WHY HOURS WORKED DECLINE LESS AFTER TECHNOLOGY SHOCKS?*

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Abstract

The contractionary effect of technology shocks on hours gradually vanishes over time in OECD countries. To rationalize this finding, we use a VAR-based decomposition of technology shocks into symmetric and asymmetric technology improvements between sectors. While hours decline dramatically when technology improves at the same rate across sectors, hours significantly increase when technology improvements occur at different rates. The latter finding together with the growing importance of asymmetric technology shocks can potentially explain the smaller decline in hours. A two-sector open economy model with production factors' mobility costs can reproduce the shrinking contractionary effect on hours estimated empirically once we allow for factor-biased technological change, home bias and let the share of asymmetric technology shocks increase over time. Extending the model to endogenous technology decisions reveals that more than 70% of the increasing share of asymmetric technology shocks is driven by the greater exposition of traded industries to innovation abroad.

Keywords: Hours worked; Symmetric and asymmetric technology shocks; Tradables and non-tradables; International openness; Factor-augmenting efficiency; CES production function; Labor reallocation; Endogenous technological change.
JEL Classification: E22; F41; J22.

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1 Introduction

Has the response of hours to permanent technology improvements changed over time? What is the main driver behind this change? Our empirical findings reveal that the impact effect on hours of a permanent technology shock hides a large and gradual structural change. More specifically, the contractionary effect of technology improvements on hours has significantly shrunk over the last fifty years in OECD countries. We show that the increasing importance of technology improvements which occur at different rates between (traded and non-traded) sectors is responsible for the gradual disappearance of the negative effect of a permanent technology shock on hours.

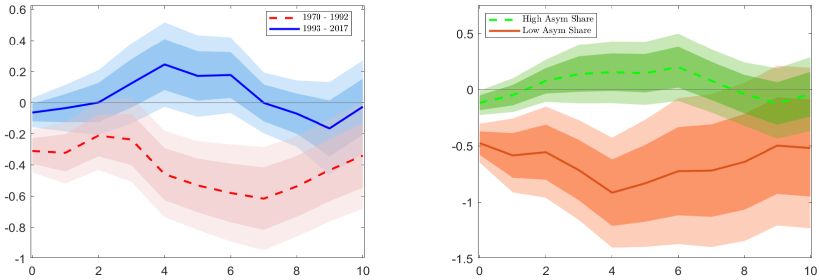
The shrinking contractionary effect of technology shocks on hours has already been documented by Galí and Gambetti [2009], Barnichon [2010], Nucci and Riggi [2013], Cantore et al. [2017] on U.S data. These papers put forward more pro-cyclical monetary policies, a reduction in hiring frictions, an increase in performance-related pay schemes, or a greater substitutability between capital and labor, respectively, to rationalize the vanishing decline of hours. While these interpretations may fit the U.S. experience, we provide evidence showing that none of these explanations can account for the vanishing decline in hours after technology shocks we document for OECD countries.[1]

Our structural interpretation of the gradual change in the link between technology and hours, rests on the open economy aspect and the multi-sector dimension of OECD countries. Open economies find it optimal to substitute foreign for domestic goods and lower labor supply after a technology shock by running a current account deficit while the dispersion in technology improvements across industries has an expansionary effect on hours by fostering labor demand in low productivity growth (non-traded) industries. As technology shocks are increasingly driven by asymmetric technology improvements, hours decline less. Besides the fact that our interpretation fits the experience of our sample of OECD countries, our line of explanation accords well with the evidence documented by Foerster et al. [2011] who find that the share of output fluctuations explained by asymmetric shocks across sectors has dramatically increased since the great moderation.

While the vanishing decline in hours after technology shocks is an empirical fact well documented for the U.S., our evidence reveals that this movement is also shared by OECD countries. In Fig. 1(a), we plot the dynamic response of hours worked to a 1% permanent increase in utilization-adjusted-total-factor-productivity (TFP) by considering two sub-periods. As shown in the dashed red line, a permanent technology shock produces a decline in hours by -0.31% on impact in the pre-1992 period while hours remain unresponsive to technology shocks in the post-1992 period (see the blue line).[2] Concomitantly,

[1]We test the four competing interpretations for our panel of seventeen OECD countries in Online Appendix M.

[2]We choose 1992 as the cutoff year for the whole sample because the Great Moderation occurs in the



(a) Response of Hours to Technology Shocks: 70-92 vs. 93-17

(b) Response of Hours to Technology Shocks: Low vs. High Share of Asym. Tech. Change

Figure 1: Structural Change in the Relationship between Hours and Technology. Notes: Fig. 1(a) shows the response of hours to a 1% permanent increase in utilization-adjusted-TFP before (dashed red line) and after (blue line) 1992. Solid and dashed lines represent point estimates and light (dark) shaded areas represent 90 (68) percent confidence intervals. Vertical axis measures deviation from the pre-shock trend/level in percent. We first identify the permanent technology shock by estimating a VAR model which includes utilization-adjusted-aggregate-TFP together with a set of variables and impose long-run restrictions. In the second step, we estimate the dynamic response of hours to the identified technology shock by using local projections. Fig. 1(b) plots the response of hours to a 1% permanent increase in utilization-adjusted-TFP for countries with low (orange line) and high (dashed green line) variance share attributable to asymmetric technology improvements ('Share of Asym. Tech. Change'). We perform a country-split on the basis of the share of the (unconditional) variance of utilization-adjusted-TFP growth driven by asymmetric technology improvements across sectors which is calculated for each country by using eq. (34). We have eight countries with a share of technological change driven by asymmetric technology improvements lower than 30% (including continental European countries and Japan) and nine countries with a share higher than 30% (including English-speaking and Scandinavian countries). Sample for both panels: 17 OECD countries, 1970-2017.

the share of the forecast error variance of utilization-adjusted-TFP growth attributable to asymmetric technology shocks between sectors has dramatically increased from 7% before 1992 to more than 44% in the post-1992 period.

Fig. 1(b) suggests that the share of asymmetric technology improvements is a major driver of the response of hours. In the group of countries where the share of asymmetric technology improvements is lower than 30% (with a mean of 22%), as shown in the orange line, hours decline by -0.48% on impact, while in the group of countries where the share of asymmetric shocks is higher than 30% (with a mean of 46%), the response of hours is muted at all time horizons (see the dashed green line). This finding is important because our estimates also reveal that (only) asymmetric technology improvements are shocks which are associated with innovation (concentrated in traded industries).

The first step of our analysis is to perform a VAR-based decomposition of aggregate technology improvements into symmetric and asymmetric technology shocks between sectors, in the same spirit as Garìn et al. [2018] who decompose economic fluctuations into a common (across sectors) and a sector-specific component. Our evidence shows that when technology improves at the same rate across sectors, hours dramatically decline by -0.47% on impact. By contrast, when technological change is concentrated toward a few industries, hours significantly increase by 0.31% on impact.

The second step of our analysis is to rationalize the magnitude of the decline in hours and its gradual disappearance we document for OECD countries. We develop an extension of the open economy setup with tradables and non-tradables pioneered by Kehoe and Ruhl [2009] and simulate the model by considering symmetric and asymmetric technology shocks

post-1992 period for European countries which account for three-fourth of our sample, see e.g., Benati [2008] for the U.K. and González Cabanillas and Ruscher [2008] for the euro area.

between sectors (calibrated to the data). Our quantitative analysis enables us to uncover two key findings. First, hours decline after permanent technology shocks because they are primarily driven by technology improvements which are symmetric across industries. Second, the decline in hours worked shrinks over time as aggregate technology shocks are increasingly influenced by technology improvements which are asymmetric between sectors.

To reach these conclusions, we conduct two quantitative exercises. We first quantify the contribution of each ingredient to the performance of the baseline model. We show that five elements are essential: international openness, barriers to factors' mobility between sectors, home bias in the domestic traded good, factor-biased technological change (FBTC henceforth), and a mix of symmetric and asymmetric technology shocks.[3]

International openness is key to producing a decline in hours after a permanent technology improvement. Because a technology shock stimulates consumption and investment, an economy open to international trade and world capital markets finds it optimal to import goods from abroad and lower labor supply by running a current account deficit. However, abstracting from factors' mobility costs between sectors and assuming that home- and foreign-traded goods are perfect substitutes leads the model to overstate the reallocation of productive resources toward the non-traded sector and the decline in total hours. Because factors' mobility costs reduce the shift of resources toward the non-traded sector, households must give up a fraction of their higher consumption of leisure to produce additional units of non-traded goods. Households must further give up leisure to meet the demand for domestic (tradable) goods when home- and foreign-produced traded goods are imperfect substitutes because consumers are reluctant to replace domestic with imported goods. While these ingredients mitigate the decline in hours caused by financial (and trade) openness, we also have to let technology improvements be biased toward labor in the traded sector (in line with our estimates) to account for the effects of a technology shock on hours. Intuitively, when traded output turns out to be more labor intensive, higher demand for labor in traded industries neutralizes the incentives to shift labor toward the non-traded sector which further mitigates the decline in hours.

While the four aforementioned ingredients ensure that the model can account for the magnitude of the decline in hours, the performance of the baseline model also implicitly rests on assuming a mix of symmetric and asymmetric technology shocks between sectors. When technology improves at the same rate in both sectors, sectoral goods' prices depreciate (because an excess supply shows up on goods' markets) which puts downward pressure on sectoral wages and cause a dramatic decline in hours (by -0.40% on impact). In contrast, asymmetric technology shocks have a strong expansionary effect on hours (by 0.28% on

[3] We could also employ the home bias terminology for non-traded goods but because consumption in non-traded goods significantly mitigates the decline in hours after a technology shock only once we allow for mobility costs between sectors, we find it more relevant to refer to the role of barriers to factors' mobility.

impact). Because asymmetric technology improvements are concentrated within traded industries, non-traded goods' prices appreciate (due to the excess demand on the non-traded goods market) which has an expansionary effect on labor demand in non-traded industries. Firms in this sector thus pay higher wages to attract workers which has a positive impact on labor supply. Since hours significantly increase when technology improvements occur at different rates across sectors or fall dramatically when technology improves at the same rate, none of the shocks taken separately can account for the evidence. We need a mix of the two to ensure that technology improvements are associated with a productivity differential between tradables and non-tradables which provides incentives to shift labor toward non-traded industries and generates upward pressure on wages.

In the second quantitative exercise, we assess the ability of our model to account for the shrinking decline in hours from -0.26% (the first thirty years) to -0.11% (the last thirty years) we document empirically after a technology shock on rolling windows (with a fixed length of thirty years). To conduct this analysis, we let the share of technology improvements driven by asymmetric technology shocks increase over time from 10% to 40% in line with our estimates based on rolling sub-samples. While our open economy setup reproduces well the shrinking contractionary effects on hours of technology shocks we document empirically, we show that FBTC is a key element to account for the evidence, in particular when we focus on the time-varying responses of sectoral hours. When we impose Hicks-neutral technological change, the restricted model generates a time-decreasing impact response of traded hours worked in contradiction with our evidence because asymmetric technology shocks encourage labor to shift toward non-traded industries. By neutralizing the incentives to shift labor away from traded industries, technological change biased toward labor in the traded sector ensures that traded hours decline less over time as the share of asymmetric technology shocks is increased, in accordance with our estimates.

To understand the key driver behind the rising importance of asymmetric technology shocks, we extend our two-sector open economy setup to endogenous technology decisions. Our results show that more than 70% of the progression of asymmetric technology shocks is driven by the greater exposition of traded industries to the international stock of knowledge. Because the stock of knowledge is found empirically to have a significant effect on technology in traded industries only, the combined effect of the increase in the world stock of ideas and the growing intensity of traded technology in the international stock of knowledge has amplified the dispersion of technology improvements between the traded and the non-traded sector and has further increased the variance share driven by asymmetric technology improvements.

The article is structured as follows. In section 2, we propose a VAR-based decomposition of technology shocks into a symmetric and an asymmetric component between sectors to rationalize the time-varying effects on hours we estimate empirically. In section 3, we develop a two-sector open economy model where factor-augmenting technology has a symmetric and an asymmetric component between sectors. In section 4, we calibrate the model to the data and assess its ability to account for the time-varying effects. To rationalize the increasing importance of asymmetric technology improvements, we extend the model to endogenous technology decisions. Finally, section 5 concludes. The Online Appendix contains more empirical results, conducts robustness checks, details the solution method, and shows extensions of the baseline model.

Related Literature. Our paper fits into several different literature strands, as we bring several distinct threads in the existing literature together.

Impact response of hours to a technology shock. There is a vast literature investigating whether a technology improvement increases or lowers hours worked. While the (impact) response of hours worked to a technology shock is still debatable as the identification of technology shocks has been subject to criticisms, see e.g., Erceg et al. [2005], Dupaigne et al. [2007], Chari et al. [2008], the literature has put forward a set of solutions to deal with both the lag-truncation and the small sample biases, among others. These solutions include the number of lags, see e.g., De Graeve and Westermark [2013], the measure of technology, see e.g., Chaudourne et al. [2014], Dupaigne and Fève [2009], the VAR specification, see e.g., Fève and Guay [2010], the behavior of hours worked (i.e., stationary or free of low-frequency movements), see e.g., Christiano et al. [2006], Francis and Ramey [2009], or econometric methods of identification, see e.g., Francis et al. [2014], Li [2022]. Most of the aforementioned works find that positive technology shocks, identified with long-run restrictions, lead to a short-run decrease in hours worked.

Time-increasing response of hours to a technology shock. The structural change in the response of hours (conditional on technology shocks) we document for OECD countries over 1970-2017 in this work corroborates the evidence by Galí and Gambetti [2009], Cantore et al. [2017] on U.S. data who report a time-increasing response of hours worked following a permanent increase in productivity. These two papers together with Barnichon [2010], Galí and Van Rens [2021], Mitra [2023], Nucci and Riggi [2013] propose four different lines of explanation which may fit well the U.S. experience but cannot account for the shrinking decline in hours in OECD countries. First, we do not find that monetary policies are significantly more pro-cyclical after technology shocks in industrialized countries. Second, our evidence reveals that technology shocks are not biased toward capital in OECD countries and the elasticity of substitution between capital and labor has remained stable over time. Third, we find a significant time-declining response of the real wage to technology shocks which is hard to reconcile with the assumption of a rising performance pay. Fourth, the evidence points out that most of the OECD countries did not experience the decline in labor market frictions observed in the United States. Our estimates also reveal that on average, in OECD countries, the relative volatility of employment has remained stable. In contrast, both our evidence and model's predictions confirm that the increasing share of asymmetric technology shocks is the main driver of the gradual disappearance of the decline in hours.

Hours and technology in open economy. Most of the existing literature investigating the effects of technology shocks on total hours worked consider a closed economy, except for Collard and Dellas [2007] who consider a one-sector RBC model in open economy. The authors must impose an elasticity of substitution between domestic and foreign goods smaller than one to give rise to a decline in hours. We empirically find however that the decline in hours is concentrated in the non-traded sector and the response of traded hours worked remains muted. To generate these findings, we have to consider a two-sector open economy where home- and foreign-produced traded goods are high substitutes, as evidence suggests, see e.g., Bajzik et al. [2020].

Innovation and effects of technology shocks on labor. The decomposition of technology shocks into a symmetric and an asymmetric component between sectors allows us to reconcile two strands of the literature. Shea [1999] and Alexopoulos [2011] find that technology shocks driven by innovation increase employment while the literature pioneered by Galì [1999] finds that technology shocks lower hours worked. Because our evidence reveals that only asymmetric technology shocks give rise to innovation, if we focus on technology improvements driven by asymmetric technology shocks, these shocks will increase significantly labor, in accordance with the first strand of the literature. By contrast, if we focus on aggregate technology shocks, hours worked will fall because symmetric technology shocks are predominant.

Multi-sector setup and asymmetric technology improvements across sectors. The literature has recently quantified the implications of sectoral heterogeneity. Jaimovich et al. [2024] estimate the welfare impact of sector-specific technological change. In the same spirit as Ngai and Pissarides [2007], Cruz and Raurich [2020], the substitutability between goods plays a key role since the gross complementarity between traded and non-traded goods determines whether labor shifts toward or away from the non-traded sector. In this regard, symmetric technology shocks produce labor effects which are similar to those documented by Broadbent et al. [2023] who consider an anticipated decline in traded TFP caused by Brexit. To rationalize the rising importance of asymmetric technology improvements across sectors, in the same vein as Comin et al. [2019], we consider a version of our two-sector model with endogenous technology decisions and assume that traded industries benefit disproportionately from R&D in line with our evidence. In contrast to the authors, we put forward the greater and increasing exposition to the international stock of knowledge of traded industries as an explanation of the growing dispersion of technology improvements between sectors.

2 Technology and Hours across Time: Evidence

In this section, we document evidence for seventeen OECD countries about the link between technology and hours across time. Below, we denote the percentage deviation from initial steady-state (or the rate of change) with a hat.

2.1 Preliminaries

Before decomposing a technology shock into a symmetric and an asymmetric component and estimate their dynamic effect on hours, we build intuition below on the transmission mechanism. The setup we have in mind to identify symmetric and asymmetric technology shocks is a two-sector open economy with a traded (i.e., an exporting) and a non-traded (i.e., non-exporting) sector. The greater exposition of traded industries to foreign competition and innovation abroad generates a productivity growth differential between tradables and non-tradables, see e.g., Benigno et al. [2022], which plays a central role in our identification. Both the international openness and multi-sector aspects of our setup are key to understanding the effect of a technology shock on hours.[4]

International openness generates a negative link between hours and technology. By producing a (positive) wealth effect, a positive technology shock encourages households to consume more goods and more leisure; by increasing the marginal revenue product of capital, a technology improvement also stimulates investment. When the economy is closed, households must give up leisure and increase labor supply to produce additional units of consumption and investment goods in order to meet their higher demand. In contrast, when the economy is open to international trade, it is optimal to import goods from abroad to meet a higher demand for traded goods and shift productive resources toward the non-traded sector to meet the demand for non-tradables. Households enjoy leisure and the decline in labor supply is financed by running a current account deficit. Quantitatively, when technology permanently improves by 1%, hours increase by 0.08% in a closed economy and decline by -0.35% in an open economy where inputs can move freely between the traded and non-traded sectors.

Once we let the movements of inputs between sectors be subject to frictions, the decline in hours to a technology shock in open economy shrinks to -0.11%. First, by reducing the shift of productive resources toward the non-traded sector, mobility costs constrain households to give up a fraction of their higher consumption of leisure to produce non-traded

[4] For reasons of space, we relegate to Online Appendix A all details about the computation of the impact effect on hours of a 1% permanent increase in utilization-adjusted-TFP and its comparison across restricted versions of our baseline model.

goods. Second, the decline in labor supply further shrinks when home- and foreign-produced traded goods are imperfect substitutes as households are now reluctant to substitute imported goods for home goods which in turn requires to produce additional units of the home-produced traded good.

The multi-sector dimension generates a positive link between hours and technology. While international openness has a strong negative impact on the link between hours and technology, the multi-sector dimension of industrialized countries generates a positive relationship. Intuitively, in an economy with multiple sectors, technology improves at different rate across sectors. The dispersion in technology improvement between sectors leads to an appreciation in relative prices in low productivity growth (non-traded) industries which seek to compensate for their productivity disadvantage. If the price-elasticity of demand for non-traded goods is smaller than one, the appreciation in the relative price of non-tradables has an expansionary effect on labor demand in these industries which pay higher wages to attract workers (who experience mobility costs). Higher wages increase labor supply and thus the dispersion of technology improvement between sectors generates a strong positive link between hours and technology.

2.2 Data Construction

We briefly discuss the dataset we use. We take data from EU KLEMS and OECD STAN to construct time series for tradables (indexed by the superscript $j = H$) and non-tradables (indexed by the superscript $j = N$). Online Appendix G provides a lot of details about the source and the construction of time series. Our sample contains annual observations and consists of a panel of 17 OECD countries. The period runs from 1970 to 2017.

Classification of industries: tradables vs. non-tradables. To classify eleven 1-digit ISIC-rev.3 industries industries as tradables or non-tradables, we use data from the World Input Output Dataset (WIOD) to calculate the openness to international trade of each industry, measured by the ratio of imports plus exports to gross output. We treat industries as tradables when trade openness is equal or larger than 20%. We thus classify "Agriculture, Hunting, Forestry and Fishing", "Mining and Quarrying", "Total Manufacturing","Transport, Storage and Communication", and "Financial Intermediation" in the traded sector. The remaining industries "Electricity, Gas and Water Supply", "Construction", "Wholesale and Retail Trade" and "Community Social and Personal Services", "Hotels and Restaurants" and "Real Estate, Renting and Business Services" are classified as non-tradables. We perform a sensitivity analysis with respect to the classification in Online Appendix K.2 and find that all conclusions hold.

We construct time series for sectoral hours worked, L^j_{it}, the hours worked share of sector j, $\nu^{L,j}_{it}$, where the subscripts i and t denote the country and the year. To capture the transmission mechanism of a technology shock in a two-sector open economy, we also analyze the movements in the value added share at constant prices, $\nu_{it}^{Y,j}$, in the relative price of non-tradables which is computed as the ratio of the non-traded value added deflator to the traded value added deflator (i.e., $P_{it} = P_t^N/\mathsf{P}_{it}^H$), and in the terms of trade denoted by $P_t^H = \mathsf{P}_{it}^H/\mathsf{P}_{it}^{H,\star}$ where P_{it}^H is the traded value added deflator of the home country i and $\mathsf{P}_{it}^{H,\star}$ captures foreign prices defined as an import share (geometric) weighted average of the traded value added deflator of the sixteen trade partners of country i. Note that the share of imports from the trade partner is averaged over 1970-2017.

Utilization-adjusted sectoral TFPs. Sectoral TFPs are Solow residuals calculated from constant-price (domestic currency) series of value added, Y_{it}^j, capital stock, K_{it}^j, and hours worked, L_{it}^j, i.e., $\hat{\text{TFP}}_{it}^j = \hat{Y}_{it}^j - s_{L,i}^j \hat{L}_{it}^j - \left(1 - s_{L,i}^j\right) \hat{K}_{it}^j$ where $s_{L,i}^j$ is the labor income share (LIS henceforth) in sector j averaged over the period 1970-2017. We construct a measure for technological change by adjusting the Solow residual with the capital utilization rate, denoted by $u_{it}^{K,j}$:[5]

$$\hat{Z}_{it}^j = \hat{\text{TFP}}_{it}^j - \left(1 - s_{L,i}^j\right) \hat{u}_{it}^{K,j}, \tag{1}$$

where we follow Imbs [1999] in constructing time series for $u_{it}^{K,j}$, as utilization-adjusted-TFP is not available at a sectoral level for most of the OECD countries of our sample over 1970-2017.[6] In Online Appendix L.3, we find that our empirical findings are little sensitive to the use of alternative measures of technology which include i) Basu's [1996] approach which has the advantage of controlling for unobserved changes in both capital utilization and labor effort, ii) and the use of time series for utilization-adjusted-TFP from Huo et al. [2023] and Basu et al. [2006]. Our preferred measure is based on Imbs's [1999] method because it fits our model setup where we consider an endogenous capital utilization rate and the last two measures can only be constructed over a shorter period of time and for a limited number of OECD countries.

2.3 Identification of Asymmetric vs. Symmetric Technology Shocks

Objective and strategy. Our objective is to demonstrate that the gradual disappearance of the negative response of hours to technology shocks is caused by the increasing importance of technology improvements which occur at different rates between sectors. To show this point, we proceed in three steps below. First, we estimate the effects on hours of a permanent technology shock. Second, we contrast the effects on hours after a symmetric technology shock with those caused by asymmetric technology shocks. Third, we estimate

[5] To construct time series for the capital stock of the traded and the non-traded sector, we have constructed the overall capital stock by adopting the perpetual inventory approach, using constant-price investment series taken from the OECD's Annual National Accounts. Next we split the gross capital stock into traded and non-traded industries by using sectoral value added shares. In Online Appendix K.3, we use the EU KLEMS dataset which provides disaggregated capital stock data (at constant prices) at the 1-digit ISIC-rev.3 level for thirteen countries of our sample over the period 1970-2017. Our estimates show that our empirical findings are unsensitive to the way the sectoral capital stocks are constructed in the data.

[6] We detail the adaptation of Imbs's [1999] method to our case where sectoral goods are produced from CES production functions in Online Appendix H.

the time-varying effects on hours of a permanent technology improvement and quantify the progression in the share of technology improvements driven by asymmetric technology shocks.

To conduct our empirical study, we compute the responses of selected variables by using a two-step estimation procedure. We first identify a permanent technology improvement by adopting the identification pioneered by Gali [1999]. Like Gali, we impose long-run restrictions in the VAR model to identify permanent technology shocks as shocks that increase permanently the level of our measure of technology. Because Erceg et al. [2005] and Chari et al. [2008] have shown that persistent non-technology shocks can disturb the identification of permanent technology shocks, we adjust TFP with the capital utilization rate. 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 the second step, we trace out the dynamic effects of the identified shock to utilization-adjusted TFP by using Jordà's [2005] single-equation method. This two-step approach is particularly suited to our purpose as we identify technology shocks once and for all and next estimate the dynamic responses of a set of variables to the identified shock and assess empirically its time-varying effects on rolling windows.

VAR Identification of symmetric vs. asymmetric technology shocks across sectors. The starting point of the identification of symmetric and asymmetric technology shocks is the sectoral decomposition of the percentage deviation of utilization-adjusted-aggregate-TFP (i.e., Z^A_{it}) relative to its initial steady-state:

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

where $\hat{Z}^H_{it}$ and $\hat{Z}^N_{it}$ measure technology improvements in the traded and the non-traded sector, respectively, and $\nu^{Y,H}$ is the value added share of tradables. Eq. (2) can be rearranged as follows

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

which enables us to decompose technological change into technology improvements which are common and asymmetric between sectors. When technology improves at the same rate in the traded and the non-traded sector, i.e., $\hat{Z}^H_{it} = \hat{Z}^N_{it}$, then the second term on the RHS of eq. (3) vanishes and technological change collapses to its symmetric component (indexed by the the subscript S), i.e., $\hat{Z}^A_{S,it} = \hat{Z}^H_{S,it} = \hat{Z}^N_{S,it}$. In contrast, the asymmetric component (indexed by the the subscript D) of aggregate technological change is captured by the second term on the RHS, i.e., $\hat{Z}^A_{D,it} = \nu^{Y,H}_i \left(\hat{Z}^H_{D,it} - \hat{Z}^N_{D,it}\right)$, which reflects the excess of technology improvements in the traded sector over those in the non-traded sector (weighted by $\nu^{Y,H}_i$).

We assume that technology in sector j is made up of a symmetric and an asymmetric component, i.e., $Z^j_{it} = \left(Z^j_{S,it}\right)^{\eta_i} \left(Z^j_{D,it}\right)^{1-\eta_i}$, where we denote by η the share of technological change which is common across sectors. Log-linearizing this expression and plugging the result into eq. (2) leads to the decomposition of aggregate technological change into a symmetric and an asymmetric component:

$$\hat{Z}^A_{it} = \eta_i \hat{Z}^A_{S,it} + (1 - \eta_i)\, \hat{Z}^A_{D,it}. \tag{4}$$

We consider two versions of the VAR model. In both cases, we estimate a reduced form VAR model in panel format on annual data with two lags and with both country fixed effects and time dummies. The first version includes utilization-adjusted-aggregate-TFP, real GDP, total hours worked and the real consumption wage. All quantities are divided by the working age population and all variables enter the VAR model in rate of growth, see Online Appendix K.1 which documents evidence about the presence of a unit-root process for all variables of interest. We impose long-run restrictions to identify technology shocks as shocks which increase permanently Z^A_{it}, see Online Appendix F which provides more details about the SVAR identification. In the second version, we augment the VAR model with the ratio of traded to non-traded utilization-adjusted-TFP ordered first. Building on our above discussion based on eq. (3), we impose long-run restrictions such that both symmetric and asymmetric technology shocks increase permanently Z^A_{it} while only asymmetric technology shocks increase Z^H_{it}/Z^N_{it} in the long-run. Technically the long-run cumulative matrix is lower triangular which implies that only asymmetric technology shocks in the first row increases both the ratio of traded to non-traded technology and aggregate technology while symmetric technology shocks in the second row leave the relative productivity of tradables unaffected.

Estimating dynamic effects. Once we have identified technology shocks from the VAR model's estimation, in the second step, we estimate the dynamic effects on selected variables (detailed later) by using Jordà's [2005] single-equation method. The local projection method amounts to running a series of regressions of each variable of interest on a structural identified shock for each horizon $h = 0, 1, 2, ...$

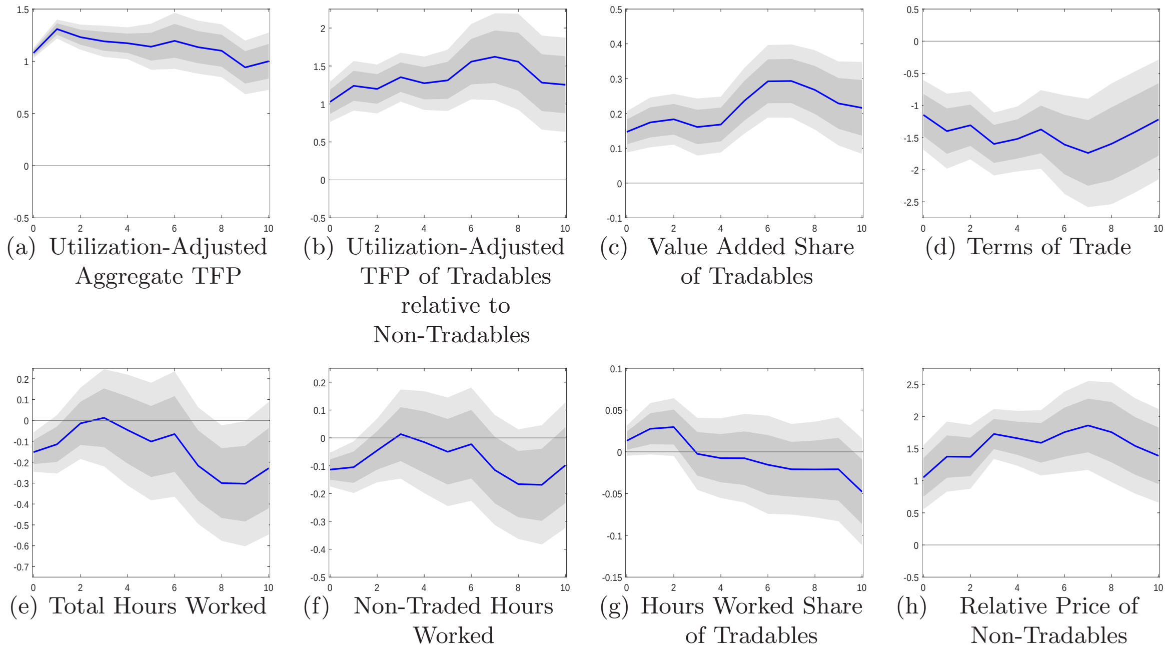
$$x_{i,t+h} = \alpha_{i,h} + \alpha_{t,h} + \psi_h(L)\, z_{i,t-1} + \gamma_h \varepsilon^Z_{i,t} + \eta_{i,t+h}, \tag{5}$$

where $\alpha_{i,h}$ are country fixed effects, $\alpha_{t,h}$ are time dummies; x is the logarithm of the variable of interest, z is a vector of control variables (i.e., past values of utilization-adjusted-TFP and of the variable of interest), $\psi_h(L)$ is a polynomial (of order two) in the lag operator. The coefficient γ_h gives the response of x at time $t + h$ to the identified technology shock $\varepsilon^Z_{i,t}$ at time t. We compute heteroskedasticity and autocorrelation robust standard errors based on Newey-West.

Robustness checks. Galí [1999] has pioneered the identification of a permanent technology improvement through long-run restrictions. Because the SVAR estimation allows for a limited number of lags, the SVAR critique has formulated some reservations with regard to the ability of the SVAR model to disentangle pure technology shocks from other shocks (which have long-lasting effects on productivity) when capital adjusts sluggishly, see e.g., Erceg et al. [2005], Dupaigne et al. [2007], Chari et al. [2008]. While the use of utilization-adjusted-TFP ensures the robustness of the identification of technology shocks, as demonstrated by Chaudourne et al. [2014], we have also conducted a series of robustness checks related to several aspects of our VAR identification of technology shocks and measures of technology which are detailed in Online Appendices K and L.

First, in Online Appendix L.1, we test whether the identified shocks to technology are correlated with non-technology shocks. Following Francis and Ramey [2005], we run the regression of identified technology shocks based on three measures of technology on (three) shocks to government spending, monetary policy, and taxation. The F-test reveals that none of the demand shocks are correlated with our identified technology shocks only when we use utilization-adjusted-TFP to measure technology. Technology shocks identified on the basis of the Solow residual (unadjusted with factors' utilization) and labor productivity are instead found to be correlated with the demand shocks. Second, following the recommendation by Chari et al. [2008] and De Graeve and Westermark [2013] who find that raising the number of lags may be a viable strategy to achieve identification when long-run restrictions are imposed on the VAR model, in Online Appendix L.2, we increase the lags from two to eight and find that all of our conclusions stand.

Third, in Online Appendix L.4, we adopt the Maximum Forecast Error Variance (FEV) approach proposed by Francis et al. [2014] which extracts the shock that best explains the FEV at a long but finite horizon of the measure of technology. We find that the response of hours when the technology shock is identified by means of the Maximum FEV is not statistically different from that obtained when imposing long-run restrictions for the median estimate as well as at the individual level (except for three out of seventeen countries). Fourth, following Fève and Guay [2010], in Online Appendix L.5, we estimate in the first step a VAR model by excluding hours and including only the rate of change in utilization-adjusted-TFP and the log ratio of consumption plus net exports to GDP and impose long-run restrictions to identify technology shocks and then in the second step, we estimate the dynamic effects by using local projections. We find no differences between our results and those obtained when we exclude hours from the first step. Fifth, as detailed in Online Appendix L.6, we build on the method proposed by Dupaigne and Fève [2009] and replace the country-level-utilization-adjusted-TFP with the import-share-weighed-average of utilization-adjusted-TFPs of the home country's trade partners which by construction is not influenced by country-specific persistent non-technology shocks. Differences are not statistically significant although hours do not fall below trend on impact because world technology shocks are further driven by asymmetric technology shocks compared with shocks to country-level utilization-adjusted-TFP.



(a) Utilization-Adjusted Aggregate TFP
(b) Utilization-Adjusted TFP of Tradables relative to Non-Tradables
(c) Value Added Share of Tradables
(d) Terms of Trade
(e) Total Hours Worked
(f) Non-Traded Hours Worked
(g) Hours Worked Share of Tradables
(h) Relative Price of Non-Tradables

Figure 2: Dynamic Effects of a Technology Shock. Notes: The solid blue line shows the dynamic responses to an exogenous increase in utilization-adjusted-aggregate-TFP by 1% in the long-run. While solid lines represent point estimates, light (dark) shaded areas represent 90 (68) percent confidence intervals based on Newey-West standard errors. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend. Sample: 17 OECD countries, 1970-2017, annual data.

2.4 Effects on Hours of a Technology Shock

We first investigate the effects of a permanent increase in utilization-adjusted-TFP normalized to 1% in the long-run and shown in Fig. 2(a). The dynamic adjustment of variables to an exogenous increase in Z_{it}^{A} is estimated by means of local projections. Solid lines in Fig. 2 represent point estimates, light (dark) shaded areas represent 90 (68) percent confidence intervals. The horizontal axis of each panel measures the time after the shock in years and the vertical axis measures deviations from trend. The response of non-traded hours worked is re-scaled by the sample average of labor compensation share of non-tradables to express the variation in L_{it}^{N} in percentage point of total hours worked.

Effects on hours. Fig. 2(e) reveals that a permanent technology improvement (of 1% in the long-run) significantly lowers hours worked by 0.15% on impact, a magnitude which is similar to the estimates documented by Galì and Gambetti [2009] on U.S. data in the post-1984 period. As shown in the quantitative analysis part, the negative effect of a technology shock on hours is moderate due to frictions into the movements of inputs between sectors and because symmetric and asymmetric technology shocks exert opposite (and thus offsetting) effects on hours. Fig. 2(f) shows that the decline in total hours worked is concentrated in the non-traded sector in the short-run while the situation is reversed from $t = 4$ as labor is reallocated toward the non-traded sector as can be seen in Fig. 2(g). The deindustrialization trend movement in the long-run is driven by the productivity growth differential between tradables and non-tradales which averages 1.2% as displayed by Fig. 2(b).

Labor reallocation. As technology improvements are concentrated in the traded sector, non-traded industries charge higher prices to compensate for the higher marginal cost, as can be seen in Fig. 2(h) which shows that the relative price of non-tradables appreciates. Because the demand for non-traded relative to traded goods is little sensitive to the relative price of non-tradables (see e.g., Mendoza [1992], Stockman and Tesar [1995]), the non-tradable content of expenditure increases which causes labor to shift toward the non-traded sector. However, labor reallocation toward the non-traded sector materializes only in the long-run. As shown later in section 4.2, there are a number of factors which prevents labor from shifting in the short-run, in particular imperfect substitutability between home- and foreign-produced traded goods. Because productivity growth is concentrated in traded industries, the value added share of tradables at constant prices increases permanently by 0.2 ppt of GDP, as displayed by Fig. 2(c), which leads to a depreciation in the terms of trade as shown in Fig. 2(d). Because home- and foreign-produced traded goods are high substitutes, as evidence suggests, see e.g., Bajzik et al. [2020], the terms of trade depreciation has a strong expansionary effect on labor demand in the traded sector by increasing both the domestic and foreign demand components for home-produced traded goods. Besides the terms of trade adjustment, both factors' mobility costs and technological change biased toward labor also play a key role as shown later in the quantitative analysis.

Intensive vs. extensive margin. Because the variations in total hours worked can be driven by changes in hours at the intensive margin (i.e., hours per worker) or at the extensive margin (i.e., employment) or both, we contrast the adjustment in total hours worked with the dynamics of hours per worker in Online Appendix K.6. Like Thomet and Wegmuller [2021] who use a panel of fourteen OECD countries, we find that the movements in the intensive margin are the dominant channel of adjustment in total hours after an aggregate technology shock, especially in the short-run, because employment adjusts only gradually.

2.5 Symmetric vs. Asymmetric Technology Shocks across Sectors

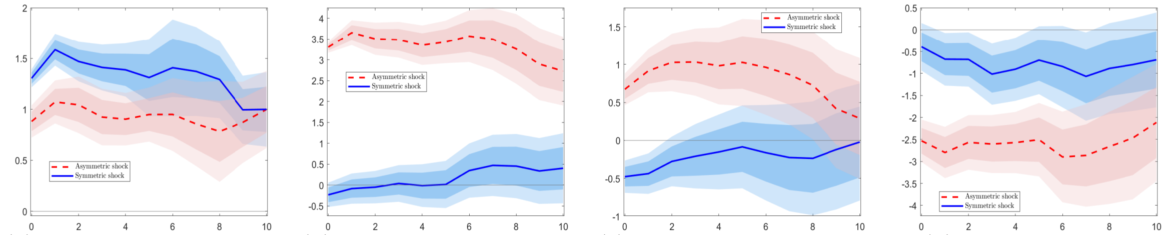
We now turn to the decomposition of the responses to a permanent technology improvement into dynamic effects driven by symmetric (shown in blue lines) and asymmetric (shown in red lines) technology shocks in Fig. 3. Blue (red) lines represent point estimates after symmetric (asymmetric) technology shocks, light (dark) shaded areas represent 90 (68) percent confidence intervals. While both shocks lead to a technology improvement by 1% in the long-run, see Fig. 3(a), the behavior of technology at a sectoral level is different. As can be seen in Fig. 3(b), asymmetric technology shocks generate a significant increase (by 2.9% on average) in utilization-adjusted-TFP of tradables relative to non-tradables while productivity growth is uniformly distributed across sectors after a symmetric technology shock since the ratio Z^H/Z^N remains unchanged at all horizons.

Effects of symmetric technology shocks. Importantly, Fig. 3(e) reveals that symmetric and asymmetric technology shocks produce distinct effects on labor as hours worked decline dramatically (by -0.47% on impact) after symmetric technology shocks while hours increase (by 0.31% on impact) after asymmetric technology shocks. These opposite effects are the result of the impact of productivity on sectoral prices. As shown in the blue line in Fig. 3(c) and Fig. 3(d), both non-traded and traded goods' prices depreciate after symmetric technology shocks which in turn put downward pressure on wages and exert a negative impact on labor supply. This negative impact is amplified by the fact that technological change is biased toward capital in the traded sector as captured by a decline in our measure of FBTC, see Fig. 3(h). As detailed in Online Appendix E, we adapt the methodology pioneered by Caselli and Coleman [2006] and Caselli [2016] to construct time series for utilization-adjusted-FBTC at a sectoral level by using the ratio of labor demand to capital demand and plugging our estimates for the elasticity of substitution between capital and labor together with time series for the labor incomes share, the capital labor ratio and the capital utilization rate.

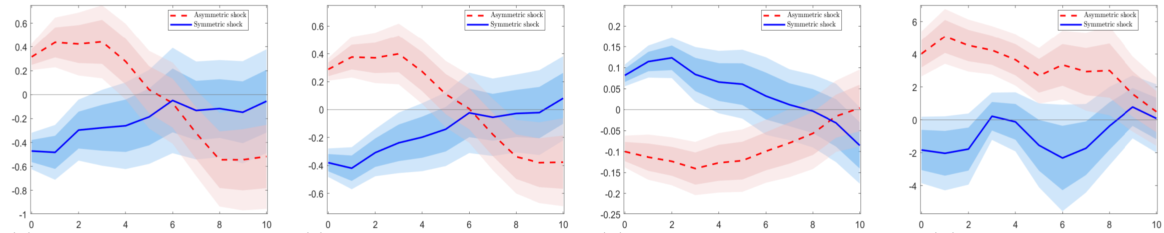
As can be seen in Fig. 3(f), the decline in total hours worked is mostly driven by the fall in hours worked in the non-traded sector. Because the elasticity of substitution between traded and non-traded goods is low (i.e., less than one), the fall in non-traded prices drives down the share of expenditure spent on non-traded goods which reduces labor demand in the non-traded sector. By contrast, because home- and foreign-produced traded goods are high substitutes, the terms of trade depreciation raises the share of home-produced traded goods and thus further increases the share of tradables. This has an expansionary effect on labor demand in the traded sector which leads to a shift of labor toward traded industries as reflected into an increase in the hours worked share of tradables displayed by the blue line in Fig. 3(g).

Effects of asymmetric technology shocks. Asymmetric technology shocks produce very distinct effects on labor. Because technology improvements are concentrated in traded industries, see the red line in Fig. 3(b), asymmetric technology shocks give rise to an excess supply for home-produced traded goods and an excess demand for non-traded goods. As shown in Fig. 3(c) (see the dashed red line), the excess demand puts upward pressure on non-traded goods prices. Because traded and non-traded goods are gross complements, the appreciation in non-traded prices increases the share of non-tradables which has a positive impact on non-traded hours worked, as displayed by Fig. 3(f).

The rise in L^N is amplified by the shift of labor toward the non-traded sector. As shown in the red line of Fig. 3(g), the hours worked share of tradables declines dramatically on impact by 0.1 ppt of total hours worked before recovering gradually. The first four years, the reallocation of labor toward the non-traded sector accounts for one-third of the rise in non-traded hours worked. To encourage workers to shift, non-traded firms must pay higher wages which puts upward pressure on non-traded wages and thus on the aggregate



(a) Utilization-Adjusted-Agg.-TFP (b) Utilization-Adjusted-TFP of H relative to N (c) Non-Traded Goods Prices (d) Terms of Trade

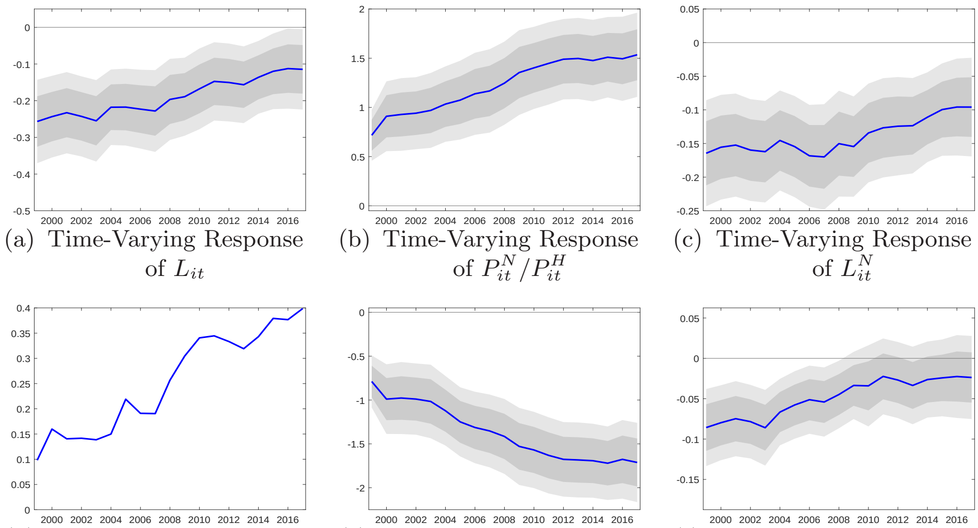


(e) Total Hours Worked (f) Non-Traded Hours Worked (g) Hours Worked Share of Tradables (h) Traded FBTC

Figure 3: Effects on Hours of Asymmetric vs. Symmetric Technology Shocks. Notes: The solid lines shows the responses to an exogenous increase in utilization-adjusted-aggregate-TFP by 1% in the long-run. Solid blue lines represent point estimates for symmetric technology shocks while dashed red lines show point estimates after asymmetric technology shocks between sectors. Light (dark) shaded areas represent 90 (68) percent confidence intervals based on Newey-West standard errors. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend. Sample: 17 OECD countries, 1970-2017, annual data.

wage which has a strong expansionary effect on labor supply as shown in Fig. 3(e) (see the red line). On impact, the rise in total hours worked mostly originates from non-traded industries and is amplified by the fact that asymmetric technology improvements are significantly biased toward labor (in the traded sector), as displayed by Fig. 3(h) (see the red line). The combined effect of the terms of trade depreciation displayed by Fig. 3(d) and the rise in the labor intensity of traded production prevents traded hours worked from decreasing.

Do asymmetric technology shocks increase innovation? Asymmetric technology shocks are technology improvements which are concentrated within traded industries. As shown in Online Appendix K.5, only these shocks are associated with higher investments devoted to innovative activity as reflected into a significant and positive increase in the stock of R&D. In Online Appendix Q.4, we run the regression of utilization-adjusted-TFP in sector j on the stock of R&D at constant prices in sector j by using cointregation techniques. By applying the Pedroni's [2000] FMOLS estimator, we find that the elasticity of traded technology w.r.t. the stock of R&D in the traded sector amounts to 0.238 while it is virtually zero in the non-traded sector. These evidence thus underlines that technology improvements which are not uniformly distributed across sectors but instead concentrated within traded industries capture technological innovation. In this regard, in Online Appendix K.5, we detect a strong positive cross-country relationship between the share of the FEV of aggregate technology shocks driven by asymmetric technology improvements and the ratio of R&D investment to value added in the traded sector. In contrast, symmetric technology shocks do not increase the stock of R&D significantly and should capture better



(a) Time-Varying Response of L_{it} (b) Time-Varying Response of P^N_{it}/P^H_{it} (c) Time-Varying Response of L^N_{it}

(d) Variance Share of Asym. Tech. Shocks (e) Time-Varying Depreciation of P^H_{it} (f) Time-Varying Response of L^H_{it}

Figure 4: Time-Varying Effects of a Technology Shock. Notes: While the vertical axis of Fig. 4(a) shows the point estimate (i.e., γ_0) for the impact response of hours (L_{it}) to a 1% permanent increase in utilization-adjusted-aggregate-TFP obtained from estimating eq. (5) on rolling subs-samples, the horizontal axis shows the end year of the corresponding window. Light (dark) shaded areas represent 90 (68) percent confidence intervals based on Newey-West standard errors. In Fig. 4(d), we show the fraction of the (conditional) variance of utilization-adjusted-TFP growth which is attributable to the variance of asymmetric technology shocks across sectors. In column 2 we show the impact responses estimated on rolling windows (of fixed length of thirty years) of the relative price of non-tradables (P^N_{it}/P^H_{it}), see Fig. 4(b), and the terms of trade (P^H_{it}), see Fig. 4(e), respectively. In column 3, we show time-varying impact responses of non-traded (L^N_{it}) and traded (L^H_{it}) hours worked to an aggregate technology shock, both re-scaled by the labor compensation share so that the sum response of sectoral hours worked are expressed in percentage point of total hours. Sample: 17 OECD countries, 1970-2017, annual data.

management practices and improvements in firm's organization.

2.6 The Time-Varying Response of Hours

Our evidence reveals that a permanent technology improvement has a contractionary effect on total hours worked on impact in OECD countries. We now investigate whether this decline has changed over the last fifty years.

The shrinking contractionary effect of technology shocks on hours. To capture the gradual and continuous change in the response of hours over time, like Cantore et al. [2017], we re-estimate the effect of a permanent technology improvement on hours by running the regression eq. (5) on rolling windows of fixed length. We focus on the impact effect captured by the estimated value γ_0 and consider a window of thirty years. More specifically, we estimate γ_0, starting from 1970-1999, repeating the estimation by moving the starting date by one year until we estimate the response over the last thirty years of the sample, i.e., over 1988-2017. We have considered windows of alternative length such as $T = 20$ and $T = 25$ and find that all the conclusions hold. As shown in Fig. 4(a), the decline in hours after a 1% permanent increase in utilization-adjusted aggregate TFP shrinks over time as total hours worked fall by -0.26% on impact over 1970-1999 and by -0.11% only over the last thirty years. Online Appendix K.6 shows that the time-increasing impact response of hours to a technology shock only operates at the intensive margin.

The increasing importance of asymmetric technology shocks. As shown in Fig. 4(d), the shrinking impact labor response is concomitant to the rise in the share of technology improvements driven by asymmetric technology shocks. The FEVD computed over rolling sub-samples reveals that the contribution of asymmetric technology shocks to the variance of aggregate technology improvements has increased substantially over time from 10% the first thirty years to 40% over the recent period. Column 2 shows further evidence pointing out the increasing importance of asymmetric technology shocks across sectors. We plot impact responses of the relative price of non-tradable and the terms of trade to an aggregate technology shock over rolling windows. Because technology improvements are not uniformly distributed across sectors and instead are concentrated toward traded industries, a technology shock produces an excess demand for non-traded goods which appreciates the relative price of non-tradables as displayed by Fig. 4(b). Conversely, an excess supply on the traded goods market shows up which leads to a depreciation in the terms of trade as can be seen in Fig. 4(e). As shown in Fig. 4(b), the appreciation in the relative price of non-tradables tends to be more pronounced while Fig. 4(e) reveals that the terms of trade depreciate more over time. The greater appreciation in the relative price of non-tradables and the more pronounced depreciation in the terms of trade suggest that aggregate technology shocks are increasingly driven by asymmetric technology improvements between sectors.

The decline in both non-traded and traded hours worked shrinks. By increasing the share of expenditure spent on non-tradables, the appreciation in the relative price of non-tradables displayed by Fig. 4(b) has a strong expansionary effect on labor demand in the non-traded sector. By amplifying the appreciation in non-traded goods prices, the growing variance share of asymmetric technology shocks, as displayed by Fig. 4(d), should increase the impact response of non-traded hours worked to aggregate technology shocks. In accordance with this hypothesis, Fig. 4(c) shows that the decline in non-traded hours worked shrinks over time. However, by giving rise to greater incentives to shift labor toward the non-traded sector, the greater appreciation in the relative price of non-tradables should lead to larger negative values for the response of traded hours worked to a technology improvement. Fig. 4(f) shows that it is not the case as the decline in traded hours worked also shrinks over time. Such a finding is driven by two factors. First, as detailed later in section 4.2, the terms of trade depreciation stimulates labor demand in the traded sector which partly offsets the incentives to shift labor toward the non-traded sector. This factor is not sufficient on its own to generate the time-increasing impact response of L^H. As shown in section 4.4, it is only once we allow for technological change biased toward labor that the model can generate the response of traded hours worked displayed by Fig. 4(f).

3 Open Economy Model with Tradables and Non-Tradables

We consider an open economy with an infinite horizon which is populated by a constant number of identical households and firms, both having perfect foresight. Like Kehoe and Ruhl [2009], Bertinelli et al. [2022], Chodorow-Reich et al. [2023], the country is assumed to be 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 so that exports are price-elastic. The open economy produces a traded good (denoted by the superscript H) which can be exported, consumed or invested and also imports consumption and investment goods (denoted by the superscript F). The economy produces a non-traded good, denoted by the superscript N, for domestic absorption only. The foreign good is chosen as the numeraire. Time is continuous and indexed by t. We provide more details about the model in Online Appendices N and O.

3.1 Firms

We denote value added in sector j by Y^j. Both the traded and non-traded sectors use physical capital (inclusive of capital utilization chosen by households), denoted by $\tilde{K}^j(t) = u^{K,j}(t)K^j(t)$, and labor, L^j, according to a constant returns-to-scale technology described by a CES production function:

$$Y^j(t) = \left[\gamma^j\left(A^j(t)L^j(t)\right)^{\frac{\sigma^j-1}{\sigma^j}} + \left(1-\gamma^j\right)\left(B^j(t)\tilde{K}^j(t)\right)^{\frac{\sigma^j-1}{\sigma^j}}\right]^{\frac{\sigma^j}{\sigma^j-1}}, \tag{6}$$

where $0 < \gamma^j < 1$ is the weight of labor in the production technology and σ^j is the elasticity of substitution between capital and labor in sector $j = H, N$. We allow for labor- and capital-augmenting efficiency denoted by $A^j(t)$ and $B^j(t)$. Factor-augmenting productivity is made up of a symmetric component (across sectors) denoted by the subscript S and an asymmetric component denoted by the subscript D:

$$A^j(t) = \left(A^j_S(t)\right)^\eta\left(A^j_D(t)\right)^{1-\eta}, \qquad B^j(t) = \left(B^j_S(t)\right)^\eta\left(B^j_D(t)\right)^{1-\eta}, \tag{7}$$

where the elasticity of factor-augmenting productivity w.r.t. its symmetric component, denoted by η, captures the share of technology improvements which are uniformly distributed between sectors. Because capital-augmenting productivity has a symmetric and an asymmetric component, capital technology utilization rate must also have both a symmetric and asymmetric component, i.e.,

$$u^{K,j}(t) = \left(u^{K,j}_S(t)\right)^\eta\left(u^{K,j}_D(t)\right)^{1-\eta}, \tag{8}$$

which ensures that symmetric and asymmetric components of TFP are well-defined.

Both sectors are assumed to be perfectly competitive and thus choose capital and labor services by taking prices P^j as given. The movements in capital and labor across sectors are subject to frictions which imply that the capital rental cost and the wage rate equal to $R^j(t)$ and $W^j(t)$, respectively, are sector-specific:

$$P^j(t)\gamma^j \left(A^j(t)\right)^{\frac{\sigma^j-1}{\sigma^j}} \left(L^j(t)\right)^{-\frac{1}{\sigma^j}} \left(Y^j(t)\right)^{\frac{1}{\sigma^j}} \equiv W^j(t), \tag{9a}$$

$$P^j(t)\left(1-\gamma^j\right) \left(B^j(t)\right)^{\frac{\sigma^j-1}{\sigma^j}} \left(u^{K,j}(t)K^j(t)\right)^{-\frac{1}{\sigma^j}} \left(Y^j(t)\right)^{\frac{1}{\sigma^j}} = R^j(t). \tag{9b}$$

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

$$S^j(t) \equiv \frac{s^j_L(t)}{1-s^j_L(t)} = \frac{\gamma^j}{1-\gamma^j}\text{FBTC}^j(t)\left(\frac{u^{K,j}(t)K^j(t)}{L^j(t)}\right)^{\frac{1-\sigma^j}{\sigma^j}}, \tag{10}$$

where $\text{FBTC}^j(t) = \left(B^j(t)/A^j(t)\right)^{\frac{1-\sigma^j}{\sigma^j}}$ is utilization-adjusted-FBTC. According to our own estimates and the evidence documented in the literature, e.g., Chirinko and Mallick [2017], Oberfield and Raval [2021], capital and labor are gross complements in production, i.e., $\sigma^j < 1$. An increase in FBTC^j means that technological change is biased toward labor which has an expansionary on the labor income share $s^j_L(t)$ in sector j.

3.2 Technology Frontier

Following Caselli and Coleman [2006] and Caselli [2016], firms within each sector $j = H, N$ must decide about the split of utilization-adjusted-TFP, $Z^j(t)$, between labor- and capital-augmenting efficiency (i.e., $A^j(t)$ and $B^j(t)$) along a technology frontier:

$$\left[\gamma^j_Z \left(A^j(t)\right)^{\frac{\sigma^j_Z-1}{\sigma^j_Z}} + \left(1-\gamma^j_Z\right)\left(B^j(t)\right)^{\frac{\sigma^j_Z-1}{\sigma^j_Z}}\right]^{\frac{\sigma^j_Z}{\sigma^j_Z-1}} \leq Z^j(t), \tag{11}$$

where $Z^j(t) > 0$ is the height of the technology frontier, $0 < \gamma^j_Z < 1$ is the weight of labor efficiency in utilization-adjusted-TFP and $\sigma^j_Z > 0$ corresponds to the elasticity of substitution between labor- and capital-augmenting productivity. Firms choose a mix of labor and capital efficiency so as to minimize the unit cost for producing. The unit cost minimization requires that the contribution of labor-augmenting productivity to technological change in sector j collapses to the LIS, i.e., $s^j_L = \gamma^j_Z \left(\frac{A^j(t)}{Z^j(t)}\right)^{\frac{\sigma^j_Z-1}{\sigma^j_Z}}$ (see Online Appendix C). Inserting this equality into the log-linearized version of the technology frontier (11) shows that technological change in sector j is a factor-income-share-weighted sum of changes in factor-augmenting efficiency:

$$\hat{Z}^j(t) = s^j_L \hat{A}^j(t) + \left(1-s^j_L\right)\hat{B}^j(t). \tag{12}$$

While the technological frontier imposes a structure on the mapping between the utilization-adjusted-TFP and factor-augmenting efficiency, as described by (12), it has the advantage of ensuring a consistency between the theoretical and the empirical approach where we used the utilization-adjusted-Solow residual to measure technological change whilst allowing for technological change to be factor-biased at the same time.

Totally differentiating (7), plugging the outcome into (12) and using the fact that aggregate technology improvement is a weighted average of sectoral technology improvements (see eq. (2)), shows that utilization-adjusted-aggregate-TFP growth can be decomposed into a symmetric and an asymmetric component across sectors:

$$\hat{Z}^A(t) = \eta \hat{Z}^A_S(t) + (1-\eta)\, \hat{Z}^A_D(t), \tag{13}$$

where $\hat{Z}^A_S(t) = \hat{Z}^H_S(t) = \hat{Z}^N_S(t)$ and $\hat{Z}^A_D(t) = \nu^{Y,H} \hat{Z}^H_D(t) + \left(1-\nu^{Y,H}\right) \hat{Z}^N_D(t)$. In the quantitative analysis, we will explore the effect of an increase in the asymmetric component captures by higher values of $1-\eta$.

3.3 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:

$$C(t) = \left[\varphi^{\frac{1}{\phi}} \left(C^T(t)\right)^{\frac{\phi-1}{\phi}} + (1-\varphi)^{\frac{1}{\phi}} \left(C^N(t)\right)^{\frac{\phi-1}{\phi}}\right]^{\frac{\phi}{\phi-1}}, \tag{14}$$

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, $C^F(t)$:

$$C^T(t) = \left[\left(\varphi^H\right)^{\frac{1}{\rho}} \left(C^H(t)\right)^{\frac{\rho-1}{\rho}} + \left(1-\varphi^H\right)^{\frac{1}{\rho}} \left(C^F(t)\right)^{\frac{\rho-1}{\rho}}\right]^{\frac{\rho}{\rho-1}}, \tag{15}$$

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 representative household supplies labor to the traded and non-traded sectors, denoted by $L^H(t)$ and $L^N(t)$, respectively, which are assumed to be imperfect substitutes (see e.g., Horvath [2000]):

$$L(t) = \left[\vartheta_L^{-1/\epsilon_L} \left(L^H(t)\right)^{\frac{\epsilon_L+1}{\epsilon_L}} + (1-\vartheta_L)^{-1/\epsilon_L} \left(L^N(t)\right)^{\frac{\epsilon_L+1}{\epsilon_L}}\right]^{\frac{\epsilon_L}{\epsilon_L+1}}, \tag{16}$$

where $0 < \vartheta_L < 1$ parametrizes the weight attached to the supply of hours worked in the traded sector and ϵ_L is the elasticity of substitution between sectoral hours worked. Like labor, we generate imperfect capital mobility by assuming that traded $K^H(t)$ and non-traded $K^N(t)$ capital stock are imperfect substitutes:

$$K(t) = \left[\vartheta_K^{-1/\epsilon_K} \left(K^H(t)\right)^{\frac{\epsilon_K+1}{\epsilon_K}} + (1-\vartheta_K)^{-1/\epsilon_K} \left(K^N(t)\right)^{\frac{\epsilon_K+1}{\epsilon}}\right]^{\frac{\epsilon_K}{\epsilon_K+1}}, \tag{17}$$

where $0 < \vartheta_K < 1$ is the weight of capital supply to the traded sector in the aggregate capital index $K(.)$ and ϵ_K measures the ease with which sectoral capital can be substituted for each other and thereby captures the degree of capital mobility across 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. Denoting the time discount rate by $\beta > 0$, at any instant of time, households derive utility from their consumption and experience disutility from working and maximize the following objective function:

$$\mathcal{U} = \int_0^\infty \Lambda\left(C(t), L(t)\right) e^{-\beta t} \mathrm{d}t, \tag{18}$$

where we consider the utility specification proposed by Shimer [2009]:

$$\Lambda\left(C, L\right) \equiv \frac{C^{1-\sigma} V(L)^{\sigma} - 1}{1-\sigma}, \quad \text{if} \quad \sigma \neq 1, \quad V(L) \equiv \left(1 + (\sigma - 1)\gamma \frac{\sigma_L}{1+\sigma_L} L^{\frac{1+\sigma_L}{\sigma_L}}\right). \tag{19}$$

These preferences are characterized by two crucial parameters: σ_L is the Frisch elasticity of labor supply, and $\sigma > 0$ determines the substitutability between consumption and leisure; if $\sigma > 1$, the marginal utility of consumption is increasing in hours worked. The inverse of σ collapses to the intertemporal elasticity of substitution for consumption. When we let σ equal to one, the felicity function is additively separable in consumption and labor,

Households supply labor $L(t)$ and capital services $K(t)$ and, in exchange, receive an aggregate wage rate $W(t)$ and an aggregate capital rental rate $R^K(t)$. Households choose the level of capital utilization in sector j, which includes both a symmetric and an asymmetric component, i.e., $u_S^{K,j}(t)$ and $u_D^{K,j}(t)$ (see eq. (8)). Both components of the capital utilization rate collapse to one at the steady-state. The capital utilization adjustment costs are assumed to be an increasing and convex function of the capital utilization rate $u_c^{K,j}(t)$:

$$C_c^{K,j}(t) = \xi_{1,c}^j \left(u_c^{K,j}(t) - 1\right) + \frac{\xi_{2,c}^j}{2}\left(u_c^{K,j}(t) - 1\right)^2, \qquad c = S, D, \quad j = H, N, \tag{20}$$

where the subscript $c = S$ ($c = D$) refers to the symmetric (asymmetric) component and $\xi_{2,c}^j > 0$ is a free parameter; letting $\xi_{2,c}^j \to \infty$ implies that $u_c^{K,j}$ is fixed at unity.

Households can accumulate internationally traded bonds (expressed in foreign good units), $N(t)$, that yield net interest rate earnings of $r^\star N(t)$. Denoting lump-sum taxes by $T(t)$, the household's flow budget constraint states that real disposable income can be saved by accumulating traded bonds, $\dot{N}(t)$, can be consumed, $P_C(t)C(t)$, invested, $P_J(t)J(t)$, or cover capital utilization adjustment costs:

$$\begin{aligned}\dot{N}(t) &\quad + P_C(t)C(t) + P_J(t)J(t) + \sum_{j=H,N} P^j(t)\left(C_S^{K,j}(t) + C_D^{K,j}(t)\right)\nu^{K,j}(t)K(t) \\ &= \quad r^\star N(t) + W(t)L(t) + R^K(t)K(t)\sum_{j=H,N}\alpha_K^j(t)\left(u_S^{K,j}(t)\right)^{\eta}\left(u_D^{K,j}(t)\right)^{1-\eta} - T(t), \end{aligned} \tag{21}$$

where we denote the share of sectoral capital in the aggregate capital stock by $\nu^{K,j}(t) = K^j(t)/K(t)$ and the capital compensation share in sector $j = H, N$ by $\alpha_K^j(t) = \frac{R^j(t)K^j(t)}{R^K(t)K(t)}$.

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

$$J(t)=\left[\varphi_J^{\frac{1}{\phi_J}}\left(J^T(t)\right)^{\frac{\phi_J-1}{\phi_J}}+\left(1-\varphi_J\right)^{\frac{1}{\phi_J}}\left(J^N(t)\right)^{\frac{\phi_J-1}{\phi_J}}\right]^{\frac{\phi_J}{\phi_J-1}}, \tag{22}$$

where $0<\varphi_J<1$ 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, $J^F(t)$:

$$J^T(t)=\left[\left(\iota^H\right)^{\frac{1}{\rho_J}}\left(J^H(t)\right)^{\frac{\rho_J-1}{\rho_J}}+\left(1-\iota^H\right)^{\frac{1}{\rho_J}}\left(J^F(t)\right)^{\frac{\rho_J-1}{\rho_J}}\right]^{\frac{\rho_J}{\rho_J-1}}, \tag{23}$$

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.

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

$$J(t)=I(t)+\frac{\kappa}{2}\left(\frac{I(t)}{K(t)}-\delta_K\right)^2 K(t), \tag{24}$$

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:

$$\dot{K}(t)=I(t)-\delta_K K(t). \tag{25}$$

Households choose consumption, worked hours, capital utilization rates, investment in physical capital and traded bonds by maximizing lifetime utility (18) subject to (21) and (25). Denoting by λ and Q' the co-state variables associated with the budget constraint and law of motion of physical capital, the first-order conditions characterizing the representative household's optimal plans are:

$$C(t)^{-\sigma}V(t)^{\sigma}=P_C(t)\lambda(t), \tag{26a}$$

$$C(t)^{1-\sigma}V(t)^{\sigma}\gamma L(t)^{\frac{1}{\sigma_L}}=\lambda(t)W(t), \tag{26b}$$

$$Q(t)=P_J(t)\left[1+\kappa\left(\frac{I(t)}{K(t)}-\delta_K\right)\right], \tag{26c}$$

$$\dot{\lambda}(t)=\lambda\left(\beta-r^{\star}\right), \tag{26d}$$

$$\begin{aligned}\dot{Q}(t)=\left(r^{\star}+\delta_K\right)Q(t)-\Bigg\{&\sum_{j=H,N}\alpha_K^j(t)u^{K,j}(t)R^K(t)\\ -\sum_{j=H,N}P^j(t)\left(C_S^{K,j}(t)+C_D^{K,j}(t)\right)\nu^{K,j}(t)&-P_J(t)\frac{\partial J(t)}{\partial K(t)}\Bigg\},\end{aligned} \tag{26e}$$

$$\frac{R^j(t)}{P^j(t)}\eta\frac{u^{K,j}(t)}{u_S^{K,j}(t)}=\xi_{1,S}^j+\xi_{2,S}^j\left(u_S^{K,j}(t)-1\right), \quad j=H,N, \tag{26f}$$

$$\frac{R^j(t)}{P^j(t)}\left(1-\eta\right)\frac{u^{K,j}(t)}{u_D^{K,j}(t)}=\xi_{1,D}^j+\xi_{2,D}^j\left(u_D^{K,j}(t)-1\right), \quad j=H,N, \tag{26g}$$

and the transversality conditions $\lim_{t\to\infty} \bar{\lambda} N(t) e^{-\beta t} = 0$ and $\lim_{t\to\infty} Q(t) K(t) e^{-\beta t} = 0$. To derive (26c) and (26e), we used the fact that $Q(t) = Q'(t)/\lambda(t)$. We impose $\beta = r^\star$ in order to generate an interior solution which implies that when new information about a shock arrives, λ jumps to fulfill the intertemporal solvency condition and remains constant afterwards.

Once households have chosen consumption, they allocate optimally a share $1 - \alpha_C$ of their consumption expenditure to non-traded goods:

$$1 - \alpha_C(t) = \frac{P^N(t) C^N(t)}{P_C(t) C(t)} = (1 - \varphi) \left(\frac{P^N(t)}{P_C(t)} \right)^{1-\phi}. \tag{27}$$

According to eq. (27), as long as $\phi < 1$, as evidence suggests, a depreciation in non-traded goods prices $P^N(t)$ drives down the share of expenditure allocated to non-traded goods while an appreciation in $P^N(t)$ increases $1 - \alpha_C$. This assumption ensures that symmetric technology shocks have a negative impact on $L^N(t)$ while asymmetric technology improvements have a strong expansionary effect on non-traded hours worked, in accordance with our empirical findings. However, the assumption $\phi < 1$ alone without frictions into the movements of inputs leads the model to considerably overstate the shift of productive resources to the non-traded sector. To generate the reallocation of productive we estimate empirically, especially labor, we allow for capital adjustment costs which mitigate the investment boom in the non-traded sector (and thus the shift of labor toward this sector) following a technology shock. The second source of frictions originates from labor and capital mobility costs across sectors as captured by $0 < \epsilon_L < \infty$ and $0 < \epsilon_K < \infty$:

$$L^N/L = (1 - \vartheta_L) \left(W^N/W \right)^{\epsilon_L} \qquad K^N/K = (1 - \vartheta_K) \left(R^N/R^K \right)^{\epsilon_K}, \tag{28}$$

where mobility costs are larger when ϵ_L and ϵ_K take lower values.

The third source of frictions comes from home bias in the domestic traded good. This assumption implies that the rise in imports is mitigated following a technology improvement compared with a situation where home- and foreign-produced traded goods would be perfect substitutes. The mechanism rests on the terms of trade depreciation caused by the technology shock which leads households to substitute home- for foreign-produced traded goods. For the terms of trade to depreciate, the price-elasticity of the demand for home-produced traded goods must be larger than one. A sufficient condition for this is $\rho > \frac{1}{\alpha^H}$ where α^H is the home content of consumption expenditure in traded goods. Home bias ensures that this condition can be fulfilled for values of ρ falling in the range of empirical estimates. Because the demand for home-produced traded goods has also a foreign component (i.e., exports), the condition is less stringent, i.e., $\phi_X + \alpha^H \rho > 1$ where ϕ_X is the price-elasticity of exports.[7] This condition ensures that the terms of trade depreciate whether technology

[7]This condition is derived by abstracting from physical capital otherwise the model would be analytically untractable. Since we are interested in impact effects and capital is a state variable which remains unchanged on impact, abstracting from physical capital serves our purpose. Analytical derivations are available from the authors upon request.

improves at the same rate across sectors, i.e., $\hat{Z}^H(t) = \hat{Z}^N(t)$, or is concentrated within traded industries, i.e., $\hat{Z}^H(t) > \hat{Z}^N(t)$. Intuitively, when (domestic and/or foreign) demand for home-produced traded goods is elastic enough w.r.t. the terms of trade, it is optimal for traded firms to lower prices to sell additional units of the home-produced traded good because the decline in P^H is covered by the fall in the marginal cost. By stimulating the demand for home-produced traded goods, the terms of trade depreciation amplifies the rise in the share of tradables (i.e., α_C takes higher values) when technology improves at the same rate in both sectors, or mitigates the decline in α_C when technology improvements are concentrated within traded industries. The terms of trade depreciation thus either amplifies the labor inflow in the traded sector or mitigates the labor outflow experienced by traded industries.

3.4 Model Closure and Equilibrium

The government finances public spending, G, on non-traded goods, G^N, home- and foreign-produced traded goods, G^H and G^F, by raising lump-sum taxes, T, i.e., $G(t) \equiv P^N(t)G^N(t) + P^H(t)G^H(t) + G^F(t) = T(t)$, where we assume without loss of generality that the government budget is balanced at each instant.

Market clearing conditions and the current account. To fully describe the equilibrium, denoting exports of home-produced goods by X^H, we impose goods market clearing conditions for non-traded and home-produced traded goods:

$$Y^N(t) = C^N(t) + J^N(t) + G^N(t) + \left(C_S^{K,N}(t) + C_D^{K,N}(t)\right) K^N(t), \tag{29a}$$

$$Y^H(t) = C^H(t) + J^H(t) + G^H(t) + X^H(t) + \left(C_S^{K,H}(t) + C_D^{K,H}(t)\right) K^H(t), \tag{29b}$$

where exports are assumed to be a decreasing function of the terms of trade, P^H:

$$X^H(t) = \varphi_X \left(P^H(t)\right)^{-\phi_X}, \tag{30}$$

where $\varphi_X > 0$ is a scaling parameter and ϕ_X is the price-elasticity of exports. Using the properties of constant returns to scale in production, $P_C(t)C(t) = \sum_g P^g(t)C^g(t)$ and $P_J(t)J(t) = \sum_g P^g(t)J^g(t)$ (with $g = F, H, N$), and market clearing conditions (29), the current account equation (21) can be rewritten as a function of the trade balance:

$$\dot{N}(t) = r^\star N(t) + P^H(t)X^H(t) - M^F(t), \tag{31}$$

where $M^F(t) = C^F(t) + G^F(t) + J^F(t)$ stands for imports.

Setting the dynamics of factor-augmenting productivity. We drop the time index below to denote steady-state values. Eq. (12) shows that technology improvements are driven by the dynamics of labor- and capital-augmenting efficiency, i.e., $\hat{Z}^j(t) = s_L^j \hat{A}^j(t) + \left(1 - s_L^j\right) \hat{B}^j(t)$. In the same spirit as Galí [1999], we abstract from trend growth and consider a technology shock that increases permanently utilization-adjusted-TFP.[8] Because we want to assess the ability of the model to reproduce the response of hours we estimate empirically, we generate the same technology adjustment we get after a permanent increase in utilization-adjusted-TFP of 1% in the long-run. Since we consider symmetric and asymmetric technology shocks, we have to set the dynamics of labor- and capital-augmenting efficiency for both shocks. Denoting the factor-augmenting efficiency by $X_c^j = A_c^j, B_c^j$ for symmetric ($c = S$) and asymmetric technology shocks ($c = D$), respectively, the adjustment of $X_c^j(t)$ toward its long-run level X_c^j expressed in percentage deviation from initial steady-state is governed by the following continuous time process:

$$\hat{X}_c^j(t) = \hat{X}_c^j + e^{-\xi_{X,c}^j t} - \left(1 - x_c^j\right) e^{-\chi_{X,c}^j t}, \quad X_c^j = A_c^j, B_c^j, \quad c = S, D, \quad j = H, N, \tag{32}$$

where $x_c^j = \hat{X}_c^j(0) - \hat{X}_c^j$, and both parameters $\xi_{X,c}^j > 0$ and $\chi_{X,c}^j > 0$ measure the speed at which productivity closes the gap with its long-run level. When $\xi_{X,c}^j \neq \chi_{X,c}^j$ (with $c = S, D$), the above law of motion allows us to generate a hump-shaped adjustment of factor-augmenting productivity in accordance with the non-monotonic adjustment found in the data. Letting time tend toward infinity into (32) leads to $\hat{X}_c^j(\infty) = \hat{X}_c^j$ where $\hat{X}_c^j$ is the steady-state (permanent) change in factor-augmenting efficiency in percentage. Inserting (32) into the log-linearized version of the technology frontier allows us to recover the dynamics of utilization-adjusted-TFP in sector j, i.e., $\hat{Z}_c^j(t) = s_L^j \hat{A}_c^j(t) + \left(1 - s_L^j\right) \hat{B}_c^j(t)$, which converges toward its new higher steady-state level.

Solving the model. The adjustment of the open economy toward the steady state is described by a dynamic system which comprises two equations that are functions of $K(t)$, $Q(t)$, and the vector of factor-augmenting productivity $V_S(t) = \left(A_S^H(t), B_S^H(t), A_S^N(t), B_S^N(t)\right)$ and $V_D(t) = \left(A_D^H(t), B_D^H(t), A_D^N(t), B_D^N(t)\right)$:

$$\dot{K}(t) = \Upsilon\left(K(t), Q(t), V_S(t), V_D(t)\right), \quad \dot{Q}(t) = \Sigma\left(K(t), Q(t), V_S(t), V_D(t)\right). \tag{33}$$

Linearizing the dynamic equations (33) in the neighborhood of the steady-state and inserting the law of motion of symmetric and asymmetric components of factor-augmenting efficiency (32) leads to a system of first-order linear differential equations which can be solved by applying standard methods. See Online Appendix P which details the solution method by Buiter [1984] for continuous time models adapted to our case.

[8] We assume that the economy starts from an initial steady-state and is hit by a permanent technology improvement like in the empirical part where we estimate the deviation of hours relative to its initial steady-state following a permanent increase in utilization-adjusted-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 utilization-adjusted-aggregate-TFP, an assumption we use implicitly to identify a permanent technology shock 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 Kehoe et al. [2018] who let the labor intensity of production vary across sectors.

4 Quantitative Analysis

In this section, we take the model to the data. For this purpose we solve the model numerically.[9] Therefore, first we discuss parameter values before turning to the effects of symmetric and asymmetric technology shocks across sectors and contrasting them with responses estimated empirically after technology shocks.

4.1 Calibration

Calibration strategy. At the steady-state, capital utilization rates, $u^{K,j}$, collapse to one so that $\tilde{K}^j = K^j$. We consider an initial steady-state with Hicks-neutral technological change and normalize $A^j = B^j = Z^j$ to 1. 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 assign values to σ^j in accordance with our estimates and the CES economy is endogenously calibrated to reproduce the ratios of the Cobb-Douglas economy.

To calibrate the reference model that we use to normalize the CES economy, we have estimated a set of ratios and parameters for the seventeen OECD economies in our dataset, see Table 9 relegated to Online Appendix I.1. Our reference period for the calibration is 1970-2017. Because we calibrate the reference model to a representative OECD economy, we take unweighted average values of ratios and parameters which are summarized in Table 1. Among the 25 parameters that the model contains, 13 have empirical counterparts while the remaining 12 parameters plus initial conditions must be endogenously calibrated to match ratios.

Twelve parameters plus initial conditions must be set to target ratios. Parameters including φ, ι, φ^H, ι^H, ϑ_L, ϑ_K, δ_K, G, G^N, G^H must be set to target a tradable content of consumption and investment expenditure of $\alpha_C = 43\%$ and $\alpha_J = 32\%$, respectively, a home content of consumption and investment expenditure in tradables of $\alpha^H = 66\%$ and $\alpha^H_J = 42\%$, respectively, a weight of labor supply and capital supply to the traded sector of $L^H/L = 36\%$, $K^H/K = 39\%$, respectively, an investment-to-GDP ratio of $\omega_J = 23\%$, a ratio of government spending to GDP of $\omega_G = 20\%$ $(= G/Y)$, a tradable and home-tradable share of government spending of $\omega_{GT} = 16\%$ $(= 1 - (P^N G^N/G))$, and $\omega_{G^H} = 12\%$ $(= P^H G^H/G)$, and we choose initial conditions so as trade is balanced. Because $u^{K,j} = 1$ at the steady-state, two parameters related to adjustment cost functions of capital utilization, i.e., ξ_1^H and ξ_1^N, are set to be equal to real capital rental rates in the traded and the

[9] 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., Turnovsky [1997].

non-traded sector, i.e., R^H/P^H and R^N/P^N, respectively.

Six parameters are assigned values which are taken directly or estimated from our own data. We choose the model period to be one year. In accordance with the last column of Table 1, the world interest rate, $r^\star$, which is equal to the subjective time discount rate, β, is set to 2.7%. In line with mean values shown in columns 11 and 12 of Table 1, 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 0.69, respectively, which leads to an aggregate LIS of 66%.

We have estimated empirically the degree of labor mobility between sectors, ϵ_L, for one country at a time. As shown in Online Appendix I.2 where we derive a structural equation, we pin down ϵ_L by running the regression in panel format on annual data of the percentage change in the hours worked share of sector j on the percentage change in the relative share of value added paid to labor in sector j over 1970-2017. The degree of labor mobility across sectors is set to 0.8, in line with the average of our estimates (see column 17 of Table 1). It is worth mentioning that this value is close to the value of 1 estimated by Horvath [2000] on U.S. data over 1948-1985 and commonly chosen in the literature allowing for imperfect mobility of labor. We have also estimated the degree of mobility of capital across sectors by running the regression of the percentage change in K_{it}^j/K_{it} on the percentage change in the relative share of value added paid to capital in sector j over 1970-2017. We choose a degree of capital mobility across sectors of 0.15, in line with the average of our estimates (see column 18 of Table 1).

To pin down the elasticity of substitution between traded and non-traded consumption goods ϕ, we use the optimal allocation of consumption expenditure between C^T and C^N (see eq. (26g)) and run the regression of the logged share of non-tradables on logged $P^N(t)/P_C(t)$. Time series for $1-\alpha_C(t)$ are constructed by using the market clearing condition for non-tradables. Building on our panel data estimates, the elasticity of substitution ϕ between traded and non-traded goods is set to 0.35 (see column 13 of Table 1), since this value corresponds to our panel data estimates, see Online Appendix I.4. It is worth mentioning that our value is close to the estimated elasticity by Stockman and Tesar [1995] who report a value of 0.44 by using cross-section data for the year 1975.

Seven parameters are taken from external research works. As pointed out recently by Best et al. [2020], there exists no consensus on a reasonable value for the intertemporal elasticity of substitution for consumption as estimates in the literature range between 0 and 2. We choose a value of $\sigma = 2$ which implies that consumption and leisure are substitutes and the intertemporal elasticity of substitution for consumption is equal to 0.5. In line with the estimates recently documented by Peterman [2016], we set the Frisch elasticity of labor supply σ_L to 3. We choose the value of parameter κ which captures the magnitude of capital adjustment costs so that the elasticity of I/K with respect to

Table 1: Data to Calibrate the Two-Sector Open Economy Model

Tradable share						Home share				Labor Share	
GDP	Cons.	Inv.	Gov.	Labor	Capital	X^H	C^H	I^H	G^H	LIS^H	LIS^N
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
0.36	0.43	0.32	0.20	0.36	0.39	0.13	0.66	0.42	0.12	0.63	0.69
Elasticities								Aggregate ratios			
ϕ	ρ	ρ_J	ϕ_X	ϵ_L	ϵ_K	σ^H	σ^N	LIS	I/Y	G/Y	r
(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
0.35	1.30	1.30	1.30	0.80	0.15	0.81	0.86	0.66	0.23	0.20	0.027

Notes: Columns 1-5 show the GDP share of tradables, the tradable content of consumption, investment and government expenditure, the tradable content of hours. Column 6 gives the ratio of exports of final goods and services to GDP; columns 7 and 8 show the home share of consumption and investment expenditure in tradables and column 9 shows the content of government spending in home-produced traded goods; ϕ is the elasticity of substitution between traded and non-traded goods in consumption; estimates of the elasticity of substitution between home- and foreign-produced traded goods ρ (with $\rho = \rho_J = \phi_X$) is taken from Bertinelli et al. [2022]; ϵ_L is the elasticity of labor supply across sectors; ϵ_K is the elasticity of capital supply across sectors; σ^j is the elasticity of substitution between capital and labor in sector $j = H, N$; LIS^j stands for the labor income share in sector $j = H, N$ while LIS refers to the aggregate LIS; I/Y is the investment-to-GDP ratio and G/Y is government spending as a share of GDP. The real interest rate is the real long-term interest rate calculated as the nominal interest rate on 10 years government bonds minus the rate of inflation which is the rate of change of the Consumption Price Index.

Tobin's q, i.e., Q/P_J, is equal to the value implied by estimates in Eberly et al. [2008]. The resulting value of κ is equal to 17.

In line with the empirical findings documented by Bems [2008] who finds that the non-tradable content of investment expenditure is stable in OECD countries, we set the elasticity of substitution, ϕ_J, between J^T and J^N to 1. We set the elasticity of substitution in consumption (investment), ρ (ρ_J), between home- and foreign-produced traded goods (inputs) to 1.3 (see columns 14-15 of Table 1) which fits estimates by Bertinelli et al. [2022] who find a value of 1.3 for $\rho = \rho_J$ for OECD countries which is close to the value of 1.5 chosen by Backus et al. [1994]. Assuming that all countries have the same elasticities, since the price elasticity of exports is a weighted average of ρ and ρ_J, we set $\phi_X = 1.3$ (see column 16 of Table 1). A value larger than one is in line with the structural estimates of the price elasticities of aggregate exports documented by Imbs and Mejean [2015].

Calibrating the CES economy. To calibrate the CES economy, we proceed as follows. First, we choose the same values for the thirteen parameters which have empirical counterparts as above, except for the labor income shares which are now endogenously calibrated. Thus in addition to σ, σ_L, κ, ϕ_J, ρ, ρ_J, ϕ_X, $r^\star$, ϵ_L, ϵ_K, ϕ, we have to choose values for the elasticity of substitution between capital and labor for tradables and non-tradables, σ^H and σ^N. We estimate σ^H and σ^N over 1970-2017 on panel data so as to have consistent estimates in accordance with our classification of industries as tradables and non-tradables and sample composition. In line with our panel data estimates, we choose $\sigma^H = 0.81$ and $\sigma^N = 0.86$ (see columns 19 and 20 of Table 1).

Given the set of elasticities above, the remaining parameters are set so as to maintain the steady-state of the CES economy equal to the normalization point. Therefore, we calibrate the model with CES production functions so that sixteen parameters φ, ι, φ^H, ι^H, ϑ_L, ϑ_K, δ_K, G, G^N, G^H, N_0, K_0, Z^H, Z^N, γ^H, γ^N are endogenously set to target $1-\bar{\alpha}_C$, $1-\bar{\alpha}_J$, $\bar{\alpha}^H$, $\bar{\alpha}^H_J$, $\bar{L}^N/\bar{L}$, $\bar{K}^N/\bar{K}$, $\bar{\omega}_J$, $\bar{\omega}_G$, $\bar{\omega}_{G^N}$, $\bar{\omega}_{G^H}$, $\bar{\upsilon}_{NX}$, $\bar{K}$, $\bar{y}^H$, $\bar{y}^N$, $\bar{s}^H_L = \theta^H$, $\bar{s}^N_L = \theta^N$, respectively, where a bar indicates that the ratio is obtained from the Cobb-

Douglas economy. In addition, we have to set the dynamic processes of factor-augmenting-efficiency and capital utilization rates.

Share η of symmetric technology shocks across sectors. Before setting the dynamic processes of symmetric and asymmetric technology shocks, we have to calibrate the share η of symmetric technology shocks across sectors. By using the fact that the adjustment in utilization-adjusted-aggregate-TFP, $\hat{Z}^A(t)$, following an aggregate technology shock must collapse to its adjustment driven by symmetric and asymmetric technology shocks, we choose the value of η minimizing the discrepancy between these two adjustments. We find a value of $\eta = 0.6$, see Online Appendix I.6 for more details.

Factor-augmenting efficiency. To set the symmetric and asymmetric components of the adjustment in factor-augmenting efficiency described by eq. (32), we first recover their dynamics in the data by adopting a wedge analysis, in the same spirit as Caselli and Coleman [2006]. As detailed in Online Appendix E.2, the log-linearized versions of labor (relative to capital) demand (10) and of the technology frontier (12) can be solved for deviations of $A^j_c(t)$ and $B^j_c(t)$ relative to their initial values. We plug estimated values for σ^j and empirically estimated responses for $s^j_L(t)$, $k^j(t)$, $u^{K,j}_c(t)$ to derive the dynamics of $A^j_c(t)$ and $B^j_c(t)$. Then, we choose parameters x^j_c, $\xi^j_{X,c}$, $\chi^j_{X,c}$ in eq. (32) so as to reproduce the dynamics of $A^j_c(t)$ and $B^j_c(t)$ we estimate empirically.

Capital utilization adjustment costs. We set the magnitude of the adjustment cost in the capital utilization rate, i.e., $\xi^j_{2,c}$, in eqs. (26f)-(26g), so as to account for empirical responses of $u^{K,j}_S(t)$ and $u^{K,j}_D(t)$, respectively, conditional on symmetric and asymmetric technology shocks across sectors.

4.2 Decomposition of Model's Performance

In this subsection, we analyze the role of the model's ingredients in driving the effects of a permanent technology improvement on hours. We show that the ability of the model to generate the decline in hours (on impact) by 0.15% we estimate empirically depends on the two-sector dimension and the open economy aspect of the setup.

Our baseline model includes four sets of elements. The first set is related to the biasedness of technology improvements toward traded industries together with the gross complementarity between traded and non-traded goods (i.e., $\phi < 1$). The second set of elements is related to barriers to factors' mobility which include labor mobility costs and costs of switching capital from one sector to another (i.e., $0 < \epsilon_L < \infty$ and $0 < \epsilon_K < \infty$). The third set of factors is related to trade openness, as reflected into imperfect substitutability between home- and foreign-produced traded goods (i.e., $0 < \rho < \infty$, $0 < \rho_J < \infty$, $0 < \phi_X < \infty$) which influences the extent of foreign borrowing. The fourth set of elements is related to an endogenous intensity in the use of physical capital (i.e., $0 < \xi^j_{2,c} < \infty$), and technology improvements which are factor-biased at a sector level (i.e., $\hat{A}^j_c(t) \neq \hat{B}^j_c(t)$).

To understand (and quantify) the role of each element, we first consider the simplest version of our model and add one ingredient at a time. This restricted version shown in column 7 of Table 2 collapses to the international RBC model by Fernández de Córdoba and Kehoe [2000] (FK henceforth) who consider a small open economy setup with tradables and non-tradables together with capital adjustment costs. In column 6, we allow for both labor and capital mobility costs across sectors. In column 5, we assume that home- and foreign-produced traded goods are imperfect substitutes. In column 2, we allow for CES production functions, FBTC and endogenous capital utilization. This model collapses to our baseline setup. We will discuss later the effects of symmetric and asymmetric technology shocks which are displayed by columns 3 and 4.

Table 2 reports the impact effect of selected variables, including total hours worked, $L(t)$, traded and non-traded hours worked, $L^H(t)$ and $L^N(t)$, the hours worked share of tradables, $\nu^{L,H}(t)$, the relative price of non-tradables and the terms of trade, $P(t)$ and $P^H(t)$. To further illustrate the transmission mechanism, we also show the adjustment in the real value added share of tradables, $d\nu^{Y,H}(t)$, and the value added share of non-tradables at current prices, $d\omega^{Y,N}(t)$. For comparison purposes, the first column displays the impact response of the corresponding variable which is estimated empirically by means of local projections which should be contrasted with the responses computed numerically shown in columns 2,5,6,7.

While we normalize the technology improvement to 1% in the long-run, panel A of Table 2 shows the adjustment of aggregate, traded and non-traded utilization-adjusted-TFP on impact. As shown in columns 2, 5, 6, 7, all model variants generate an increase in utilization-adjusted-aggregate-TFP by 0.94% on impact in line with the evidence and give rise to a technology improvement in tradables and non-tradables of 1.66% and 0.56% close to our estimates.

First ingredient: Barriers to factors' mobility. In column 7 of Table 2, we report results from a restricted version of the baseline model where we consider a two-sector small open economy model with capital adjustment costs which collapses to the FK model. In this model's version, home- and foreign-produced traded goods are perfect substitutes so that terms of trade are exogenous (and constant over time). Labor and capital can move freely across sectors. Production functions are Cobb-Douglas so that technological change is Hicks-neutral. We also abstract from endogenous capital utilization rates.

Contrasting the model's predictions shown in column 7 with empirically estimated values reported in column 1, the restricted version of the model substantially overstates the decline in total hours worked. Intuitively, as long as home- and foreign-produced goods are perfect substitutes, it is optimal to import traded goods and reallocate labor (and capital) toward

Table 2: Impact Effects of a Technology Improvement on Hours

	Data	CES: FBTC and uK			CD: IM & TOT	CD: IML & IMK	CD: PM
	LP	AGG	SYM	ASYM	AGG	AGG	AGG
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A.Technology							
Aggregate technology, $dZ^A(t)$	0.93	0.94	1.19	0.58	0.95	0.95	0.95
T technology, $dZ^H(t)$	1.53	1.66	1.06	2.57	1.66	1.66	1.66
N technology, $dZ^N(t)$	0.55	0.56	1.26	-0.50	0.56	0.56	0.56
T capital utilization, $du^{K,H}(t)$	-0.24	-0.11	0.09	-1.81	0.00	0.00	0.00
N capital utilization, $du^{K,N}(t)$	0.12	0.03	0.11	0.00	0.00	0.00	0.00
B.Hours							
Hours, $dL(t)$	-0.15	-0.07	-0.40	0.28	-0.26	-0.42	-0.70
Traded Hours, $dL^H(t)$	-0.04	-0.03	-0.11	-0.02	-0.15	-0.28	-0.57
Non-Traded Hours, $dL^N(t)$	-0.11	-0.05	-0.30	0.29	-0.12	-0.14	-0.13
Hours Share of Tradables, $d\nu^{L,H}(t)$	0.01	-0.00	0.03	-0.11	-0.06	-0.14	-0.33
C.Relative Prices							
Relative price of N, $d(P^N/P^H)(t)$	1.05	1.63	-0.43	4.69	1.56	2.11	1.15
Terms of trade, $dP^H(t)$	-1.15	-1.09	-0.44	-1.99	-0.93	0.00	0.00
D.VA Shares							
VA share of T (constant prices) $d\nu^{Y,H}(t)$	0.18	0.23	-0.02	0.47	0.22	0.14	-0.08
VA share of N (current prices) $d\omega^{Y,N}(t)$	0.05	0.13	-0.07	0.57	0.13	0.34	0.34

Notes: This table shows impact effects of a 1% permanent increase in utilization-adjusted-aggregate-TFP in the baseline model (columns 2-4) and in restricted versions of the model (columns 5-7). 'T' refers to traded industries while 'N' refers to non-tradables. Panel A shows the impact effects for technology variables, panel B displays the impact effects on hours, panel C shows the relative price effects, panel D displays the impact responses of the value added share of tradables (at constant prices) and the value added share of non-tradables (at current prices). In column 1, we show impact responses of corresponding variables that we estimate empirically by means of local projections. Columns 2, 5, 6, 7 show impact effects we estimate numerically. Column 3 shows numerical results following a symmetric technology shock across sectors which increases utilization-adjusted-aggregate-TFP by 1% in the long-run. Column 4 shows numerical results following an asymmetric technology shock across sectors which increases utilization-adjusted-aggregate-TFP by 1% in the long-run. Column 7 shows numerical results for an open economy model with tradables and non-tradables with capital adjustment costs, perfect mobility of labor and capital, perfect substitutability between home- and foreign-produced traded goods. In column 6, we augment the previous model with imperfect mobility of labor and capital. In column 5, we augment the previous model with imperfect substitutability between home- and foreign-produced traded goods so that terms of trade are endogenous. In columns 2-4, we consider the baseline model which allows for endogenous capital utilization rate, CES production functions and FBTC.

the non-traded sector. Because labor and capital are not subject to mobility costs, the hours worked share of tradables falls dramatically by -0.33 percentage point of total hours worked, thus leading the restricted model to generate a decline in traded hours worked by -0.57 ppt of total hours worked while we empirically find a fall by -0.04 ppt only. The corollary of the shift of resources toward the non-traded sector and the surge of imports is that the open economy runs a large current account deficit. Under these assumptions, households find it optimal to lower hours worked (see the first line of panel B) by -0.7% which considerably overstates the decline estimated in the data (i.e., -0.15%).

In column 6, we consider the same model as in column 7 except that we allow for both labor and capital mobility costs. The frictions into the movements of factors substantially mitigate the shift of productive resources toward the non-traded sector. In particular, as shown in the last line of panel B, the decline in the hours worked share of tradables shrinks from -0.33 ppt of total hours worked (column 7) to -0.14 ppt (column 6). Because less productive resources move toward the non-traded sector, households must give up a significant share of the rise in leisure, thus resulting in a shrinking decline in total hours worked to meet the demand for non-traded goods. The fall in hours by -0.42% is still too large compared with what we estimate empirically (i.e., -0.15%).

Second ingredient: Imperfect substitutability between home- and foreign-

produced traded goods. As shown in column 5, the ability of the model to account for the evidence improves once we allow for imperfect substitutability between home- and foreign-produced traded goods. More specifically, as households are getting more reluctant to substitute imported goods for domestic goods, there is a shift of demand toward home-produced traded goods. The reallocation of labor toward non-traded industries further shrinks from -0.14 ppt to -0.06 ppt of total hours worked (see the fourth row of panel B). Therefore traded hours worked fall less because as shown in the second row of panel C, the terms of trade depreciate by -1.15% (close to what we estimate empirically) which stimulates the demand for home-produced traded goods. Imports increase less which results in a smaller current account deficit. Because the economy must meet the demand for home-produced traded goods, the fall in labor supply further shrinks from -0.42% to -0.26%.

Third ingredient: Factor-biased technological change. The model's predictions square well with our evidence once we let technological change to be factor-biased and allow for an endogenous use of capital. As shown in panel B, labor no longer shifts toward the non-traded sector (see the fourth row) while the decline in total hours worked is much less pronounced than in restricted versions of the model. Intuitively, once we let sectoral goods to be produced by means of CES production functions and because technological change is biased toward labor in the traded sector, traded production becomes more labor intensive which prevents labor from shifting toward non-traded industries and thus mitigates the decline in traded hours worked. The baseline model generates a fall in $L^H(t)$ by -0.03 ppt of total hours worked close to what we estimate empirically (i.e., -0.04 ppt). Although our model slightly understates the fall in total hours (-0.07% vs. -0.15% in the data) because it understates the decline in non-traded hours on impact, the model reproduces well the dynamics of hours worked as shown later.

Fourth ingredient: mix of symmetric and asymmetric technology shocks. So far, we have seen that the model must include frictions into the movement of inputs across sectors to account for the labor effects of a permanent technology improvement. We now highlight the necessity to consider a mix of symmetric and asymmetric technology shocks. To stress this aspect, columns 3 and 4 of Table 2 show the impact effects of symmetric and asymmetric technology shocks separately.[10]

We first focus on the effects of a symmetric technology shock displayed by column 3. As shown in panel A, technology improvements are uniformly distributed between the traded and the non-traded sector. As can be seen in the first row of panel B, a symmetric technology shock generates a decline in hours worked by -0.40% close to what we estimate empirically (-0.47% in the data). Intuitively, a symmetric technology shock across sectors lowers the marginal cost in both sectors which leads both traded and non-traded firms to

[10]Relegated to Online Appendix J for reasons of space, we show impact responses computed numerically for symmetric and asymmetric technology shocks across restricted versions of the baseline model.

cut prices. Lower prices put downward pressure on wages which generates a dramatic fall in labor supply. A symmetric technology shock also gives rise to a current account deficit which amplifies the decline in total hours worked.

In line with the evidence, the fall in total hours worked mostly originates from the non-traded sector. Because the elasticity of substitution between traded and non-traded goods is smaller than one (i.e., $\phi < 1$), the depreciation in non-traded goods prices lowers the share of expenditure allocated to non-traded goods (see the second row of panel D) and depresses labor demand in the non-traded sector. The terms of trade depreciation further tilts the demand toward traded goods which leads to a shift of labor toward the traded sector, as captured by $d\nu^{L,H}(0) = 0.03$ ppt.

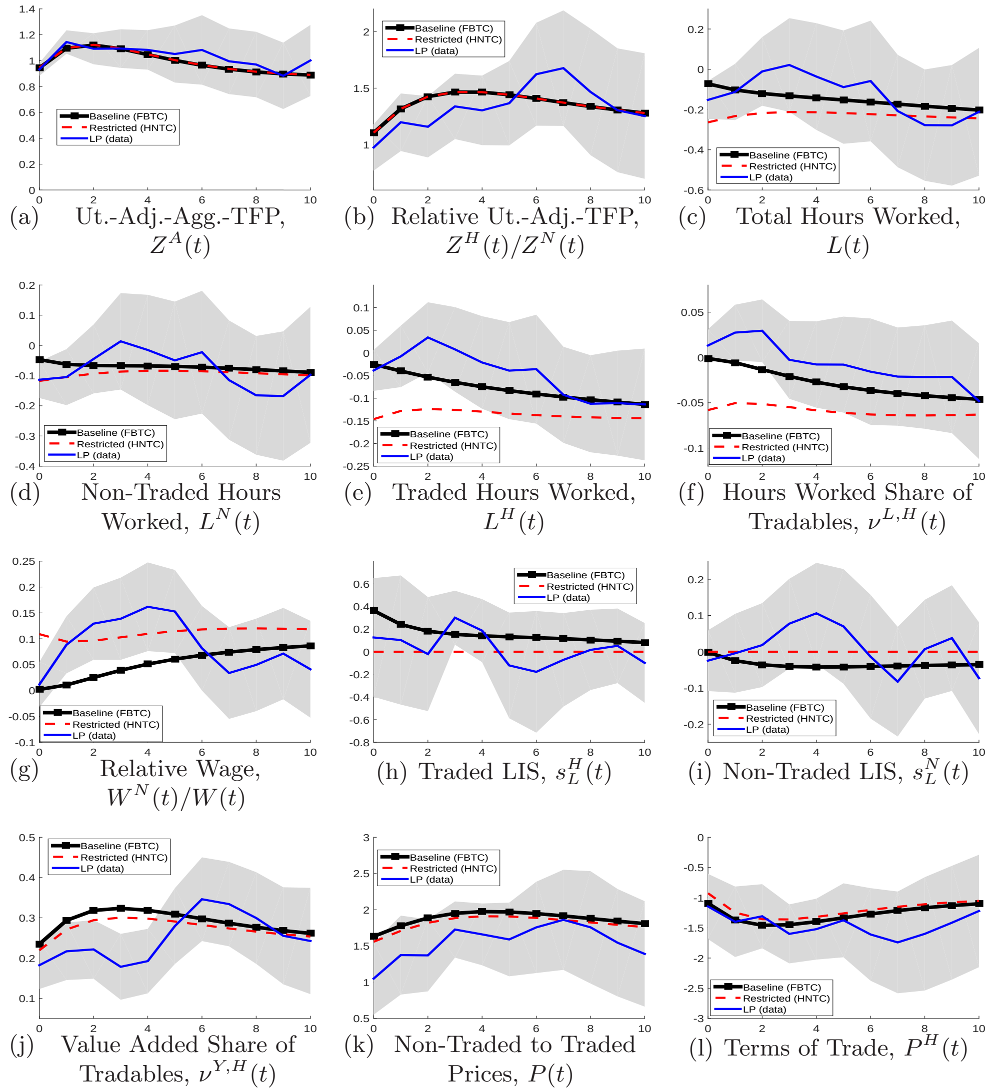
Asymmetric technology shocks generate opposite effects. As shown in the first line of panel B in column 4, an asymmetric shock produces an increase in hours by 0.28% close to what we estimate empirically (i.e., 0.31% in the data). In contrast to a symmetric technology shock, panel A shows that technology improvements are concentrated in the traded sector. To compensate for the rise in the marginal cost, non-traded firms set higher prices (see the first row of panel C). The share of non-tradables increases (see the second row of panel D) which has an expansionary effect on labor demand in the non-traded sector and leads to a shift of labor away from traded industries (see the last row of panel B). This results in a decline in traded hours worked which is mitigated by technological change biased toward labor in the traded sector. In line with empirical findings, the rise in total hours worked mostly originates from the non-traded sector.

Because technology shocks uniformly distributed across sectors produce a dramatic decline in $L(0)$ and technology shocks concentrated toward the traded sector have an expansionary effect on hours worked, they cannot account separately for the moderate decline in hours (by 0.15%) we estimate after a permanent technology improvement. Therefore, it is only once we consider a mix of symmetric and asymmetric technology shocks that we can account for the effects of an aggregate technology shock on hours worked.

4.3 Dynamic Effects of a Permanent Technology Improvement

While in Table 2, we restrict our attention to impact effects, in Fig. 5, 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.[11] We also contrast theoretical responses from the baseline model with the predictions of a restricted model which imposes Hicks-neutral technological change (HNTC henceforth) shown in dashed red lines. As shown in Fig. 5(a), both the baseline model and its restricted version experience the same technology improvement.

[11] For reasons of space, we relegate to Online Appendix I.8 the dynamics of utilization-adjusted-TFP, capital utilization rates and FBTC for tradables and non-tradables following a symmetric and an asymmetric



(a) Ut.-Adj.-Agg.-TFP, $Z^A(t)$ (b) Relative Ut.-Adj.-TFP, $Z^H(t)/Z^N(t)$ (c) Total Hours Worked, $L(t)$

(d) Non-Traded Hours Worked, $L^N(t)$ (e) Traded Hours Worked, $L^H(t)$ (f) Hours Worked Share of Tradables, $\nu^{L,H}(t)$

(g) Relative Wage, $W^N(t)/W(t)$ (h) Traded LIS, $s_L^H(t)$ (i) Non-Traded LIS, $s_L^N(t)$

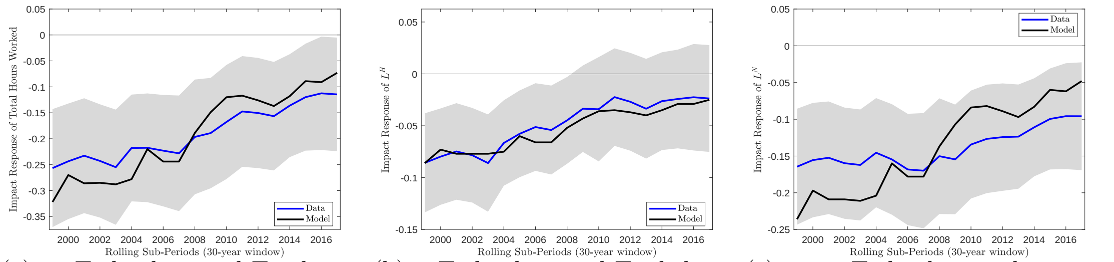
(j) Value Added Share of Tradables, $\nu^{Y,H}(t)$ (k) Non-Traded to Traded Prices, $P(t)$ (l) Terms of Trade, $P^H(t)$

Figure 5: Theoretical vs. Empirical Responses Following a Technology Shock. Notes: 'LP (data)' refers to the solid blue line which displays point estimate from local projections with shaded areas indicating 90% confidence bounds; 'Baseline (FBTC)' refers to the thick solid black line with squares which displays model predictions in the baseline scenario with capital utilization rates together with FBTC, while 'Restricted (HNTC)' refers to the dashed red line which shows predictions of a model with Cobb-Douglas production functions (which amount to shutting down FBTC) and abstracting from endogenous capital utilization.

Dynamics. As displayed by Fig. 5(c), both models generate a decline in hours worked but only the baseline model with technological change biased toward labor can account for the dynamics of total hours worked. The reason for this is that as shown in Fig. 5(e), the model imposing HNTC overstates the decline in L^H by generating a strong reallocation of labor away from traded industries as displayed by Fig. 5(f). This shift is caused by the concentration of technology improvements within traded industries, see Fig. 5(b), which in turn leads non-traded industries to set higher prices. As the appreciation in the relative price of non-tradables builds up over time, as displayed by Fig. 5(k), more labor shifts toward non-traded industries as households allocate a greater share of their expenditure to non-traded goods.

However, the so-called deindustrialization movement reflected into the decline in the hours worked share of tradables is gradual and shows up only in the long-run in the data.

technology shock together with an aggregate technology shock.



(a) Technology and Total Hours Worked (b) Technology and Traded Hours Worked (c) Technology and Non-Traded Hours Worked

Figure 6: Time-Varying Impact Effects of a Technology Shock. Notes: The figure shows impact responses of total, traded and non-traded hours worked to a 1% permanent increase in utilization-adjusted aggregate TFP. The solid blue line shows the impact response we estimate empirically on rolling sub-periods by using Jordà's [2005] single-equation method. Shaded areas indicate the 90 percent confidence bounds based on Newey-West standard errors. The solid black line shows the impact response we compute numerically by letting the share of technology improvements driven by asymmetric technology shocks increase in accordance with the values taken from the FEVD we estimate on rolling windows and shown in Fig. 4(d). The horizontal axis shows the end year of the corresponding window and the vertical line displays the point estimate of the impact effect of technology on hours worked.

The reason is that the reallocation of productive resources across sectors is subject to frictions. First, the terms of trade depreciation displayed by Fig. 5(l) caused by the rise in the value added share of tradables, see Fig. 5(j), mitigates the rise in the share of non-tradables. Second, as shown in Fig. 5(g), the technology improvement produces a differential between the non-traded and the aggregate wage rate as a result of labor mobility costs which further hamper the reallocation of labor. Third, as shown in Fig. 5(h) and Fig. 5(i), traded output becomes more labor intensive than non-traded output, especially in the short-run, which hampers the shift of labor away from traded industries. It is only once we allow for these three elements that the model can account for the dynamics of total hours worked, see Fig. 5(c).

4.4 Time-Varying Impact Effects of a Permanent Technology Shock

Time-increasing response of hours worked. The main objective of our paper is to rationalize the time-increasing impact response of hours worked to a 1% permanent technology improvement we document empirically as shown in the blue line in Fig. 6(a). To assess the ability of our open economy model with tradables and non-tradables to account for the reduction in the decline in hours we estimate empirically, we keep the same calibration and estimate the impact response of hours worked to a 1% permanent technology improvement by letting the share of asymmetric technology shocks $1-\eta$ increase over time in line with our empirical estimates over rolling windows (see Fig. 4(d)). As shown in the black line in Fig. 6(a), as we lower the share of technology shocks uniformly distributed across sectors from 90% to 60%, the baseline model can generate the shrinking contractionary effect of technology improvements on hours we estimate empirically (see the blue line). Intuitively, because asymmetric technology shocks increase labor supply, their increasing importance (partly) offsets the negative effect of symmetric technology shocks on hours.

Sectoral decomposition of the time-varying response of hours worked. In Fig. 6(b) and Fig. 6(c), we investigate the ability of the baseline model's predictions shown in the black line to account for the shrinking contractionary effect (on impact) of a 1%

permanent technology improvement on both traded and non-traded hours worked. As it stands out, the model reproduces well the time-increasing impact response of $L^H(t)$ as it generates a shrinking decline from -0.086 ppt (-0.086 ppt in the data) the first thirty years to -0.025 ppt (-0.024 ppt in the data) the last thirty years. The performance of the model relies upon one key ingredient which is FBTC.

Relegated to Online Appendix J.2 for reasons of space, a model imposing HNTC would produce a time-decreasing impact response of L^H, traded hours worked declining on impact by -0.12 ppt over 70-99 and by -0.15 ppt over 88-17, because asymmetric technology shocks reallocate labor toward non-traded industries and exert a strong negative impact on L^H. By allowing for technological change strongly biased toward labor in the traded sector which neutralizes the incentives to shift labor away from traded industries in the short-run, the baseline model can account for the shrinking contractionary effect of a technology improvement on L^H. We may notice that the baseline model can also generate the time-increasing impact response of L^N in line with the data as the black line lies within the confidence bounds of the empirical point estimate.

4.5 Why are Technology Shocks More Asymmetric across Sectors?

We have shown that the growing contribution of asymmetric technology shocks across sectors to technology improvements is responsible for the time-increasing response of total hours worked. One important question is: why technology improvements are increasingly driven by asymmetric technology shocks across sectors over time? We put forward the greater exposition of traded industries to the international stock of knowledge to rationalize the growing contribution of asymmetric technological change to the variance of aggregate technology improvements.

We denote utilization-adjusted-TFP by TFP below instead of Z which now stands for the stock of knowledge in the model with endogenous technology decisions. As shown in Online Appendix I.7, the share of the (unconditional) variance of the rate of growth of utilization-adjusted-aggregate-TFP, $\hat{\text{TFP}}^A(t)$, driven by its asymmetric component (between sectors), $\hat{\text{TFP}}^A_D(t)$, reads:

$$\frac{\text{Var}\left(\hat{\text{TFP}}^A_D(t)\right)}{\text{Var}'\left(\hat{\text{TFP}}^A(t)\right)} = \left(\nu^{Y,H}\right)^2 \frac{\text{Var}\left(\hat{\text{TFP}}^H(t) - \hat{\text{TFP}}^N(t)\right)}{\text{Var}'\left(\hat{\text{TFP}}^A(t)\right)}, \tag{34}$$

where $\text{Var}'\left(\hat{\text{TFP}}^A(t)\right)$ denotes the variance of aggregate technological change adjusted with the covariance of symmetric and asymmetric components. Eq. (34) reveals that the contribution of asymmetric technology improvements to the variance of technological change is increasing in both the value added share of tradables, $\nu^{Y,H}$, and the dispersion in technology improvement between the traded and the non-traded sector, $\frac{\text{Var}\left(\hat{\text{TFP}}^H(t) - \hat{\text{TFP}}^N(t)\right)}{\text{Var}'\left(\hat{\text{TFP}}^A(t)\right)}$. As shown below, by amplifying the asymmetry in technological change between tradables and non-tradables, the growing exposition of traded industries to innovation abroad can rationalize a (significant) fraction of the rise in the share of the variance of technological change driven by its asymmetric component.

To quantify the role of innovation abroad in driving the increasing variance share of asymmetric technology improvements, we extend the setup by Corhay et al. [2020] to a two-sector open economy where households decide about investment in tangible and intangible assets and the stocks of physical capital and R&D are allocated across sectors in accordance to their return. Online Appendix Q.1-Q.3 details the steps to extend the model laid out in section 3 to endogenous technology decisions. The starting point is to specify the production functions and the factors driving technological change. Because we are interested in estimating the impact of an increase in the international stock of R&D on utilization-adjusted-sectoral-TFP, we abstract from FBTC and thus assume a Cobb-Douglas production technology by augmenting the production function with the stock of knowledge $\mathsf{Z}^j(t)$ which has an impact measured by ν^j on utilization-adjusted-TFP in sector j, i.e., $Y^j(t) = \left(\mathsf{Z}^j(t)\right)^{\nu^j} \left(L^j(t)\right)^{\theta^j} \left(\tilde{K}^j(t)\right)^{1-\theta^j}$. The stock of knowledge accumulated by sector j to improve technology is made up of the domestic stock of R&D, $Z^j(t)$, and an international stock of R&D, $Z^W(t)$. Formally, the aggregate stock of knowledge is a geometric weighted average of the domestic and international stock of knowledge, as described by $\mathsf{Z}^j(t) = \left(Z^j(t)\right)^{\zeta^j} \left(Z^W(t)\right)^{1-\zeta^j}$ where ζ^j captures the country-specific content of the stock of knowledge while $1-\zeta^j$ captures its international component which is pinned down by using a principal component analysis that we apply to utilization-adjusted-TFP, see Online Appendix L.6.

One key parameter is ν^j which measures the impact of a 1% increase in the stock of R&D in sector j on utilization-adjusted-TFP in sector j. To pin down this parameter, we use data from Stehrer et al. [2019] (EU KLEMS database) which allows us to construct time series for the capital stock in R&D for both the traded and non-traded sectors. Data are available for thirteen countries over 1995-2017. We have run the regression of the logged utilization-adjusted-TFP in sector j on the logged stock of R&D at constant prices by using cointegration techniques. We find a FMOLS estimate of the long-term relationship of 0.1499 for the traded sector and 0.0007 for the non-traded sector. Both are significant at 5% and 10% level, respectively. To pin dow the elasticity of utilization-adjusted-TFP of tradables (non-tradables) w.r.t. the domestic stock of knowledge, we have to adjust 0.1499 (0.0007) with $\zeta^H = 0.63$ ($\zeta^N = 0.70$) which gives 0.238 (0.001).

In Online Appendix Q.4, we plot the dynamic adjustment of utilization-adjusted-TFP of tradables and non-tradables following a shock to the international stock of knowledge $Z^W(t)$ which increases the world utilization-adjusted-TFP by 1% in the long-run. Because ν^N is close to zero, a shock to $Z^W(t)$ has no effect on utilization-adjusted-TFP of non-tradables.

In contrast, a shock to $Z^W(t)$ increases utilization-adjusted-TFP of tradables by 0.92% at horizon $t = 10$ when the international component of traded technology $1 - \zeta^H$ collapses to its estimated value of 37% over 1970-1992 and by 1.24% (at $t = 10$) when $1 - \zeta^H$ collapses to its estimated value of 49% over 1993-2017. As traded industries are more exposed to the international stock of knowledge $Z^W(t)$, a permanent rise in the stock of ideas leads to greater technology improvements in traded industries and importantly amplifies the productivity growth differential between the traded and the non-traded sector.

Table 3: Contribution of International Stock of R&D to the Increasing Share of Asymmetric Technological Change

Period	Variance $\hat{\text{TFP}}^H(t) - \hat{\text{TFP}}^N(t)$ (1)	Variance $\hat{\text{TFP}}^A(t)$ (2)	$\frac{\text{Var}\left(\hat{\text{TFP}}^H(t)-\hat{\text{TFP}}^N(t)\right)}{\text{Var}'\left(\hat{\text{TFP}}^A(t)\right)}$ (1)/(2) (3)	Share Asymmetric Tech. Change (in %) (4)
A.Total				
1970-1992	0.000096	0.000077	1.25	18.7%
1993-2017	0.000072	0.000028	2.60	38.9%
B.International				
1970-1992	0.000040	0.000050	0.52	7.7%
1993-2017	0.000041	0.000023	1.48	22.1%

Notes: In columns 1 and 2, we show the variance of the utilization-adjusted-TFP growth differential between tradables and non-tradables, i.e., and the rate of the growth of the utilization-adjusted-aggregate-TFP. Column 3 shows the ratio of Var $\left(\hat{\text{TFP}}^H(t) - \hat{\text{TFP}}^N(t)\right)$ to Var′ $\left(\hat{\text{TFP}}^A(t)\right)$. Column 4 displays the share of the variance of technological change which is driven by its asymmetric component, i.e., computes the RHS of eq. (34). In panel A, we consider the seventeen OECD countries average. In panel B, we have created artificial data by 1) estimating numerically the effect of a 1% permanent increase in the world utilization-adjusted-TFP on the utilization-adjusted-TFP of tradables and non-tradables by considering two sub-periods, i.e., 70-92 and 93-17, by setting the world component of sectoral utilization-adjusted-TFP, ζ^j, to their estimated values by means of PCA, 2) calculating the growth rate of $\text{TFP}^j(t)$ by using the elasticities of $\text{TFP}^H(t)$ and $\text{TFP}^N(t)$ w.r.t. to the world stock of knowledge which stand at 0.92 and 1.23 for tradables over 70-92 and 93-17, respectively, and 0.004 for non-tradables over the two sub-periods, and by using the growth rate of $Z^W(t)$, 3) calculating the contribution of variance of the productivity growth differential between tradables and non-tradables as if the differential were only driven by the increase in $Z^W(t)$. Sample: 17 OECD countries, 1970-2017, annual data.

Once we have estimated by how much utilization-adjusted-TFP increases in sector j when the world utilization-adjusted-TFP increases by 1% in the long-run, we construct artificial time series for utilization-adjusted-TFP predicted by the progression in the world utilization-adjusted-TFP. Table 3 shows the variance of the productivity growth differential between tradables and non-tradables and the variance of aggregate productivity growth in columns 1 and 2, respectively. The ratio of the former to the latter is displayed by the third column. The share of variance of utilization-adjusted-aggregate-TFP growth attributed to asymmetric technology improvements between sectors is shown in column 4. In panel A, we use raw data for a representative OECD economy. By using eq. (34), we find that the share of the variance of aggregate technological change driven by asymmetric technological change has increased from 18.7% (over 70-92) to 38.9% in the post-1992 period. In panel B, we use artificial time series we have generated by considering a technology improvement only driven by international R&D spillovers. As detailed in Online Appendix Q.4, we derive a formula to split the share attributable to asymmetric technology improvements into a country-specific and an international component. We find that the share of the variance of technological change attributable to asymmetric technology improvements and driven only by the access to the international stock of ideas has almost tripled, passing from 7.7% before 1992 to 22.1% in the post-1992 period. While the progression of the international stock of ideas and the greater exposition of traded industries to these ideas does not fully explain the increase by 20 ppt in the share of the asymmetric component of technological change, it can account for 71% of this progression, i.e., 14 ppt.

5 Conclusion

In this paper, we investigate the effects of technology improvements on hours across time. We find empirically that a 1% permanent increase in utilization-adjusted-aggregate-TFP produces a decline in hours which gradually vanishes over time. To rationalize the reduction in the decline in hours after a permanent technology improvement, we put forward the increasing contribution of asymmetric technology shocks across sectors to the variations in utilization-adjusted-aggregate-TFP. Because asymmetric technology shocks are found empirically to significantly increase hours, their growing importance (estimated from the forecast error variance decomposition on rolling sub-samples) can potentially mitigate the negative impact on hours caused by permanent technology improvements. Because symmetric technology shocks have a strong negative impact on hours and drive the lion's share of the variations in technology improvements, hours worked fall in OECD countries when technology improves.

To test our assumption, we simulate an open economy model with tradables and non-tradables and investigate the overall effect on hours of symmetric and asymmetric technology shocks. The model can generate the magnitude of the decline in hours worked we estimate empirically once we include barriers to factors' mobility, home bias, and factor-biased technological change. When we increase the contribution of asymmetric shocks to technology improvements from 10% to 40%, the model can generate the shrinking contractionary effect of a permanent technology improvement on both total and sectoral hours, in line with our estimates. This performance crucially relies upon the assumption of technological change biased toward labor in the traded sector.

References

Alexopoulos, Michelle (2011) Read All about It!! What Happens Following a Technology Shock? *American Economic Review*, 101(4), 1144-1179.

Backus, David K, Patrick J, Kehoe, and Finn E. Kydland (1994) Dynamics of the Trade Balance and the Terms of Trade: The J-Curve? *American Economic Review*, 84(1), 84-103.

Bajzik, Jozef, Tomas Havranek, Zuzana Irsova, and Jiri Schwarz (2020) Estimating the Armington Elasticity: The Importance of Study Design and Publication Bias. *Journal of International Economics*, 127(C).

Barnichon, Régis (2010). Productivity and Unemployment over the Business Cycle. *Journal of Monetary Economics*, 57(8), pp. 1013-25.

Basu, Susanto, Miles S. Kimball, John G. Fernald (2006) Are Technology Improvements Contractionary? *American Economic Review*, 96(5), 1418-48.

Basu, Susanto (1996) Procyclical Productivity: Increasing Returns or Cyclical Utilization? *The Quarterly Journal of Economics*, 111(3), 719-751.

Bems, Rudolfs (2008) Aggregate Investment Expenditures on Tradable and Nontradable Goods. *Review of Economic Dynamics*, 4, 852-883.

Benati, Luca (2008) The "Great Moderation" in the United Kingdom. *Journal of Money, Credit and Banking*, 40(1), pp. 121-147.

Benigno, Gianluca, Luca Fornaro, and Martin Wolf (2022) Reserve Accumulation, Growth and Financial Crises. *Journal of International Economics*, vol. 139.

Bertinelli, Luisito, Olivier Cardi, and Romain Restout (2022) Labor Market Effects of Technology Shocks Biased toward the Traded Sector. *Journal of International Economics*, vol. 138(C).

Best, Michael Carlos, James S. Cloyne, E. Ilzetzki, H. J. Kleven (2020) Estimating the Elasticity of Intertemporal Substitution Using Mortgage Notches. *Review of Economic Studies*, 87(2), 656-690.

Broadbent, Ben, Federico Di Pace, Thomas Drechsel, Richard Harrison and Silvana Tenreyro (2023) The Brexit Vote, Productivity Growth and Macroeconomic Adjustments in the United Kingdom; *Review of Economic Studies*, forthcoming.

Buiter, Willem H. (1984) Saddlepoint Problems in Continuous Time Rational Expectations Models: A General Method and some Macroeconomic Examples. *Econometrica*, 52, pp. 665-80.

Cantore, Cristiano, Filippo Ferroni, and Miguel León-Ledesma (2017) The Dynamics of Hours Worked and Technology. *Journal of Economic Dynamics and Control*, 82, 67-82.

Caselli, Francesco (2016) Technology Differences over Time and Space. Princeton University Press.

Caselli, Francesco, and Wilbur John Coleman II (2006) The World Technology Frontier. *American Economic Review*, 96(3), 499-522.

Chang, Yongsung, and Jay H. Hong (2006) Do Technological Improvements in the Manufacturing Sector Raise or Lower Employment? *American Economic Review*, 96 (1), 352-368.

Chari, Varadarajan V., Kehoe, Patrick J. and Ellen R., McGrattan (2008) Are Structural VARs with Long-Run Restrictions Useful in Developing Business Cycle Theory? *Journal of Monetary Economics*, 55(8), 1337-1352.

Chaudourne, Jeremy, Fève, Patrick, and Alain Guay (2014) Understanding the Effect of Technology Shocks in SVARs with Long-Run Restrictions. *Journal of Economic Dynamics and Control*, 41(C), 154-172.

Chirinko, Robert S., and Debdulal Mallick (2017) The Substitution Elasticity, Factor Shares, and the Low-Frequency Panel Model. *American Economic Journal: Macroeconomics*, 9(4), pp 225-253.

Chodorow-Reich, Gabriel, Loukas Karabarbounis, and Rohan Kekre (2023) The Macroeconomics of the Greek Depression. *American Economic Review*, *American Economic Review*, 113(9), pp. 2411-2457.

Christiano, Lawrence J., Martin Eichenbaum and Robert Vigfusson (2006) Assessing Structural VARs. NBER Chapters, in: NBER Macroeconomics Annual 2006, Volume 21, 1-106, National Bureau of Economic Research, Inc.

Collard, Fabrice, and Harris Dellas (2007) Technology Shocks and Employment. *Economic Journal*, 117(523), 1436-1459.

Comin Diego, Danial Lashkari, and Marti Mestieri (2019) Structural Transformation of Innovation. Mimeo.

Corhay, Alexander, Howard Kung, and Lukas Schmid (2020) Q: Risks, Rents, or Growth? Mimeo.

Cruz, Edgar, and Xavier Raurich (2020) Leisure Time and the Sectoral Composition of Employment. *Review of Economic Dynamics*, 38, 198-219.

De Graeve, Ferre and Andreas Westermark (2013) Un-truncating VARs. Mimeo. Riksbank.

Dupaigne, Martial, Patrick Fève, and Julien Matheron. (2007) Technology Shocks, Non-stationary Hours and DSVAR. *Review of Economic Dynamics*, 10(2), 238-255.

Dupaigne, Martial and Patrick Fève (2009) Technology Shocks Around the World. *Review of Economic Dynamics*, 12(4), pp 592-607.

Eberly, Janice Sergio Rebelo, and Nicolas Vincent (2008) Investment and Value: A Neoclassical Benchmark. *NBER Working Papers* 13866.

Erceg, Christopher J., Luca Guerrieri and Christopher Gust (2005) Can Long-Run Restrictions Identify Technology Shocks. *Journal of the European Economic Association*, 3(6), 1237-1278.

Fernández de Córdoba, Gonzalo and Timothy J. Kehoe (2000) Capital Flows and Real Exchange Rate Fluctuations Following Spain's Entry into the European Community. *Journal of International Economics*, 51(1), 49-78.

Fève, Patrick, and Alain Guay (2010) Identification of Technology Shocks in Structural Vars'. *Economic Journal*, 120(549), 1284-1318.

Foerster, Andrew T., Pierre-Daniel G. Sarte, and Mark W. Watson. (2011) Sectoral versus Aggregate Shocks: A Structural Analysis of Industrial Production. *Journal of Political Economy*, 119, 1-38.

Francis, Neville and Valerie A. Ramey (2005) Is the Technology-Driven Real Business Cycle Hypothesis Dead? Shocks and Aggregate Fluctuations Revisited. *Journal of Monetary Economics*, 52(8), 1379-1399.

Francis, Neville and Valerie A. Ramey (2009) Measures of Per Capita Hours and Their Implications for the Technology-Hours Debate. *Journal of Money, Credit and Banking*, 41, 1071-97.

Francis, Neville, Michael T. Owyang, Jennifer E. Roush, and Riccardo DiCecio (2014) A Flexible Finite-Horizon Alternative to Long-Run Restrictions with an Application to Technology Shocks. *The Review of Economics and Statistics*, 96(4), 638-664.

Galí, Jordi (1999) Technology, Employment and the Business Cycle: Do Technology Shocks Explain Aggregate Fluctuations? *American Economic Review*, 89(1), 249-271.

Galí, Jordi, and Luca Gambetti (2009) On the Sources of Great Moderation. *American Economic Journal: Macroeconomics*, 1(1), 26-57.

Galí, Jordi, and Van Rens, Thijs (2021) The Vanishing Procyclicality of Labour Productivity. *Economic Journal*, 131, 302-326.

Garìn, Julio, Michael Pries and Eric Sims (2018) The Relative Importance of Aggregate and Sectoral Shocks and the Changing Nature of Economic Fluctuations. *American Economic Journal: Macroeconomics*, 10(1), 119-148.

González Cabanillas, Laura, and Eric Ruscher (2016) The Great Moderation in the Euro Area: What Role have Macroeconomic Policies played? *European Economy Discussion Papers*, n°331.

Havranek, Tomas, Zuzana Irsova, Lubica Laslopova, Olesia Zeynalova (2021) Skilled and Unskilled Labor Are Less Substitutable than Commonly Thought. *CEPR Discussion Papers* 15724.

Horvath, Michael (2000) Sectoral Shocks and Aggregate Fluctuations. *Journal of Monetary Economics*, 45, 69-106.

Huo, Zhen, Andrei A. Levchenko, Nitya Pandalai-Nayar (2023) Utilization-Adjusted TFP across Countries: Measurement and Implications for International Comovement. *Journal of International Economics*, forthcoming.

Imbs, Jean (1999) Technology, Growth and the Business Cycle. *Journal of Monetary Economics*, 44(1), 65-80.

Imbs, Jean, and Isabelle Mejean (2015) Elasticity Optimism. *American Economic Journal: Macroeconomics*, 7(3), 43-83.

Bergman, Nittai K., Nir Jaimovich, Itay Saporta-Eksten (2024) The distributional impact of sectoral supply and demand shifts: A unified framwork. *NBER Working Paper* 32271.

Jordà, Òscar (2005) Estimation and Inference of Impulse Responses by Local Projections. *American Economic Review*, 95(1), 161-182.

Kehoe, Timothy J. and Kim J., Ruhl (2009) Sudden Stops, Sectoral Reallocations, and the Real Exchange Rate. *Journal of Development Economics*, 89(2), 235-249.

Kehoe, Timothy, Kim J. Ruhl, and Joseph B. Steinberg (2018) Global Imbalances and Structural Change in the United States. *Journal of Political Economy*, 126 (2), 761-796.

Li, Huacheng (2022) The Time-Varying Response of Hours Worked to a Productivity Shock *Journal of Money, Credit and Banking*, forthcoming.

Mendoza, Enrique, G. (1992) The Effects of Macroeconomic Shocks in a Basic Equilibrium Framework. *Staff Papers IMF*, 39(4), 855-889.

Mitra, Aruni (2023) The Productivity Puzzle and the Decline of Unions *Journal of Economic Dynamics and Control*, 33(3), 597-613.

Ngai, Rachel L., and Christopher A. Pissarides (2007) Structural Change in a Multisector Model of Growth. *American Economic Review*, 97(1), 429-443.

Nucci, Francesco and Marianna Riggi (2013) Performance Pay and Changes in U.S. Labor Market Dynamics. *Journal of Economic Dynamics and Control*, 37 (12), 2796-2813.

Oberfield, Ezra, and Devesh Raval (2021) Micro Data and Macro Technology. *Econometrica*, 89(2), 703-732.

Pedroni, Peter (2000) Fully Modified OLS for Heterogeneous Cointegrated Panels. *Advances in Econometrics*, vol. 15, edited in B. Baltagi: Nonstationary Panels, Panel Cointegration and Dynamic Panels, 93-130.

Peterman, William B. (2016) Reconciling Micro And Macro Estimates Of The Frisch Labor Supply Elasticity. *Economic Inquiry*, 54(1), 100-120.

Shea, John (1999) What Do Technology Shocks Do? NBER Chapters, in: NBER Macroeconomics Annual 1998, volume 13, 275-322, National Bureau of Economic Research, Inc.

Shimer, Robert (2009) Convergence in Macroeconomics: The Labor Wedge *American Economic Journal: Macroeconomics*, 1(1), 280-297.

Stehrer, Robert, Alexandra Bykova, Kirsten Jäger, Oliver Reiter and Monika Schwarzhappel (2019) Industry Level Growth and Productivity Data with Special Focus on Intangible Assets. Statistical Report No. 8.

Stockman Alan C. and Linda L. Tesar (1995) Tastes and Technology in a Two-Country Model of the Business Cycle: Explaining International Comovements. *American Economic Review* 85(1), 168-185.

Thomet, Jacqueline and Philipp Wegmueller (2021) Technology Shocks And Hours Worked: A Cross-Country Analysis. *Macroeconomic Dynamics*, 25(4), 1020-1052.

Turnosvsky, Stephen J. (1997) International Macroeconomic Dynamics. MIT press.