j(t)}{A^j(t)}\right)^{\frac{1-\sigma^j}{\sigma^j}}. \tag{26}$$

When technological change is assumed to be Hicks-neutral, productivity increases uniformly across inputs, i.e., $\hat{A}^j(t) = \hat{B}^j(t)$. Hence sectoral LISs are only affected through changes in $k^j(t)$. When capital shifts away from sector j, $s_L^j(t)$ declines since evidence reveals that capital and labor are gross complements in production, i.e., $\sigma^j < 1$. By contrast, when technological change is factor-biased, an increase in capital relative to labor efficiency, $B^j(t)/A^j(t)$, impinges on the sectoral LIS directly and indirectly through changes in $k^j(t)$. The measure of FBTC in sector j is: $\text{FBTC}^j(t) = \frac{1-\sigma^j}{\sigma^j}\left(\hat{B}^j(t) - \hat{A}^j(t)\right)$. Technological change biased toward labor in sector j, i.e., $\text{FBTC}^j(t) > 0$, stimulates the demand of labor and lowers the demand of capital in this sector. As we shall see in the quantitative analysis, because $\text{FBTC}^j(t) > 0$ overturns the negative impact on the LIS caused by the decline in k^j, s_L^j increases.

Finally, aggregating over the two sectors gives us the resource constraint for capital:

$$K^H(t) + K^N(t) = K(t). \tag{27}$$

3.3. Technology frontier

Eq. (26) can be used to determine the direction and the extent of the change in relative capital efficiency which is consistent with observed changes in S^j and k^j. In order to be consistent with our empirical strategy, we need to specify a technology frontier which determines how TFP in sector j is split between capital and labor efficiency for a given change in relative capital efficiency inferred from (26). A natural way to map A^j and B^j into Z^j is to assume that besides optimally choosing factor inputs, firms also optimally choose the technology of production. Following Caselli and Coleman (2006) and Caselli (2016), the menu of possible choices of the technology of production is represented by a set of possible (A^j, B^j) pairs which are chosen along a technology frontier which is assumed to take a Cobb-Douglas form:

$$Z^j(t) = \left(A^j(t)\right)^{\alpha^j(t)}\left(B^j(t)\right)^{1-\alpha^j(t)}, \tag{28}$$

where Z^j measures the height of the technology frontier and α^j is a positive parameter which determines the weight of labor-augmenting efficiency. In Online Appendix T.7, we alternatively assume that labor- and capital-augmenting efficiency are aggregated by means of a CES function and find that the same results we derive below hold. Firms choose labor and capital efficiency, A^j and B^j, along the technology frontier described by Eq. (28) that minimize the unit cost function. The optimal trade-off between A^j and B^j that minimizes the unit cost is such that the weight of labor efficiency (i.e., α^j) collapses to its contribution to the decline in the unit cost (i.e., s_L^j) so that (28) can be rewritten as follows:

$$Z^j(t) = \left(A^j(t)\right)^{s_L^j(t)}\left(B^j(t)\right)^{1-s_L^j(t)}, \tag{29}$$

where the weight s_L^j is time-varying because the production function (24) takes a CES form with $\sigma^j \neq 1$. While the technological frontier imposes a structure on the mapping between TFP and factor-augmenting efficiency, as described by (29), it has the advantage to ensure a consistency between the theoretical and the empirical approach where technological shifts can be Hicks-neutral or factor-biased.

3.4. Model closure and equilibrium

To fully describe the equilibrium, we impose goods market clearing conditions for non-traded and home-produced traded goods:

$$Y^N(t) = C^N(t) + J^N(t), \qquad Y^H(t) = C^H(t) + J^H(t) + X^H(t), \tag{30}$$

where X^H stands for exports of home-produced goods. In the lines of Kehoe and Ruhl (2009), we assume that the size of the open economy on world goods market is large enough to influence the price of its export good. Foreign demand for the home-produced traded good is a decreasing function of terms of trade, $P^H(t)$:

$$X^H(t) = \varphi_X\left(P^H(t)\right)^{-\phi_X}, \tag{31}$$

where $\varphi_X > 0$ is a scaling parameter, and ϕ_X is the elasticity of exports w.r.t. P^H.

Log-linearizing(29) shows that sectoral TFPs dynamics are driven by the dynamics of labor- and capital-augmenting efficiency, i.e., $\hat{Z}^j(t) = s_L^j\hat{A}^j(t) + \left(1 - s_L^j\right)\hat{B}^j(t)$. We drop the time index below to denote steady-state values. Like Galí (1999), we abstract from trend growth and consider a technology shock that increases permanently traded relative to non-traded productivity.[13] The adjustment of $A^j(t)$ and $B^j(t)$ toward their long-run (higher) level expressed in percentage deviation from initial steady-state is governed by the following continuous time process:

$$\hat{A}^j(t) = \hat{A}^j + \bar{a}^j e^{-\xi^j t}, \quad \hat{B}^j(t) = \hat{B}^j + \bar{b}^j e^{-\xi^j t}, \tag{32}$$

where $\bar{a}^j$ and $\bar{b}^j$ are parameters, and $\xi^j > 0$ measures the speed at which productivity closes the gap with its long-run level. Once $A^j(t)$ and $B^j(t)$ have completed their adjustment, they increase permanently to a new higher level, i.e., letting time tend toward infinity into (32) leads to $\hat{A}^j(\infty) = \hat{A}^j$ and $\hat{B}^j(\infty) = \hat{B}^j$ where $\hat{A}^j$ and $\hat{B}^j$ are steady-state (permanent) changes in labor- and capital-augmenting efficiency in percentage. Inserting (32) into the log-linearized version of the technology frontier allows us to recover the dynamics of TFP in sector j:

$$\hat{Z}^j(t) = \hat{Z}^j + \bar{z}^j e^{-\xi^j t}, \tag{33}$$

where $\bar{z}^j = s_L^j \bar{a}^j + \left(1 - s_L^j\right)\bar{b}^j$ and $\hat{Z}^j(\infty) = \hat{Z}^j = s_L^j \hat{A}^j + \left(1 - s_L^j\right)\hat{B}^j$ is the permanent change (in percentage) in TFP in sector j.

The adjustment of the open economy toward the steady-state is described by a dynamic system which comprises six equations that are functions of $K(t)$, $Q(t)$, $A^j(t)$, $B^j(t)$:

$$\dot{K}(t) = \Upsilon\left(K(t), Q(t), A^H(t), B^H(t), A^N(t), B^N(t)\right), \tag{34a}$$

$$\dot{Q}(t) = \Sigma\left(K(t), Q(t), A^H(t), B^H(t), A^N(t), B^N(t)\right), \tag{34b}$$

$$\dot{A}^j(t) = -\xi^j\left(A^j(t) - \tilde{A}\sim^j\right), \qquad \dot{B}^j(t) = -\xi^j\left(B^j(t) - \tilde{B}\sim^j\right), \tag{34c}$$

where $j = H, N$. The first dynamic equation corresponds to the non-traded goods market clearing condition (30) and the second dynamic equation corresponds to (19e) which equalizes the rates of return on domestic equities and foreign bonds, $r^\star$, once we have substituted appropriate first-order conditions. Eqs. (34c) are the law of motion of labor- and capital-augmenting efficiency, respectively, in sector j. Linearizing (34a)–(34b) around the steady-state and denoting by ω_k^i the kth element of eigenvector ω^i related to eigenvalue ν_i, the general solution that characterizes the adjustment toward the new steady-state can be written as follows: $V(t) - V = \sum_{i=1}^{6} \omega^i D_i e^{\nu_i t}$ where V is the vector of state and control variables. Denoting the positive eigenvalue by $\nu_2 > 0$, we set $D_2 = 0$ to eliminate explosive paths and determine the five arbitrary constants D_i (with $i = 1, \ldots, 6$, $i \neq 2$) by using the five initial conditions, i.e., $K(0) = K_0$, $A^j(0) = A_0^j$, and $B^j(0) = B_0^j$ for $j = H, N$.

Using the properties of constant returns to scale in production, identities $P_C(t)C(t) = \sum_g P^g(t)C^g(t)$ and $P_J(t)J(t) = \sum_g P^g(t)J^g(t)$ (with $g = F, H, N$) along with market clearing conditions (30), the current account Eq. (12) can be rewritten as a function of exports and imports denoted by $M^F(t) = C^F(t) + J^F(t)$:

$$\dot{N}(t) = r^\star N(t) + P^H(t) X^H(t) - M^F(t). \tag{35}$$

Eq. (35) can be written as a function of state and control variables, i.e., $\dot{N}(t) \equiv r^\star N(t) + \Xi(K(t), Q(t), A^H(t), B^H(t), A^N(t), B^N(t))$. Linearizing around the steady-state, inserting the solutions for $K(t)$, $Q(t)$ together with (34c), solving and invoking the transversality condition, yields the solution for traded bonds:

$$N(t) - N = \sum_{i=1, i\neq 2}^{6} \Phi_N^i e^{\nu_i t}, \tag{36}$$

[13] We assume that the economy starts from an initial steady-state and is hit by a technology shock which increases permanently traded relative to non-traded TFP. In the same spirit as Galí (1999), the accumulation of permanent technology shocks gives rise to a unit root in the time series for the relative productivity of tradables, an assumption we use to identify a permanent technology shock biased toward tradables in the empirical part. We do not characterize the convergence of the economy toward a balanced growth path which is supposed to exist, in line with the theoretical findings by Acemoglu and Guerrieri (2008), Alvarez-Cuadrado et al. (2018), Kehoe et al. (2018) who allow labor income shares to vary across sectors. In the lines of Kehoe et al. (2018), the balanced growth path we have in mind is one where sectoral productivity growth rates must eventually be equal. Indeed, the data reveals an asymptotic (and hump-shaped) but very persistent convergence of traded toward non-traded TFP productivity growth which started in the 90s. This convergence is consistent with our identifying assumption since it is a very lengthy process. Panel unit root tests reported in Appendix O.1 show clearly that time series for the ratio of traded to non-traded TFP are I(1), thus confirming that the convergence process is far from being completed.

where $\Phi_N^i = \frac{E_i D_i}{r^\star - \nu_i}$ with $E_i = \Xi_K \omega_1^i + \Xi_Q \omega_2^i + \Xi_{A^H} \omega_3^i + \Xi_{B^H} \omega_4^i + \Xi_{A^N} \omega_5^i + \Xi_{B^N} \omega_6^i$; partial derivatives of Ξ w.r.t. K, Q, A^j, B^j, are evaluated at the steady-state. Eq. (36) gives the trajectory for $N(t)$ consistent with the intertemporal solvency condition: $N - N_0 = \sum_{i=1, i\neq 2}^{6} \Phi_N^i$.

4. Quantitative analysis

In this section, we take the model to the data. For this purpose we solve the model numerically.[14] Therefore, first we discuss parameter values before turning to the effects of a technology shock biased toward the traded sector.

4.1. Calibration

4.1.1. Calibration strategy

To ensure that the initial steady-state with CES production functions is invariant when σ^j is changed, we normalize CES production functions by choosing the initial steady-state in a model with Cobb-Douglas production functions as the normalization point. Once we have calibrated the initial steady-state with Cobb-Douglas production functions, we calibrate the CES economy to the data such that Z^j and γ^j together with other parameters are endogenously calibrated to reproduce the ratios of the Cobb-Douglas economy, including the sectoral LISs, see Online Appendix Q.1. This normalization procedure guarantees that we start from the same initial steady-state regardless of the value of σ^j. To calibrate the reference model we use to normalize the CES economy, we estimated a set of ratios and parameters for the seventeen OECD economies in our dataset. Our reference period for the calibration corresponds to the period 1970–2013. Table 8 in Online Appendix M.1 summarizes our estimates of the ratios and estimated parameters for all countries in our sample.

We first calibrate the model to a representative OECD country and investigate whether the model can account for the evidence we document empirically when one parameter at a time is modified. Later, we move a step further and calibrate the model to country-specific data and explore whether the model can rationalize our empirical findings once we let all parameters of interest vary across countries. To capture the key properties of a typical OECD economy, we take unweighted average values of ratios which are shown in the last line of Table 8. Among the 24 parameters that the model contains, 18 have empirical counterparts while the remaining 6 parameters, i.e., φ, ι, φ^H, ι^H, ϑ, δ_K together with initial conditions (N_0, K_0) must be endogenously calibrated to match ratios $1-\alpha_C$, $1-\alpha_J$, α^H, α_J^H, $\frac{L^N}{L}$, ω_J, and $\upsilon_{NX} = \frac{NX}{P^H Y^H}$ with $NX = P^H X^H - C^F - I^F$. More details about the calibration procedure can be found in Online Appendix Q.1–Q.2. We choose the model period to be one year and set the world interest rate, $r^\star$, which is equal to the subjective time discount rate, β, to 4%. Table 9 in Online Appendix M.1 summarizes the parameter values.

4.1.2. Preferences

We start with the household's decision to move from one sector to another. Our panel data estimates of the elasticity of labor supply across sectors, ϵ, over the period 1970–2013 range from a low of 0.01 for Norway to a high of 3.2 for the United states. See Online Appendix M.4 for panel data estimations. We choose a value of 1.6 for the degree of labor mobility which is the median of our estimates. The weight of labor supply to the non-traded sector, $1-\vartheta$, is set to 0.6 to target a share of non-tradables in total hours worked of 63% in line with our estimates.

Following Stockman and Tesar (1995), we choose a value for the elasticity of substitution ϕ between traded and non-traded goods of 0.44 which is the value commonly used in the international RBC literature. This value falls in the range of our panel data estimates for the whole sample which vary between 0.66 and 0.33 depending on whether the testable equation includes or not a country-specific linear time trend, see Online Appendix M.4 which shows our panel data estimations of ϕ and Online Appendix N.2 which details the steps of derivation of the testable equation. The weight of consumption in non-tradables $1-\varphi$ is set to target a non-tradable content in total consumption expenditure (i.e., $1-\alpha_C$) of 53%, in line with the average of our estimates. In accordance with our empirical findings, see Online Appendix M.6, we set the elasticity of substitution, ρ, in consumption between home- and foreign-produced traded goods to 1.5 which corresponds to value commonly adopted in the literature, see e.g., Backus et al. (1994). The weight of consumption in home-produced traded goods φ^H is set to target a home content of consumption expenditure in tradables (i.e. α^H) of 77%, in line with the average of our estimates.

Our SVAR estimates show that a permanent shock to traded relative to non-traded TFP increases significantly total hours worked both on impact and in the long-run, see Fig. 17a in Online Appendix M.2. The initial response of hours worked depends on two parameters. The IES for consumption σ_C determines the strength of the wealth effect which impinges negatively on labor supply whilst the Frisch elasticity of labor supply σ_L determines the magnitude of the impact response of total hours worked. As pointed out recently by Best et al. (2020), there exists no consensus on a reasonable value for the IES for which the most cited estimates in the literature range between 0 and 2. Whilst $\sigma_C = 1$ is a common assumption in the literature, as is well known (and demonstrated analytically in Online Appendix P) this value leads the wealth and substitution effect to cancel out so that total hours worked remain unresponsive to a technology shock. Because a value for σ_C smaller than two would require implausibly large values for σ_L to replicate the impact response of total hours worked, see Fig. 16b in Online Appendix M.2, we choose a value of two for the IES for consumption which squares well with the estimates documented by Crossley and Low (2011),

[14] Technically, the assumption $\beta = r^\star$ requires the joint determination of the transition and the steady state since the constancy of the marginal utility of wealth implies that the intertemporal solvency condition depends on eigenvalues' and eigenvectors' elements, see e.g., Turnosvsky (1997).

Gourinchas and Parker (2002), and Gruber (2013).[15] Once we have set $\sigma_C = 2$, we choose a value of 1.6 for σ_L to reproduce the impact response of 0.09% of total hours worked that we estimate empirically.[16] This value of σ_L falls in the range of estimates of the macro Frisch elasticity of labor supply documented by Peterman Peterman (2016) which vary between 1.5 and 1.75 for the population aged between 20 and 55, and between 20 and 60, respectively. As shown in Fig. 17a in Online Appendix M.2, whilst the reference model with Cobb-Douglas production functions can reproduce the impact response estimated empirically, it is only when we allow for CES production functions and FBTC, that we can reproduce the dynamics of total hours worked we estimate empirically because technological change biased toward labor increases the demand of labor along the transitional path. It is worth mentioning that an alternative solution to generate a positive response of total hours worked to an asymmetric technology shock would be to allow for Greenwood et al. (1988) (GHH thereafter) preferences. Whilst hours worked $L(t)$ rise on impact following a permanent asymmetric technology shock, the low value of σ_L which must be chosen to avoid overestimating the impact response of $L(t)$ leads the model to understate the dynamic adjustment of total hours worked along the transitional path, see Fig. 17b in Online Appendix M.2.

4.1.3. Production and investment

We now turn to production-side parameters. We assume that physical capital depreciates at a rate $\delta_K = 9.3\%$ to target an investment-GDP ratio of 24%. In line with our estimates, the shares of labor income in traded and non-traded value added, s_L^H and s_L^N, are set to 0.63 and 0.68, respectively. We consider an initial steady-state with HNTC and normalize $A^j = B^j = Z^j$ to 1. We set the elasticity of substitution, ϕ_J, between J^T and J^N to 1, in line with the empirical findings documented by Bems (2008) for OECD countries. Further, the weight of non-traded investment $(1-\varphi_I)$ is set to target a non-tradable content of investment expenditure of 62%. In accordance with our estimates, we set the elasticity of substitution, ρ_J, in investment between home- and foreign-produced traded inputs to 1.5. The weight of home-produced traded investment ι^H is set to 0.62 to target a home content of investment expenditure in tradables (i.e. α_J^H) of 51%. We choose the value of parameter κ so that the elasticity of I/K with respect to Tobin's q, i.e., Q/P_J, is equal to the value implied by estimates in Eberly and Vincent (2008). The resulting value of κ is equal to 17.

4.1.4. Demand components

Government spending on traded G^T and non-traded goods G^N are considered for calibration purposes. We set G^N and G^T so as to yield a non-tradable share of government spending, ω_{G^N}, of 90%, and government spending as a share of GDP, ω_G, of 20%. We choose initial conditions so that trade is initially balanced. Since net exports are nil, the investment-to-GDP ratio, ω_J, and government spending as a share of GDP, ω_G, implies a consumption-to-GDP ratio of $\omega_C = 56\%$. It is worth mentioning that the tradable content of GDP is endogenously determined by the market clearing condition for traded goods, i.e., $P^H Y^H/Y = \omega_C \alpha_C + \omega_J \alpha_J + \omega_{G^T} \omega_G = 38\%$. Building on structural estimates of the price elasticities of aggregate exports documented by Imbs and Mejean (2015), we set the export price elasticity, ϕ_X, to 1.7 in the baseline calibration (see column 19 of Table 8). Because trade is balanced, export as a share of GDP, $\omega_X = P^H X^H/Y$, is endogenously determined by the import content of consumption, $1-\alpha^H$, and investment expenditure, $1-\alpha_J^H$, along with ω_C and ω_J.

4.1.5. CES production functions

Since the model with Cobb-Douglas production functions is the normalization point, when we calibrate the model with CES production functions, φ, ι, φ^H, ι^H, ϑ, δ_K, N_0, K_0, Z^j, γ^j are endogenously set to target $1-\bar{\alpha}_C$, $1-\bar{\alpha}_J$, $\bar{\alpha}^H$, $\bar{\alpha}_J^H$, $\bar{L}^N/\bar{L}$, $\bar{\omega}_J$, $\bar{\upsilon}_{NX}$, $\bar{K}$, $\bar{y}^j$, $\bar{s}_L^j$, respectively, where a bar indicates that the ratio is obtained from the Cobb-Douglas economy, and we consider an initial steady-state with HNTC, i.e., $A^j = B^j = Z^j$, see Online Appendix Q.3 which provides more details. Drawing on Antràs, 2004, we estimate the elasticity of substitution between capital and labor for tradables and non-tradables and set σ^H and σ^N to 0.69 and 0.72, respectively (as shown in last line of columns 17 and 18 of Table 8); see Online Appendix M.5 for the empirical strategy and panel data estimations of σ^j.

4.2. Factor-augmenting efficiency and sectoral TFP dynamics

Since our VAR evidence documented in Section2.3 reveals that technological change is factor-biased, we need to set the dynamics for factor efficiency, $B^j(t)$ and $A^j(t)$. We first derive the change in capital relative to labor efficiency, by log-linearizing (26) which describes the demand for factors of production:

[15] When we restrict attention to the period 1970–2007, we find that total hours worked are unresponsive to asymmetric technology shocks across sectors and thus a value of one for the IES squares well with our evidence over this period. Since we find that total hours worked increase significantly following a shock to a productivity differential, the positive response is caused by the period 2007–2013. During this period, the value for the IES has increased sharply, as suggested by the empirical study by Cundy (2018) who reports a value of 2.8 for the IES between 2009 and 2014.

[16] As explained at length in the Online Appendix M.2, because we normalize the CES economy by choosing the initial steady-state in a model with Cobb-Douglas production functions as the normalization point, and since FBTC has no impact in the latter economy, we cannot choose σ_L so as to minimize the distance between the theoretical and the empirical response during the whole period of adjustment because doing this would amount to choosing parameters to reproduce labor market effects without taking into account factor-biased technological change. We thus choose σ_L to reproduce the impact response of $L(t)$ in the reference model with Cobb-Douglas production functions.

$$\left(\hat{B}^j(t) - \hat{A}^j(t)\right) = \left[\sigma^j / \left(1 - \sigma^j\right)\right]\hat{S}^j(t) - \hat{k}^j(t), \tag{37}$$

all variables being expressed in percentage deviation from the initial steady-state. Next, given the adjustment of relative capital efficiency inferred from (37), we have to determine the dynamics of $B^j(t)$ and $A^j(t)$ consistent with the dynamics of sectoral TFP we estimate empirically. Log-linearizing the technology frontier (29) in the neighborhood of the initial steady-state leads to $\hat{Z}^j(t) = s_L^j \hat{A}^j(t) + \left(1 - s_L^j\right)\hat{B}^j(t)$. The latter equation together with (37) can be solved for labor and capital-augmenting efficiency:

$$\hat{A}^j(t) = \hat{Z}^j(t) - \left(1 - s_L^j\right)\left\{\left[\sigma^j / \left(1 - \sigma^j\right)\right]\hat{S}^j(t) - \hat{k}^j(t)\right\}, \tag{38a}$$

$$\hat{B}^j(t) = \hat{Z}^j(t) + s_L^j\left\{\left[\sigma^j / \left(1 - \sigma^j\right)\right]\hat{S}^j(t) - \hat{k}^j(t)\right\}. \tag{38b}$$

Plugging estimated values for σ^j and empirically estimated responses for $s_L^j(t)$ and $k^j(t)$, $Z^j(t)$, into the above equations enables us to recover the dynamics for $A^j(t)$ and $B^j(t)$ consistent with the demand of factors of production (37) and adjustment of sectoral TFPs. To ensure that our method to generate time series for sectoral FBTC captures technological change, in Online Appendix K, we test Acemoglu (2003) model assumptions who endogeneizes FBTC. We find that countries where TFP gains are concentrated in capital (labor) intensive industries also experience a rise in capital (labor) relative to labor (capital) efficiency, in accordance with Acemoglu (2003) model assumptions, which lends credence to the ability of the time series of B^j/A^j we generate to reflect FBTC.

Once we have determined the underlying dynamic process for labor and capital efficiency by using (38), we have to choose values for exogenous parameters $\bar{a}^j$, $\bar{b}^j$, and ξ^j, which are consistent with the law of motion (32). We choose $\bar{a}^j$, $\bar{b}^j$ by setting $t = 0$ into (32) which yields $\bar{a}^j = -\left(\hat{A}^j - \hat{A}^j(0)\right)$, and $\bar{b}^j = -\left(\hat{B}^j - \hat{B}^j(0)\right)$. Making use of the time series generated by (38a) and (38b) gives us $\bar{a}^H = -0.029840$, $\bar{b}^H = -0.202769$, $\bar{a}^N = 0.234035$, $\bar{b}^N = -0.500629$. By using the fact that $\bar{z}^j = s_L^j \bar{a}^j + \left(1 - s_L^j\right)\bar{b}^j$ (see eq. (33)), we have $\bar{z}^H = -0.093566$ and $\bar{z}^N = 0.000164$ for the parameters governing the gap which must be fulfilled when sectoral TFP converges toward its long-run equilibrium. To determine the value for the speed of adjustment of sectoral TFP, we solve (33) for ξ^j, i.e., $\xi^j = -\frac{1}{t}\ln\left(\frac{\hat{Z}^j(t) - \hat{Z}^j}{\bar{z}^j}\right)$; setting $t = 3$ leads to $\xi^H = 0.570885$ for the traded sector and $\xi^N = 1.166821$ for the non-traded sector which gives us the best fit of the response of $\hat{Z}^j(t)$ estimated empirically. Once we have the dynamic paths for $\hat{Z}^H(t)$ and $\hat{Z}^N(t)$, we can compute the dynamics for the shock to the TFP differential between tradables and non-tradables (see eq. (4)):

$$\hat{Z}(t) = a\hat{Z}^H(t) - b\hat{Z}^N(t), \tag{39}$$

where $\hat{Z}(\infty) = \hat{Z} = a\hat{Z}^H - b\hat{Z}^N$ is normalized to 1% in the long-run.

In Fig. 12 which is relegated to Online Appendix J for reason of space, we contrast the empirical response functions (shown in blue lines) of the TFP differential between tradables and non-tradables as well as sectoral TFPs with the theoretical response functions (shown in black lines with squares) generated by the law of motion (32)–(33) together with (39). As can be seen in Fig. 12, the theoretical responses perform well in reproducing the evidence and thus the dynamic Eqs. (32)–(33) which govern the adjustment of factor-augmenting efficiency and $Z^j(t)$ are consistent with data.

4.3. Reallocation and redistributive effects: Model performance

In this subsection, we analyze the role of FBTC, terms of trade, and imperfect mobility of labor in shaping the reallocation and redistributive effects in an open economy in response to a 1% permanent increase in TFP of tradables relative to TFP of non-tradables. In order to assess quantitatively the role of each ingredient in driving the sectoral effects of a technology shock biased toward tradables, we report results from restricted versions of the baseline model. These restricted versions collapse to the international RBC model by Fernández de Córdoba and Kehoe (2000) (FK henceforth) who consider variants of a small open economy setup with tradables and non-tradables. Our quantitative analysis reveals that the model can account for the sectoral composition effects of asymmetric technology shocks we estimate empirically once we allow for imperfect mobility of labor (i.e., $0 < \epsilon < \infty$), assume that the demand for home-produced traded goods is elastic enough w.r.t. the terms of trade, and let technological change be factor-biased. A sufficient condition for the price-elasticity of the demand for home-produced traded goods to be high enough is that $1 < \rho < \infty$, $1 < \rho_J < \infty$, and $1 < \phi_X < \infty$ in line with our own estimates, see Online Appendix M.6, and evidence documented

Table 1
Impact and long-run effects of a 1% permanent increase in traded relative to non-traded TFP.

	VAR ($t = 0$)	Impact ($t = 0$) theoretical responses					VAR ($t = 10$)	Long-run ($t = 10$) theoretical responses				
	Data	Bench FBTC	HNTC $\hat{A}^j(t) = \hat{B}^j(t)$	FK-IML ($\rho \to \infty$)	FK-PML ($\epsilon \to \infty$)	Subst. ($\phi = 1.2$)	Data	Bench FBTC	HNTC $\hat{A}^j(t) = \hat{B}^j(t)$	FK-IML ($\rho \to \infty$)	FK-PML ($\epsilon \to \infty$)	Subst. ($\phi = 1.2$)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
A. Labor and VA												
Traded labor, $dL^H(t)$	−0.01	−0.00	−0.03	−0.10	−0.23	0.03	0.01	0.01	−0.02	−0.02	−0.06	0.05
Non-traded labor, $dL^N(t)$	0.10	0.11	0.12	0.14	0.21	0.05	0.15	0.15	0.13	0.15	0.18	0.06
Traded value added, $dY^H(t)$	0.24	0.22	0.22	0.14	0.05	0.32	0.27	0.27	0.28	0.29	0.27	0.39
Non-traded value added, $dY^N(t)$	0.01	0.01	0.00	0.06	0.11	−0.07	0.06	0.02	0.03	0.07	0.09	−0.04
B. Labor Reallocation												
Labor share of tradables, $d\nu^{L,H}(t)$	−0.04	−0.04	−0.06	−0.12	−0.22	0.00	−0.05	−0.05	−0.06	−0.07	−0.10	0.01
Output share of tradables, $d\nu^{Y,H}(t)$	0.13	0.13	0.13	0.06	−0.01	0.21	0.14	0.16	0.16	0.15	0.13	0.25
Non-traded wage, $\left(\hat{W}^N(t) - \hat{W}(t)\right)$	0.01	0.04	0.06	0.12	0.00	0.00	0.06	0.04	0.06	0.07	0.00	−0.00
Traded wage, $\left(\hat{W}^H(t) - \hat{W}(t)\right)$	−0.02	−0.07	−0.11	−0.20	0.00	0.00	−0.12	−0.07	−0.11	−0.11	−0.00	0.00
C. Relative Prices												
Relative price of non-trad., $\hat{P}(t)$	0.99	0.97	1.00	1.10	0.90	0.89	1.06	1.08	1.10	1.11	0.99	0.97
Terms of trade, $\hat{P}^H(t)$	−0.41	−0.27	−0.29	0.00	0.00	−0.37	−0.44	−0.37	−0.40	0.00	0.00	−0.47
D. FBTC and LISs												
Traded FBTC	0.50	0.51	0.00	0.00	0.00	0.00	0.58	0.58	0.00	0.00	0.00	0.00
Non-Traded FBTC	0.07	0.11	0.00	0.00	0.00	0.00	0.36	0.36	0.00	0.00	0.00	0.00
Traded capital-labor, $dk^H(t)$	−0.08	−0.13	−0.06	−0.03	−0.08	−0.04	−0.14	−0.12	−0.02	0.01	−0.02	0.00
Non-traded capital-labor, $dk^N(t)$	−0.01	0.03	−0.01	−0.04	0.07	−0.05	−0.04	−0.04	0.03	0.01	0.07	−0.01
Traded LIS, $ds_L^H(t)$	0.09	0.08	−0.01	0.00	0.00	−0.01	0.10	0.10	−0.01	0.00	0.00	0.00
Non-traded LIS, $ds_L^N(t)$	0.01	0.02	−0.00	0.00	0.00	−0.01	0.07	0.07	0.00	0.00	0.00	−0.00

Notes: Impact ($t = 0$) and long-run ($t = 10$) effects of a 1% permanent increase in traded relative to non-traded TFP. Panels A, B, C, D show the deviation in percentage relative to steady-state for sectoral variables. Panel A shows the effects on sectoral sectoral hours worked and sectoral value added while panel B displays the responses of the labor share and value added share of tradables together with changes in sectoral wages relative to the aggregate wage. Panel C shows the responses of the relative price of non-tradables and the terms of trade. Panel D displays FBTC, changes in sectoral capital-labor ratios and sectoral LISs. Responses of relative wages and relative prices are percentage deviation from initial steady-state (denoted with a hat). Sectoral value added and value added share are expressed in percent of initial GDP while sectoral labor and labor shares are expressed in percent of initial total hours worked; changes in capital-labor ratios are expressed in percent of the aggregate stock of capital while responses of sectoral LISs are measured in percent of value added of the corresponding sector. In columns 3–6 and 9–12, we consider restricted versions of our baseline model, results of which are shown in columns 2 and 8. 'FK-PML' refers to the small open economy model by Fernández de Córdoba and Kehoe (2000) with tradables and non-tradables, capital adjustment costs and perfect mobility of labor (we let the elasticity of labor supply across sectors tend toward infinity and assume that home-produced and foreign-produced traded goods are perfect substitutes). 'FK-IML' corresponds to the FK model augmented with imperfect mobility of labor across sectors (we set $\epsilon = 1.6$ while keeping $\rho = \rho_J \to \infty$ so that terms of trade remain fixed). 'HNTC' refers to a semi-small open economy model with endogenous terms of trade, labor mobility costs, CES production functions while imposing Hicks-neutral technological change (i.e., $\hat{A}^j(t) = \hat{B}^j(t)$). In columns 6 and 12, we consider the same model as 'HNTC' and set ϕ to 1.2 instead of 0.44 to shut down labor reallocation across sectors. In our baseline calibration (labelled 'Bench' in columns 2 and 8), we set $\epsilon = 1.6$, $\phi = 0.44$, $\sigma_L = 1.6$, $\kappa = 17$, $\rho = \rho_J = 1.5$, $\phi_X = 1.7$, $\sigma^H = 0.69$, $\sigma^N = 0.72$ and allow for labor- and capital-augmenting technological change inferred from (38a)–(38b).

Bajzik et al. (2020).[17] Whilst FBTC is key to replicating the dynamics of the sectoral LISs, the differential in FBTC between tradables and non-tradables increases the ability of the model to account for the reallocation of labor we estimate empirically.

In Table 1, we report the simulated impact (i.e., at $t = 0$) and long-run (i.e., at $t = 10$) effects. While columns 1 and 7 show impact and long-run responses from our VAR model for comparison purposes, columns 2 and 8 show results for the baseline model. Columns 5 and 11 display results for a restricted version of our model which collapses to the FK model with capital adjustment costs. In this restricted model, we impose perfect mobility of labor, exogenous terms of trade and Cobb-Douglas

[17] In Online Appendix P.2 and P.3, we solve analytically a model without capital and determine formally a necessary condition which says that for the terms of trade to depreciate, $\phi_X + \alpha^H \rho$ must be higher than a threshold of 0.79. Because we set $\phi_X = 1.695$, this condition is fulfilled and therefore it is always profitable to lower P^H as traded firms improve technology. When we consider a model with capital accumulation, we find numerically that for the terms of trade to depreciate, we must have $\phi_X > 0.52$ and $\rho = \rho_J > 0.67$.

production functions. In the next columns, we add one ingredient at a time. In columns 4 and 10, we consider the same model except that we allow for imperfect mobility of labor across sectors (i.e., we set $\epsilon = 1.6$). This version collapses to the FK model with capital adjustment as well as labor mobility costs. In columns 3 and 9, we allow for imperfect mobility of labor and endogenous terms of trade (i.e., we set $\rho = \rho_J = 1.5$). We also allow for CES production functions while assuming HNTC.

4.3.1. Baseline model

We first assess the ability of the baseline model with imperfect mobility of labor, endogenous terms of trade and FBTC to account for our evidence on the reallocation and redistributive effects. Columns 2 and 8 of Table 1 show impact and long-run effects for the baseline model. To begin with, as can be seen in panel A of Table 1, the baseline model is able to account for the sectoral composition effects we estimate empirically. First, as in the data, the traded sector drives real GDP growth since Y^H and Y^N increases by 0.22% and 0.01% of GDP, respectively, close to our VAR evidence (0.24% and 0.01%, resp.). Conversely, the non-traded sector drives the rise in total hours worked as L^H remains unresponsive on impact and L^N rises by 0.11% of total hours worked, in line with our empirical findings (−0.01% for L^H and 0.10% for L^N). As can be seen in panel C, incentives for increasing L^N are brought about by an appreciation in the relative price of non-tradables (i.e., 0.97% at $t = 0$ and 1.08% at $t = 10$) which is larger than the productivity differential, in accordance with our estimates (0.99% at $t = 0$ and 1.06% at $t = 10$). Intuitively, a technology shock generates a positive wealth effect which encourages households to increase consumption in both traded and non-traded goods. Since the technology shock is biased toward the traded sector, an excess demand for non-traded goods and an excess supply for traded goods show up. Because the elasticity of substitution between traded and non-traded goods is smaller than one (i.e., $\phi < 1$), the relative price of non-tradables appreciates disproportionately which has an expansionary effect on labor (and capital) demand in the non-traded sector. The movement of productive resources, especially labor, toward non-tradable sectors is stronger in a financially open economy as the access to foreign borrowing amplifies the demand boom for non-tradables.

The labor outflow experienced by the traded sector is mitigated however by the fall in the relative price of home-produced traded goods brought about by productivity gains concentrated in the traded sector. Panel C shows that the terms of trade deteriorate by 0.27% on impact (0.41% in the data) and 0.37% in the long-run (0.44% in the data). Intuitively, for given factor prices, as technology improves in the traded sector and thereby puts downward pressure on the marginal cost, the terms of trade depreciate. By encouraging households to consume more home-produced traded goods, the decline in P^H mitigates the reallocation of productive resources, especially labor, away from the traded sector and toward the non-traded sector.

The shift of labor toward the non-traded sector is further mitigated by the presence of labor mobility costs. As can be seen in panel B, non-traded firms pay higher wages to encourage workers to shift, thus producing a positive wage differential for non-tradables and a negative wage differential for tradables, close to our estimates, especially in the long-run (see column 8).

Inspection of the first row of panel B reveals that the model generates a decline in the share of tradables in total hours worked (i.e., $\nu^{L,H}$) by the same amount than that is estimated empirically (i.e., 0.04% of total hours worked). The reason is that technological change is more biased toward labor in the traded than in the non-traded sector which has a positive impact on labor demand in the former sector and thus hampers the shift of labor toward the non-traded sector. Labor reallocation accounts for 38% (43% in the data) of the rise in non-traded hours worked on impact. In the long-run, the contribution of the shift of labor is lower at 33% (34% in the data).

In addition to producing a labor outflow, the large appreciation in $P = P^N/P^H$ also drives capital out of the traded sector. Since labor is subject to mobility costs and technological change is biased toward labor, the capital-labor ratio, k^H, falls substantially (see panel D). Because technological change biased toward labor overturns the negative impact on the LIS caused by the decline in k^H, s_L^H unambiguously increases. If capital and labor were immobile across sectors, the change in the value added share of tradables at constant prices would collapse to $d\nu^{Y,H} = \nu^{Y,H}(1 - \nu^{Y,H})\left(\hat{Z}^H - \hat{Z}^N\right)$. Since $\nu^{Y,H} = 0.4$ approximately and the productivity differential is 1% in the long-run, a back of the envelope calculation indicates that $\nu^{Y,H}$ would increase by 0.24% of GDP in the long-run. As can be seen in the second line of panel B, the reallocation of productive resources away from the traded sector mitigates the rise in $\nu^{Y,H}$ which increases by 0.16% (0.14% in the data) of GDP only.

4.3.2. Restricted model: perfect mobility of labor, exogenous terms of trade and HNTC

In columns 5 and 11, we consider a restricted model imposing perfect mobility of labor across sectors (i.e., we set $\epsilon \to \infty$), exogenous terms of trade (i.e., we let ρ and ρ_J tend toward ∞) and Cobb-Douglas production functions. When we contrast VAR evidence reported in column 1 with numerical results displayed by column 5, we find that the restricted model can generate qualitatively the sectoral effects we estimate empirically but fails to account for their magnitude. A direct implication of abstracting from labor mobility costs is that the model cannot account for the sectoral wage differential which materializes after one year (see the last two rows of panel B of Table 1). When labor mobility costs are absent and terms of trade remain fixed, the restricted model considerably overstates the decline in the labor share of tradables. The fall in $\nu^{L,H}$ is almost six times larger to what we estimate empirically on impact (i.e., −0.22% vs. −0.04% in the data, see the first row of panel B). As a result, the model predicts a dramatic fall in traded hours worked (−0.23% vs. −0.01% in the data) and considerably understates the rise in traded value added (0.05% vs. 0.24% in the data). By overestimating the reallocation of labor toward the non-traded sector, the model overpredicts the rise in L^N (0.21% vs. 0.10% in the data, see panel A) as well as in Y^N (0.11% vs. 0.01% in the data). The excess demand for non-traded goods is thus mitigated which leads the model to predict an appreciation in the relative price of non-tradables (see panel C of Table 1) by 0.90% below what is estimated empirically (0.99%).

4.3.3. Restricted model: exogenous terms of trade and HNTC

Columns 4 and 10 show results for the same restricted model as above except that we allow for imperfect mobility of labor across sectors (i.e., we set $\epsilon = 1.6$). As expected, labor mobility costs substantially hamper the reallocation of labor away from the traded sector. More specifically, as shown in the first row of panel B, labor mobility costs almost halve the fall in the labor share of tradables, i.e., $d\nu^{L,H}(0) = -0.12$ % instead of -0.22% in a model imposing perfect mobility of labor. However, the decline in $\nu^{L,H}(0)$ is still three time larger to what is estimated empirically. Intuitively, when we let ρ and ρ_J tend toward infinity, home- and foreign-produced traded goods are perfect substitutes. Because non-traded goods must be produced domestically while traded goods can be imported, the small open economy finds it optimal to run a large current account deficit and reallocate productive resources, especially labor, toward the non-traded sector. Imports increase significantly more than in a model assuming $1< \rho < \infty$ and $1< \rho_J < \infty$ because the terms of trade no longer depreciate which leads the model to overstate the demand boom for non-tradables, as reflected in an appreciation in the relative price of non-tradables by 1.1% above what is estimated empirically (0.99% in the data, see the first row of panel C of Table 1). By overstating the shift of labor between sectors, the model imposing $\rho \rightarrow \infty$ and $\rho_J \rightarrow \infty$ considerably understates the rise in traded value added (see the third row of panel A of Table 1) and thus the increase in the value added share of tradables at constant prices (see the second row of panel B of Table 1).

4.3.4. Restricted model: HNTC

In columns 3 and 9 of Table 1, we consider a model with endogenous terms of trade and labor mobility costs together with CES production functions. While the latter ingredient has no impact on results because we impose HNTC, the combination of the adjustment in the relative price of home-produced traded goods and imperfect mobility of labor improves the performance of the model. Overall, on impact, the model assuming HNTC performs as well as the baseline model, except for the reallocation of labor and the responses of LISs. To have a clearer picture of the performance of the model imposing HNTC, it is useful to start with the redistributive effects shown in panel D of Table 1. Contrasting the long-run responses for k^j and s_L^j (column 9) with responses estimated empirically (column 7) reveals that a model assuming HNTC significantly overstates the demand for capital in both sectors (e.g., $\hat{k}^H = -0.02\%$ instead of -0.14% in the data). The decline in k^H drives down the traded LIS in contradiction with our evidence which reveals that s_L^H increases by 0.10%. Conversely, by allowing for technological change biased toward labor, as captured by a rise in $\left(B^j(t)/A^j(t)\right)^{\frac{1-\sigma^j}{\sigma^j}}$ (see the first two rows of panel D), the baseline model can generate an increase in sectoral LISs (see columns 2 and 8) in line with our estimates. The model imposing HNTC also overstates the fall in the labor share of tradables, as can be seen in columns 3 and 9 of Table 1 (see the first row of panel B, i.e., $d\nu^{L,H}$). Conversely, because $\mathrm{FBTC}^H(t) > \mathrm{FBTC}^N(t)$ has a positive impact on tradable hiring which hampers the movement of labor toward the non-traded sector, the decline in $\nu^{L,H}(t)$ predicted by the baseline model squares well with the evidence.

4.3.5. Dynamics

While in Table 1, we restrict our attention to impact and long-run responses, in Fig. 7, we contrast theoretical (displayed by solid black lines with squares) with empirical (displayed by solid blue lines) dynamic responses with the shaded area indicating the 90% confidence bounds. We also contrast theoretical responses from the baseline model with the predictions of the Fernández de Córdoba and Kehoe (2000) model which includes frictions in factor mobility between sectors (generated by capital adjustment as well as labor mobility costs). The results for the FK model which shuts down the terms of trade channel and imposes HNTC are shown in dashed red lines.

By abstracting from endogenous terms of trade and FBTC, the restricted (i.e., FK) model fails to account for the evidence along a number of dimensions. It overpredicts the wage differential, understates the decline in the traded capital-labor ratio, overstates the decline in the labor share of tradables and as displayed by the last column, it cannot account for the rise in sectoral LISs.

The performance of the model increases once we allow for endogenous terms of trade, CES production functions together with FBTC. As shown by the solid black line with squares in Fig. 7, the dynamics of relative prices and the sectoral wage differential which materializes after one year are captured fairly well by the baseline model (see the first column). The increase in the productivity differential over time further appreciates the relative price of non-tradables, P^N/P^H, and amplifies the terms of trade deterioration. The time-increasing appreciation in P^N/P^H has an expansionary effect on L^N as displayed by Fig. 7e while L^H remains unresponsive (see Fig. 7a). Despite the fact that labor keeps on shifting toward the non-traded sector as can be seen in the lower part of Fig. 7d, the rise in the productivity of tradables prevents the value added share of tradables at constant prices, $\nu^{Y,H}$, from declining (see the upper part of Fig. 7d).

As can be seen in Fig. 7b and Fig. 7f, the combined effect of the rise in capital relative to labor efficiency and the gross complementarity between capital and labor in production generates an increase in sectoral LISs whilst Fig. 7b shows that the decline in k^H is amplified in line with the evidence. In Online Appendix J, we contrast the model predictions with empirical estimates for k^N. Whilst it misses the decline in k^N on impact, the baseline model gives rise to a declining path for k^N driven by technology change biased toward labor, in accordance with the evidence.

4.4. Sensitivity analysis and extensions

In this subsection, we explore the role of financial openness for asymmetric technology shocks, summarize the main findings of the sensitivity analysis we have conducted w.r.t. preferences' assumptions and the reliability of empirical IRFs, and discuss how

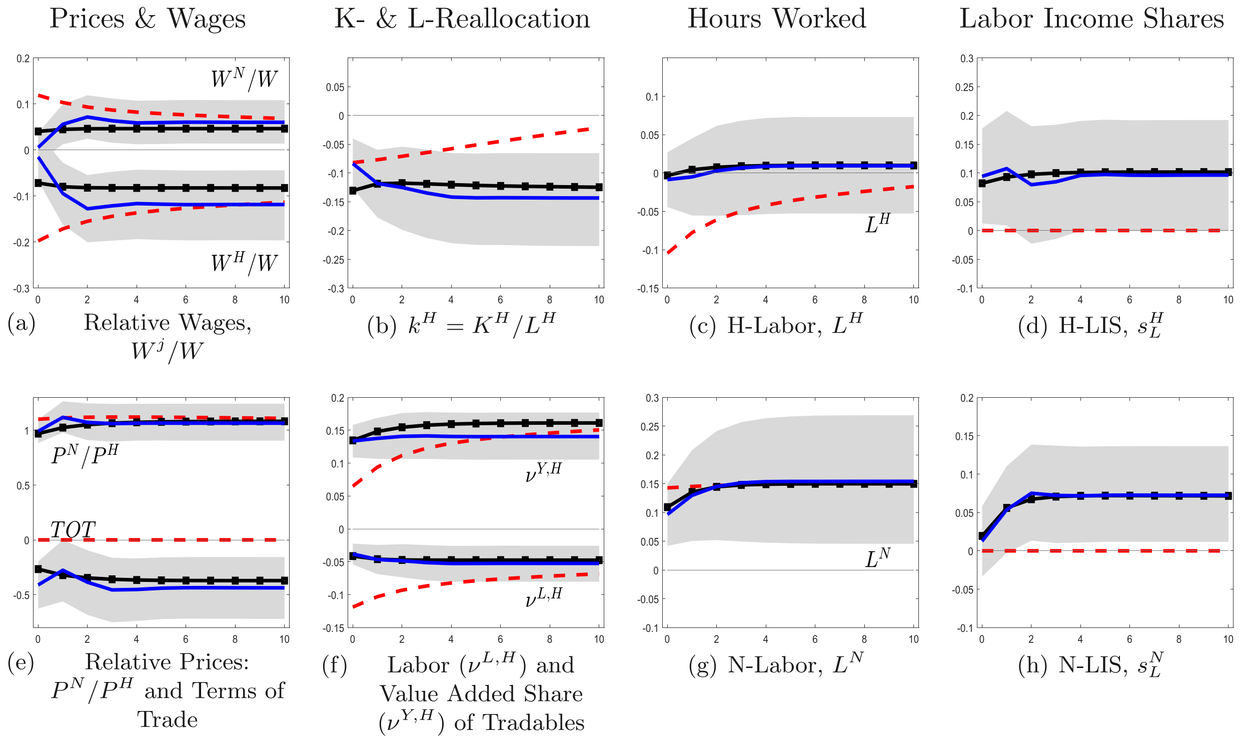


Fig. 7. Sectoral effects of a permanent technology shock biased toward tradables: Model vs. data. *Notes:* Solid blue lines display point estimates of VAR model with shaded area indicating 90% confidence bounds; solid black lines with squares display baseline model predictions, i.e., when we allow for IML ($\epsilon = 1.6$), endogenous terms of trade ($\rho = \rho_J = 1.5$), gross complementarity between capital and labor in production (i.e., $\sigma^H = 0.687$, $\sigma^N = 0.716$), and technological change biased toward labor, i.e., $\text{FBTC}^H = 0.58\%$ and $\text{FBTC}^N = 0.36\%$ in the long-run; dashed red lines show predictions of a restricted model where terms of trade are exogenous and technological change is Hicks-neutral.

the increasing importance of asymmetric technology shocks could modify the response of total hours worked to aggregate technology shocks.

4.4.1. Implications of financial openness

In columns 6 and 12 of Table 1, we consider the same model with HNTC as in columns 3 and 9, and set the elasticity of substitution between traded and non-traded goods, ϕ, to 1.2 instead of 0.44. This value is such that the labor share of tradables, $\nu^{L,H}$, remains unchanged on impact, as can be seen in the first row of panel B, and thus there is no labor reallocation between the two sectors. Interestingly, this threshold value of 1.2 for ϕ is higher than the value of 1 in a closed economy setup, see e.g., Ngai and Pissarides (2007). As demonstrated analytically in the Online Appendix P.1, this threshold value of 1 also holds in an open economy setup without capital since the net foreign asset position remains fixed so that $\nu^{L,H}$ increases only when ϕ is above one. By contrast, in an open economy setup with capital accumulation, the threshold value for ϕ is higher. Intuitively, access to foreign borrowing allows households to increase consumption and to avoid a large increase in labor supply which amplifies the excess demand for non-traded goods because traded goods can be imported. The current account deficit thus amplifies the reallocation of labor toward the non-traded sector. Note that we impose HNTC in columns 6 and 12 to shut down the effect of FBTC and thus to isolate the pure effect caused by financial openness.

4.4.2. Robustness to preferences' assumptions

In Online Appendix V.5, we conduct a sensitivity analysis w.r.t. the IES for consumption. We find that choosing values for σ_C equal or lower than one leads the model to understate the responses of sectoral hours worked but has little impact on the value added and labor share of tradables together with relative prices. In Online Appendix V.2–V.4, we re-estimate the dynamic effects of a permanent increase in traded relative to non-traded TFP by considering Greenwood et al. (1988) preferences which eliminate the wealth effect (from labor supply), by allowing for non-separability in preferences between consumption and leisure in the lines of Shimer (2009), by allowing for external habits (which generate time non separability in preferences) in the lines of Carroll et al. (2000) in addition to non-separability between consumption and leisure. Although it somewhat understates the increase in hours worked along the transitional path, a model assuming Greenwood et al. (1988) preferences performs reasonably well in reproducing the sectoral effects we estimate empirically as long as we assume a low value for σ_L because GHH preferences eliminate the wealth effect which makes labor supply highly elastic w.r.t. the technology shock on impact. Conversely, the performance of a model assuming Shimer (2009) preferences augmented or not with external habits is lower than the performance of our baseline model. The reason is that the coefficient of relative risk aversion collapses to the parameter determining the substitutability between consumption and leisure. When we allow consumption and leisure to be gross substitutes, the IES for consumption is low so that the wealth effect exerts a strong negative impact on hours worked.

4.4.3. Further investigation of reliability of empirical IRFs

The SVAR critique questions the reliability of empirical IRFs generated from the estimation of the VAR model which in turn casts doubt on the performance of the model. As stressed by Christiano et al. (2006), the identification of temporary technology shocks is not subject to biases. In Online Appendix V.6, we estimate empirically the dynamic effects of a temporary shock shock to aggregate TFP and contrast them with the baseline model's predictions. We find that the baseline model with the same calibration as that described in Section4.1 can account for the empirical IRFs we generate following a temporary aggregate technology shock. Not only does it mean that the model is validated by the data, it also means that the empirical IRFs obtained from long-run restrictions in Section2 are unbiased because they fit the theoretical responses of the model.

4.4.4. Implications for the response of total hours worked to aggregate technology shocks

We view our analysis of asymmetric technology shocks across sectors as a step toward a better understanding of the labor market effects of aggregate technology shocks which are a combination of symmetric and asymmetric technology shocks across sectors. By generating an expansionary effect on hiring in the non-traded sector which accounts for two-thirds of labor, asymmetric technology shocks have a positive impact on total hours worked and all the more so in countries where sectoral technological change is biased toward labor. Conversely, symmetric technology shocks have a negative impact on total hours worked through two channels. By giving rise to a fall in non-traded prices which lowers labor demand in the non-traded sector (because $\phi < 1$), symmetric technology shocks exert a negative impact on total hours worked. In addition, technological change is biased toward capital in both sectors following symmetric technology shocks, as evidence documented in Online Appendix V.9 shows, which amplifies the negative impact on $L(t)$. When we compute numerically the effects of a 1% permanent increase in aggregate TFP, see Online Appendix V.9, we find that the response of total hours worked increases as asymmetric technology shocks account for a greater share of the variations in aggregate TFP. The growing importance of asymmetric technology shocks could therefore rationalize the time-increasing response of total hours worked to aggregate technology shocks, as documented empirically by Galí and Gambetti (2009) and Cantore et al. (2017).

4.5. Redistributive and reallocation effects across countries

We now move a step further and calibrate our model to country-specific data. Our objective is to assess the ability of our baseline model to account for the cross-country dispersion in the reallocation and redistributive effects we estimate empirically by shedding some light on the role of FBTC.

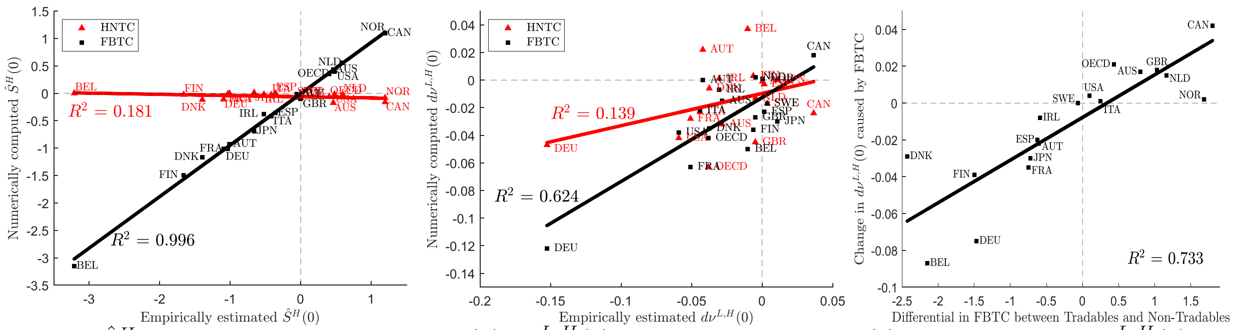
4.5.1. Calibration to country-specific data

To conduct this analysis, we calibrate our model to match key ratios of the 17 OECD economies in our sample, as summarized in Table 8 in Online Appendix M.1, while ϵ, ϕ, σ^j, ϕ_X, ρ, ρ_J, are set in accordance with estimates shown in the last seven columns of Table 8. The remaining parameters, i.e., σ_L, σ_C, ϕ_J, κ take the same values as those summarized in Table 9 in Online Appendix M.1. As discussed in Section4.1, we consider the initial steady-state with Cobb-Douglas production functions as the normalization point and calibrate the reference model to the data. Next exogenous parameters in the CES economy are endogenously calibrated to replicate the ratios targeted in the Cobb-Douglas economy.

To compute FBTC for each country, we proceed as in Section4.2 except that to estimate (38a)–(38b), we use country-specific estimates of σ^j and country-specific estimated responses of $s_L^j(t)$, $k^j(t)$, $Z^j(t)$. Once we have recovered time series for FBTC in sector $j = H, N$ for each country, we choose parameters $\bar{a}^j$ and $\bar{b}^j$ by setting $t = 0$ into (32) and we choose parameter ξ^j by choosing time t in Eq. (33) which gives the best fit of sectoral TFP dynamics to the data. Once the model is calibrated, we estimate numerically the effects of a 1% permanent increase in traded relative to non-traded TFP.

4.5.2. Redistributive effects across countries

We first assess the ability of the model to account for the cross-country dispersion in the responses of LISs we estimate empirically. In the first column of Fig. 8, we plot impact responses of the ratio of factor income shares in the traded sector, S^H, we compute numerically (vertical axis) against impact responses of S^H we estimate empirically (horizontal axis). To have a sense of the importance of FBTC in driving the cross-country redistributive effects, we contrast the model predictions when we impose HNTC which are displayed by red triangles with the model predictions when assuming FBTC shown in black squares. It is worth mentioning that $\hat{S}^j(t) = \frac{\hat{s}_L^j(t)}{1 - s_L^j}$ and thus the response of S^j is similar to that of the LIS which is scaled by the capital income share. As it stands out, a model imposing HNTC cannot account for international differences in the responses of sectoral LISs. Intuitively, the shifts of capital between sectors generated by a model imposing HNTC are not large enough on their own to reproduce the cross-country dispersion in the responses of LISs. Conversely, by influencing sectoral LISs directly and indirectly through the shifts of capital, the baseline model with FBTC is able to generate a wide cross-country dispersion in the responses of LISs



(a) $\hat{S}^H(0)$: Model vs. Data (b) $d\nu^{L,H}(0)$: Model vs. Data (c) Difference in $d\nu^{L,H}(0)$ caused by FBTC

Fig. 8. Cross-country relationships under FBTC and HNTC hypothesis: Model vs. Data. *Notes*: The first two columns of Fig. 8 plot impact responses of the traded LIS and labor share of tradables computed numerically (vertical axis) against the responses of the corresponding variables estimated empirically (horizontal axis). In each panel, we contrast the predictions from a model imposing HNTC shown in red triangles with the predictions of the baseline model assuming FBTC shown in black squares. The red trend line shows the fit of the model to the data when imposing HNTC while the black trend line shows the fit of the model to the data when assuming FBTC. The last column plots the change in labor reallocation caused by sector differences in FBTC (vertical axis) against the differential in FBTC between tradables and non-tradables (horizontal axis) on impact.

which fits well the data as the correlation between model predictions and the data is 0.99 for the traded sector. A similar conclusion is reached for the non-traded sector relegated to the Online Appendix J.

4.5.3. Reallocation effects across countries

In the second column of Fig. 8, we plot impact responses of the labor share of tradables we compute numerically (vertical axis) against impact responses of the same variable we estimate empirically (horizontal axis). Black squares show model predictions when we allow for FBTC while red triangles show model predictions when we impose HNTC. The red trend line shows the fit of the model to the data when imposing HNTC and the black trend line shows the model fit when we assume FBTC. As is evident from trend lines, the ability of the model to account for the cross-country dispersion in the responses of $\nu^{L,H}$ is higher when we allow for FBTC (as shown in the black trend line). The correlation between numerical and empirical estimates stands at 0.79 with FBTC and falls to 0.38 when we shut down this feature. Intuitively, a sectoral differential in FBTC modifies sectoral labor demand and thus either amplifies or mitigates the shift of labor across sectors in a way that increases the ability of the baseline model to account for the cross-country dispersion in the reallocation effects. One most prominent example is Germany which experiences technological change biased toward capital in the traded sector and technological change biased toward labor in the non-traded sector. The former lowers labor demand in the traded sector while the latter stimulates labor demand in the non-traded sector. The shift of labor toward the non-traded sector is thus amplified which allows the baseline model to generate a decline in $\nu^{L,H}$ by 0.12% close to our estimates (i.e., -0.15%). Conversely, a model imposing HNTC produces a decline in $\nu^{L,H}$ which is more than three times smaller to what we estimate empirically.

4.5.4. Reduction or amplification of labor reallocation caused by sector differences in FBTC

The differential in FBTC between tradables and non-tradables varies considerably across countries and influences the shift of labor across sectors. To give a sense of the variation of labor reallocation caused by sector differences in FBTC, we compute the difference in the change in the labor share of tradables, $d\nu^{L,H}(t)$, between the baseline model assuming FBTC and a model imposing HNTC. Fig. 8c plots the change in $\nu^{L,H}(t)$ caused by sector differences in FBTC (vertical axis) against the differential in FBTC between tradables and non-tradables (horizontal axis) on impact. For countries which lie in the north-east, technological change is more biased toward labor in the traded than the non-traded sector (i.e., $\text{FBTC}^H - \text{FBTC}^N > 0$) which in turn exerts a positive impact on $\nu^{L,H}$ and thus reduces labor reallocation toward the non-traded sector (compared with a model imposing HNTC). The reduction in labor reallocation toward the non-traded sector averages 0.012% of total hours worked which represents 42% of the cross-country average labor reallocation. Conversely, for countries which lie in the south-west, technological change is more biased toward labor in the non-traded than in the traded sector (i.e., $\text{FBTC}^H - \text{FBTC}^N < 0$). For these economies, the decline in the labor share of tradables doubles because technology makes non-traded production more labor intensive and tilts labor demand toward the non-traded sector.

5. Conclusion

Motivated by the evidence documented by Foerster et al. (2011) and Garìn et al. (2018), we explore the labor market effects caused by asymmetric technology shocks across sectors in an open economy setup. To conduct this analysis, we use a panel of 17 OECD countries over 1970–2013 and adopt the identification approach of technology shocks proposed by Galí (1999). Since we consider an open economy, we differentiate between a traded and a non-traded sector. When we estimate the effects of a technology shock which increases permanently traded relative to non-traded TFP, our evidence reveals that the non-traded sector alone drives total hours worked growth; 35% of the rise in non-traded hours worked is attributable to the reallocation of labor on average which lowers the labor share of tradables by 0.05 percentage point of total hours worked.

To rationalize our VAR evidence, we put forward an open economy version of the neoclassical model with tradables and non-tradables. Our quantitative analysis reveals that the low substitutability between traded and non-traded goods in consumption and financial openness leads the model to substantially overstate the decline in the labor share of tradables. To account for the magnitude of the reallocation effects we document empirically, we consider three key elements. Like Kehoe and Ruhl (2009), we first allow for endogenous terms of trade. The high substitutability between home- and foreign-produced traded goods ensures that it is profitable for traded firms to cut prices as technology improves. By stimulating the demand for home-produced traded goods, the terms of trade depreciation hampers the shift of labor toward the non-traded sector. The second element is labor mobility costs which strengthen the terms of trade channel by further hampering labor reallocation.

We put forward FBTC as a third key ingredient. Adapting the methodology of Caselli and Coleman (2006) to our setup, we use the demand of inputs and our estimates of the elasticity of substitution between capital and labor to construct time series for FBTC. Our VAR estimates reveal that technological change is biased toward labor in both sectors following a shock to traded relative to non-traded TFP which is consistent with the rise in sectoral LISs we find in the data. Once we include the three aforementioned elements, the model reproduces well the labor market effects we estimate empirically for the whole sample.

Taking advantage of the panel data dimension of our sample, we detect empirically a strong and positive cross-country relationship between the responses of sectoral LISs and factor-biased technological shifts. When focusing on the reallocation effects, we find empirically that countries where technological change is more biased toward labor in the traded than in the non-traded sector experience a smaller decline in the labor share of tradables. When we calibrate the model to country-specific data, our model can account for the cross-country redistributive and reallocation effects we estimate empirically once we let FBTC vary across sectors and between countries.

In this work, we exclusively focus on a permanent increase in traded relative to non-traded TFP and restrict our attention to its sectoral composition effects. A fruitful extension of our analysis would be to analyze the effects of aggregate TFP shocks driven by both symmetric and asymmetric technology shocks across sectors in the same spirit as Garìn et al. (2018). As mentioned at the end of Section4.4, the growing importance of asymmetric technology shocks (relative to symmetric technology shocks) over time could rationalize the time-increasing correlation between labor growth and productivity growth, a finding documented by Galí and Gambetti (2009) and Cantore et al. (2017).

While in our paper, we restrict attention to industrialized countries, emerging countries also experience technological change biased toward the traded sector, see e.g., Rodrik (2013). It should be checked whether the contribution of asymmetric technology shocks across sectors has also increased over time in emerging countries and generated labor reallocation effects by the same magnitude that we estimate for OECD countries. Whilst our model treats the rest of the world as exogenous, extending our framework to a two-country model would be a fruitful avenue for future research to investigate the effects of technology shocks in emerging countries.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jinteco.2022.103645.

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