Catch-Up Growth and Inter-Industry Productivity Spillovers

Bolhuis, Marijn

University of Toronto

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Marijn Bolhuis†

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Abstract

Developing economies tend to export more skill-intensive products as they become more productive. This paper provides a new tractable, quantitative framework to examine the role of inter-industry productivity spillovers in this development process. I start by documenting that a country's comparative advantage tends to increase in industries that employ occupations that are used most intensively in current exports. In the model, productivity growth is driven by occupation-specific dynamic scale economies, which generate productivity spillovers between occupationally similar sectors. By exploiting cross-sector heterogeneity in foreign demand shocks, I find that dynamic scale economies are substantial in high-skilled production but negligible in low-skilled production. As a result, inter-industry productivity spillovers are larger in richer countries, and access to foreign markets allows developing countries to shift labor into sectors that contribute more to aggregate productivity growth. The model can account for a substantial share of the variation in aggregate and industry-level labor productivity growth across developing economies. Counterfactual exercises suggest that inter-industry spillovers play a quantitatively substantial role in accounting for slow cross-country convergence. Moreover, spillovers increase the gains from trade, especially in developing economies with a comparative advantage in manufacturing.

JEL Classification: F1; F4; F6; O1; O3; O4;

Keywords: Productivity; Convergence; Spillovers; Dynamic scale economies; Comparative advantage; Exports

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†Department of Economics, University of Toronto, 150 St. George Street, Toronto, Ontario, Canada M5S 3G7. Email: marijn.bolhuis@mail.utoronto.ca

1 Introduction

Developing countries that catch up successfully to the global economic frontier tend to experience rapid growth in labor productivity. What is the role of a country's production structure as a driver of this productivity growth? The notion that what a country produces matters for aggregate productivity has a long history in macroeconomics and international trade, dating back to at least Marshall's concept of external economies of scale (Marshall, 1890). In a dynamic setting, the sectoral composition of production matters for growth in the presence of dynamic scale economies that are heterogeneous across sectors (Krugman, 1987). A well-established theoretical literature has elaborated several mechanisms through which these scale economies can manifest themselves, such as learning-by-doing (e.g. Young (1991) ; Matsuyama (1992)) and human capital spillovers (Lucas Jr (1988) ; Stokey (1991)). More recently, empirical work on this question has focused on how external demand conditions and a country's structure of comparative advantage interact to affect real income and sector-level productivity growth.[1] A common finding in this literature is that 'what you export matters' (Hausmann et al., 2007): on average, countries that export in technologically more advanced sectors tend to experience faster real income growth (Bartelme et al., 2019).

Until now the empirical literature on dynamic scale economies has focused on whether countries' production structures affect growth heterogeneously across sectors, without providing a structural framework to interpret these findings. The theoretical literature provides explanations for these empirical correlations but does not assess their quantitative significance. This paper aims to fill this gap by developing a quantitative general equilibrium, multi-sector trade model that is tractable enough to estimate dynamic scale economies and quantify their importance for long-run productivity growth. In contrast to most of the theoretical literature (e.g. Krugman (1987), Matsuyama (1992); Mendoza (2010)) I introduce dynamic scale economies as inter- rather than intra-industry productivity spillovers. My main reason for doing so is to be consistent with empirical evidence on export competitiveness: while countries' productivity (or comparative advantage) in individual sectors tends to exhibit strong convergence (Levchenko and Zhang (2016); Hanson et al. (2018); Daruich et al. (2019)) relative to other sectors, countries tend to experience relatively faster productivity growth in sectors that are closely

[1] See Prebisch (1959), Galor and Mountford (2006) and O'Rourke et al. (2019) for examples of research on adverse dynamic scale economies in agriculture, and Van der Ploeg (2011) for a review of the voluminous resource curse (or Dutch Disease) literature. Other work goes beyond strict sector-level distinctions and emphasizes the importance of skill intensity (e.g. Atkin (2016), Blanchard and Olney (2017)), and complexity (Hidalgo et al. (2007) ; Hidalgo and Hausmann (2009) ; Hausmann and Hidalgo (2011)) of exports.

related to those in which they are initially most competitive (Bahar et al., 2019). [2]

The specific goal of this paper is to quantify the importance of inter-industry productivity spillovers for cross-country differences in aggregate productivity growth and the gains from trade integration. I start out by documenting two empirical facts that motivate my structural framework. First, I show that as developing economies become more productive, they tend to experience a shift in comparative advantage from low- to high-skill intensive sectors, which suggests that they become relatively more productive in high-skill intensive production. Second, I document that a country's comparative advantage tends to increase in industries that employ occupations that are used most intensively in current exports. This evidence of spillovers in productivity is mainly present in high-skilled manufacturing industries.

Motivated by these empirical patterns, I develop a tractable quantitative model that generates inter-industry spillovers through dynamic scale economies at the level of occupational groups ('tasks'). Workers in the same occupation -but potentially employed in different sector- accumulate knowledge through learning-by-doing and by adopting new ideas from others. As all sectors in the economy combine different combinations of tasks in production, these interactions give rise to varying degrees of connectedness between sectors. The accumulation of knowledge has two distinctive features. First, the strength of spillovers may differ by occupational group due to different degrees of increasing returns to scale in knowledge creation. Second, task productivity growth is subject to convergence (or 'fishing-out'), as more productive workers are less likely to find new, productivity-improving ideas.

Despite generating endogenous productivity growth arising from a country's production structure, my framework remains tractable enough to estimate model parameters and perform counterfactuals using closed form solutions. I show that a model equilibrium over multiple time periods can be summarized as a series of static equilibria connected by a law of motion of task productivity growth that only depends on previous sectoral employment shares and levels of task productivity. Moreover, conditional on estimates of supply and demand side parameters, the model can can be solved in counterfactual changes using exact hat algebra (Dekle et al., 2007) without relying on estimates of initial productivity levels and trade costs.

My procedure for estimating task-specific dynamic scale economies evolves in two steps. First, I use the model's implied gravity equation to estimate sector-specific unit cost levels across countries.

[2]This paper is the first, to my knowledge, to construct an endogenous growth model with dynamic scale economies as inter-industry productivity spillovers. Johnson (2017) models inter-industry spillovers and learning-by-doing as a source of changes in comparative advantage but does not allow dynamic scale economies to differ across occupations.

Richer countries tend to be more competitive in advanced sectors that use high-skilled tasks intensively. Next, I estimate the task-specific spillover parameters by relating changes in sector-specific unit costs to countries' export structures. To address endogeneity issues arising from supply side factors, I consider only variation in export structure induced by foreign demand shocks. I implement my approach on UN COMTRADE data from 1962 to 2000, and use detailed occupation-specific data from O*NET to assign occupations to groups based on their task content.

I find significant heterogeneity in the extent of dynamic scale economies of different tasks. Spillovers are generally increasing in the skill level of the occupational groups. As a result, allocating labor to sectors that use high-skilled labor more intensively has a greater effect on aggregate productivity growth. Across clusters of sectors, spillovers are lowest in agriculture and highest in advanced manufacturing. When I use the estimated parameters to assess model fit, the framework performs well at predicting cross-country differences in aggregate and sector-level labor productivity growth for the period 1970-2000. The model-implied sector-level accumulated spillovers explain more than 20 percent of the variation in long run changes in effective unit costs among a sample of 60 tradable sectors. In terms of aggregate labor productivity growth over the same period, the model explains 20 percent of the variation in changes in real GDP growth.

Counterfactual exercises suggest inter-industry spillovers matter quantitatively for cross-country convergence in aggregate productivity, as well as the gains from trade integration. Through the lens of the model, spillovers are larger in advanced economies as these tend to export and consume relatively more high-skill intensive goods (Caron et al., 2014). As a result, inter-industry spillovers could potentially account for the lack of catch up in levels of aggregate labor productivity between developing and advanced economies during the 1970 to 2000 period (Johnson and Papageorgiou, 2019). I assess to what extent spillovers can account for slow unconditional (beta) convergence by exploring a counterfactual in which I set any dynamic scale economies to zero. Indeed, without spillovers a typical country at one tenth of the frontier in 1970 experiences 0.39 to 1.23 percentage points per year faster catch up to the frontier.

Finally, I assess how inter-industry spillovers affect the gains from trade and to what extent these gains depends on a country's initial patterns of comparative advantage. Given that domestic demand in poorer countries tends to be concentrated in the technologically least advanced sectors, the model implies that the availability of foreign demand for goods from sectors with high spillovers is crucial for achieving catch-up to the frontier. In particular, trade integration leads to both static and dynamic gains if it shifts countries' exports towards high spillover sectors while integrating with trade partners that can provide its preferred imports at lower cost. [3]

I explore a series of counterfactuals in which I keep a country's trade costs at their 1970 level, and construct the ensuing counterfactual path of productivity levels. In most countries, dynamic gains of trade are substantial and equal roughly one third of the average static gains. I find considerable heterogeneity across countries in terms of the dynamic gains from trade. Countries with a comparative advantage in agriculture tend to have lower dynamic gains, which is not surprising given that estimated spillovers are low in this sector. At the same time, estimated gains are generally higher in countries with an initial comparative advantage in low-skilled manufacturing. These results suggest that labor abundant countries gain more from trade integration than commodity exporters, as low-skilled manufacturing serves as a stepping stone towards the production of more technologically advanced goods. [4]

Related Literature and Contributions. This paper adds to the trade and growth literature in four ways. First, it contributes to the literature that emphasizes the importance of countries' production and export structure for economic growth and income disparities across countries. One theoretical branch of this literature argues that under some circumstances, trade may increase disparities between countries due to the existence of dynamic scale economies that differ by sector. Potential reasons for such divergence are sector-specific learning-by-doing (Krugman (1987) ; Young (1991) ; Matsuyama (1992); Redding (1999) ; Mendoza (2010) ; Whang (2017)) human capital externalities (Lucas Jr (1988) ; Stokey (1991)), as well as trade-induced differencs in incentives to accumulate physical capital (Krugman (1981) ; Bajona and Kehoe (2010) ; Basco and Mestieri (2019)) and technology (Feenstra (1996) ; Matsuyama (2019)). Empirical research in this literature emphasizes the importance of a country's production structure for growth, such as emphasis on producing a mix of diversified and complex products (e.g. Hidalgo et al. (2007); Hausmann et al. (2007); Hidalgo and Hausmann (2009); Hausmann and Hidalgo (2011) ; Rodrik (2011); Eicher and Kuenzel (2016)), on the effect of export skill

[3] This intuition is borne out by empirical evidence on the exports of 20th century East Asian growth miracles that have been relatively technologically advanced. In the case of Korea, for example, the United States and Japan provided large foreign demand for steel and ships in the 1980s, and cars and electronics in the 1990s. In the case of China, the U.S. and Europe have formed the largest foreign markets in the form of toys and simple electronics in the 1990s and 2000s, and machinery, TVs and personal computers in the 2010s. Indeed, Rodrik (2006) and Schott (2008) argue that Chinese exports have been considerably more technologically sophisticated than exports of developing economies with similar income levels.

[4] This is in line with the recent empirical work of Hanson (2017), who documents that labor-abundant East Asian countries tend to cycle through ever more skill- and capital-intensive offshoring industries, while these patterns are not present in primary commodity exporters.

intensity on fertility and human capital accumulation (e.g. Galor and Mountford (2008), Atkin (2016), Blanchard and Olney (2017)), and on the importance of agricultural diversification for long-run development (e.g. Fiszbein (2017)). This paper is the first, to my knowledge, that aims to quantify the importance of dynamic scale economies for cross-country convergence.

Second, this study responds to the broad literature on the importance of trade and idea flows for endogenous growth (e.g. Alvarez et al. (2013), Sampson (2015), Perla et al. (2015), Buera and Oberfield (2017)). In recent years, this literature has built on the seminal work of Eaton and Kortum (2001) and Eaton and Kortum (2002) by introducing innovation, imitation, and idea diffusion into standard multi-country general equilibrium models.[5] Theoretically, this paper is most closely related to Buera and Oberfield (2017), who develop a tractable model of idea diffusion through international trade, which allows them to quantify the contribution of trade barriers to TFP differences across countries and over time.[6] I contribute to this literature by developing a new multi-sector framework with inter-industry spillovers that remains tractable enough to identify spillovers and to perform counterfactuals under only limited assumptions.

Third, this paper is nested in the growth literature that documents factor efficiency differences between countries (e.g. Caselli et al. (2006), Jones (2014), Rossi (2017), Malmberg (2017), Morrow and Trefler (2017)). A robust conclusion in this literature is that skilled labor tends to be relatively more productive in richer countries.[7] Through the lens of this paper's framework, these factor efficiency differences are the result of dynamic scale economies that are stronger for high-skilled production. As

[5]On the theoretical side, Eaton and Kortum (2001) develop a multi-country international general equilibrium model of innovation, economic growth and international trade. Alvarez et al. (2013), Sampson (2015) and Perla et al. (2015) build on this work by examining how free trade not only encourages the selection of efficient producers but also facilitates the diffusion of ideas between the most efficient exporters. Somale (2017), Cai and Li (2012), Cai and Li (2015) and Santacreu (2015) study how R& D is shaped by international trade.

[6]Deng (2016) extends the model of Buera and Oberfield (2017) by incorporating multiple sectors and allowing for reduced-form inter-industry knowledge spillovers between sectors, potentially in different countries. My set-up differs from his in terms of the source of productivity growth, estimation of parameters, and treatment of counterfactuals. In my model, endogenous productivity growth is the result of interactions between workers in the same occupational groups, rather than between entrepreneurs. Moreover, I estimate the model's parameters using foreign demand shocks rather than calibrating them. Finally, in my model counterfactuals can be expressed in relative changes due to the dynamic scale economies specification, thus obviating the need to estimate exogenous parameters such as trade costs, productivity levels and some sector-specific productivity parameters.

[7]Caselli (2016) provides a good survey of this literature. Caselli et al. (2006) find substantial skill bias in cross-country technology differences if skilled and unskilled labor are imperfect substitutes. Jones (2014) shows that variation in human capital across countries can explain a much bigger share of cross-country income differences in a generalized development accounting framework. Other recent work aims to document factor efficiency differences using micro data. For example, Rossi (2017) uses comparable cross-country census data and finds that the skill premium varies little with GDP per capita despite large differences in relative skill supply between poor and rich countries. By harmonizing repeated cross-sections of labor surveys, Lagakos et al. (2018) show that experience-wage profiles are much steeper for experienced and educated workers in richer countries. Morrow and Trefler (2014), Morrow and Trefler (2015), Morrow and Trefler (2017) and Malmberg (2017) use international trade data to estimate effective factor prices and also find that skilled labor is more productive in richer countries. This trade-based approach has its origins in the earlier work of Trefler (1993) and Trefler (1995) on productivity-adjusted factor price equalization in Heckscher-Ohlin-Vanek (HOV) models.

such, this paper connects the empirical literature on factor efficiency differences with the theoretical literature on multi-factor dynamic general equilibrium models.

Finally, this paper contributes to the literature on dynamic comparative advantage that examines how and why countries' patterns of comparative advantage evolve (e.g. Romalis (2004), Hanson (2017), Hanson et al. (2018), Daruich et al. (2019)).[8] While this literature has documented fast turnover ('churning') of comparative advantage over time, there is little work on *why* this churning occurs.[9] This paper contributes to this literature by offering a new endogenous growth theory of dynamic comparative advantage based on changes in occupational-specific productivity levels that are driven by dynamic scale economies.

Paper Organization. This paper is organized as follows. Section II presents two stylized facts that help frame the subsequent theoretical and empirical analysis. Section III covers the theoretical framework. Section IV contains the estimation strategy, and section V describes the data. Section VI explores two quantitative exercises. Section VII offers conclusions.

2 Motivating Facts

I first highlight two key facts about structural transformation of skill-intensive production and comparative advantage. As a first fact, I document that countries' tradable production becomes more skill-intensive as aggregate productivity increases. I use newly classified cross-country data on sector-specific employment to document skill-biased structural change (Buera et al., 2015) in a broad panel of mainly developing economies. First, labor moves out of agriculture into mining and low-skilled manufacturing sectors. As countries develop further, these sectors contract too as labor further shifts into sectors intensive in the use of high-skilled labor. This pattern holds in a new cross-country employment panel from IPUMS International (1960-2011) and within the United States for the pe-

[8] Romalis (2004) examines how countries that rapidly accumulate a production factor see their exports shift to industries that intensively use that factor by integrating monopolistic competition and transport costs into a multi-country Heckscher-Ohlin model. In more recent papers, Ciccone and Papaioannou (2009) and Shikher (2017) emphasize the importance of educated labor endowments for shifts in comparative advantage and productivity. Chor (2010) incorporates sectoral productivity growth in a multi-sector EK model but focuses on reduced-form effects of changes in a country's institutional characteristics on productivity growth. Cai and Stoyanov (2016) argue that within countries, population ageing is associated with a specialization in industries that use age-appreciating skills more intensively. Hanson et al. (2018) and Daruich et al. (2019) document substantial shifts in comparative advantage and export specialization over time, but do not aim to explain why these shifts occur. A recent paper that is most closely related to this one Hanson (2017), who documents that countries that start with a comparative advantage in labor-intensive manufacturing cycle through offshoring industries from less- (apparel, toys) to more skill-intensive (electronics, machinery) sectors.

[9] The scarcity of research on changes in comparative advantage over time contrasts with the voluminous body of work on the determinants of cross-country differences in comparative advantage, which is too large to discuss here. For an overview, see Leamer (1984) and Nunn and Trefler (2014).

riod 1850-2010. Second, I also document a strong positive association between countries' GDP per capita and their revealed comparative advantage in skill-intensive sectors. While skill-biased structural change in value added and employment could be driven entirely by non-homothetic preferences (e.g. Kongsamut et al. (2001)) or an increase in the relative price of skill-intensive goods (e.g. Ngai and Pissarides (2007)),[10] this second pattern suggests that countries' relative price of skill-intensive tradable goods decreases as they become richer.[11] I confirm this cross-country pattern by observing the same shift in revealed comparative advantage within a sample of fast-growing East Asian countries.

As a second fact, I document that countries' revealed comparative advantage (RCA) -a measure of sector-specific inverse unit costs- tends to shift towards occupationally similar sectors, while also exhibiting convergence over time. This first pattern suggests that current production (in sectors with a high RCA) tends to foster above average productivity growth in sectors with a similar production structure.[12] At the same time, the second pattern confirms fast 'churning' of comparative advantage (Hanson et al. (2015) ; Daruich et al. (2019)) such that sector-specific unit costs tend to exhibit mean reversion.

2.1 Fact 1

Fact 1: *As countries become more productive, employment and comparative advantage shift from low- to high-skill intensive production.*

Employment

To facilitate exposition, I aggregate tradable sectors into three clusters: (i) Agriculture and Food (agriculture, forestry, fisheries, food, beverages, and tobacco) (ii) Low-Skilled Manufacturing and Mining (textiles, clothing, leather, footwear, wood products, furniture, recyling, and mining), and (iii) High-Skilled Manufacturing (minerals, fuels, metals, rubbers, plastics, paper, printing, chemicals, machinery, transport and electronic equipment).[13] I use new internationally comparable census data from

[10] For the latter, it is also necessary that goods from different sectors are complements for consumers.

[11] See also Malmberg (2017). Note that this result does not necessarily conflict with Buera et al. (2015), as I only consider tradable sectors (agriculture, mining and manufacturing). Buera et al. (2015) focus on services.

[12] See also Bahar et al. (2019), who explore different empirical channels through which countries diversify their exports over time.

[13] The pattern of skill-biased structural change in tradable sectors described here also holds at a more granular level of sector classification. See Appendix A for plots of sector-level tradable employment against log GDP p.w., where sectors are classified at the ISIC 3.0 2 digit level. The elasticity of the employment share w.r.t. to GDP p.w. is lowest in agriculture (-.44) and broadly increases with skill intensity in the following order: textiles/clothing (.42), furniture/recycling/n.e.c (.50), leather/footwear (.52), wood products (.56), food/beverages (.65), non-metallic minerals (.69), mining (.73), fuels (.99), metals (1.1), rubbers/plastics (1.2), paper/printing (1.2), chemicals (1.3), machinery (1.4), transport equipment (1.4) and electronic equipment (1.4).

IPUMS International to document structural transformation in *employment* from low- to high-skilled sectors.[14] These data cover a wide range of countries and time periods, and -in contrast to the usual evidence- advanced economies are underrepresented.[15] Figure 1 plots employment shares in the three tradable clusters against log real GDP per worker. As poorer countries develop, labor shifts monotonically out of agriculture and food into industrial sectors. At first, low-skilled manufacturing and mining experience an increase in employment, but these sectors contract as a country's income increases further. Employment in more skill-intensive manufacturing expands monotonically.

A potential concern about these new employment data is that they only document a cross-sectional relationship between employment shares and GDP per capita. To address this, I examine structural transformation in employment *within* the United States from 1850 to 2010 using census data. Figure 1 plots the corresponding series. As in the cross-sectional IPUMS International sample, structural transformation of employment within the U.S. involves shifting labor from agriculture low-skilled industrial sectors and subsequently into more knowledge-intensive manufacturing.

Comparative Advantage

Employment (nor value added) data do not provide a clear insight into sector-specific productivity trends. I use international trade data to shed light on the latter. An advantage of using trade data in this setting is that it is recorded at a detailed industry level across a wide range of countries and historical time periods. At the same time, measures of comparative advantage reflect differences in inverse unit costs when interpreted through the lens of any gravity model.[16]

First, I define a the Revealed Comparative Advantage (RCA) (Balassa, 1965) of country n in sector k at time t as:

$$RCA_{n,t}^{k} = \frac{X_{n,t}^{k}/X_{n,t}}{X_{t}^{k}/X_{t}} \tag{1}$$

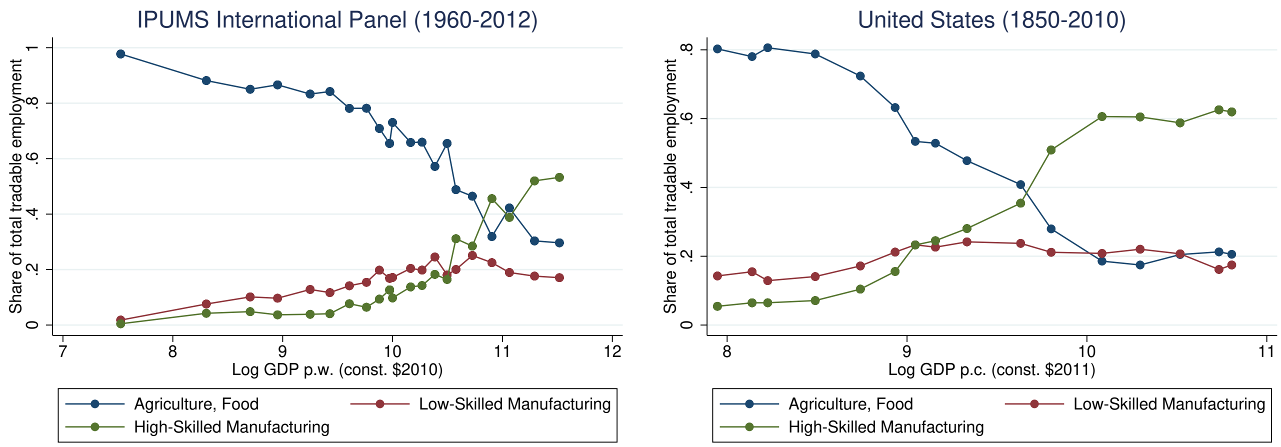
where $X_{n,t}^{k}$, $X_{n,t}$, X_{t}^{k}, and X_t denote a country's exports in sector k, its total exports, global exports in sector k, and global total exports. RCA thus measures how specialized a country is in a given sector relative to the global mean. I construct the RCA of the three clusters for a wide range of countries using trade data from World Trade Flows (Feenstra et al. (2005)) for the period 1970-2000.

[14] A recent paper by Duernecker and Herrendorf (2016) uses the same data to examine structural change in 'service' and 'goods' occupations.

[15] In total, IPUMS International covers 94 countries, 365 censuses, and over 1 billion person records, from 1960 to 2013. Several large advanced economies have no or only limited public census records, such as Japan, Germany, United Kingdom, Italy, Korea, Russia, and Australia.

[16] For other papers that use trade data to infer productivity differences across countries and over time, see Levchenko and Zhang (2016) , and Malmberg (2017).

Figure 1: Structural Transformation of Employment in Tradable Clusters



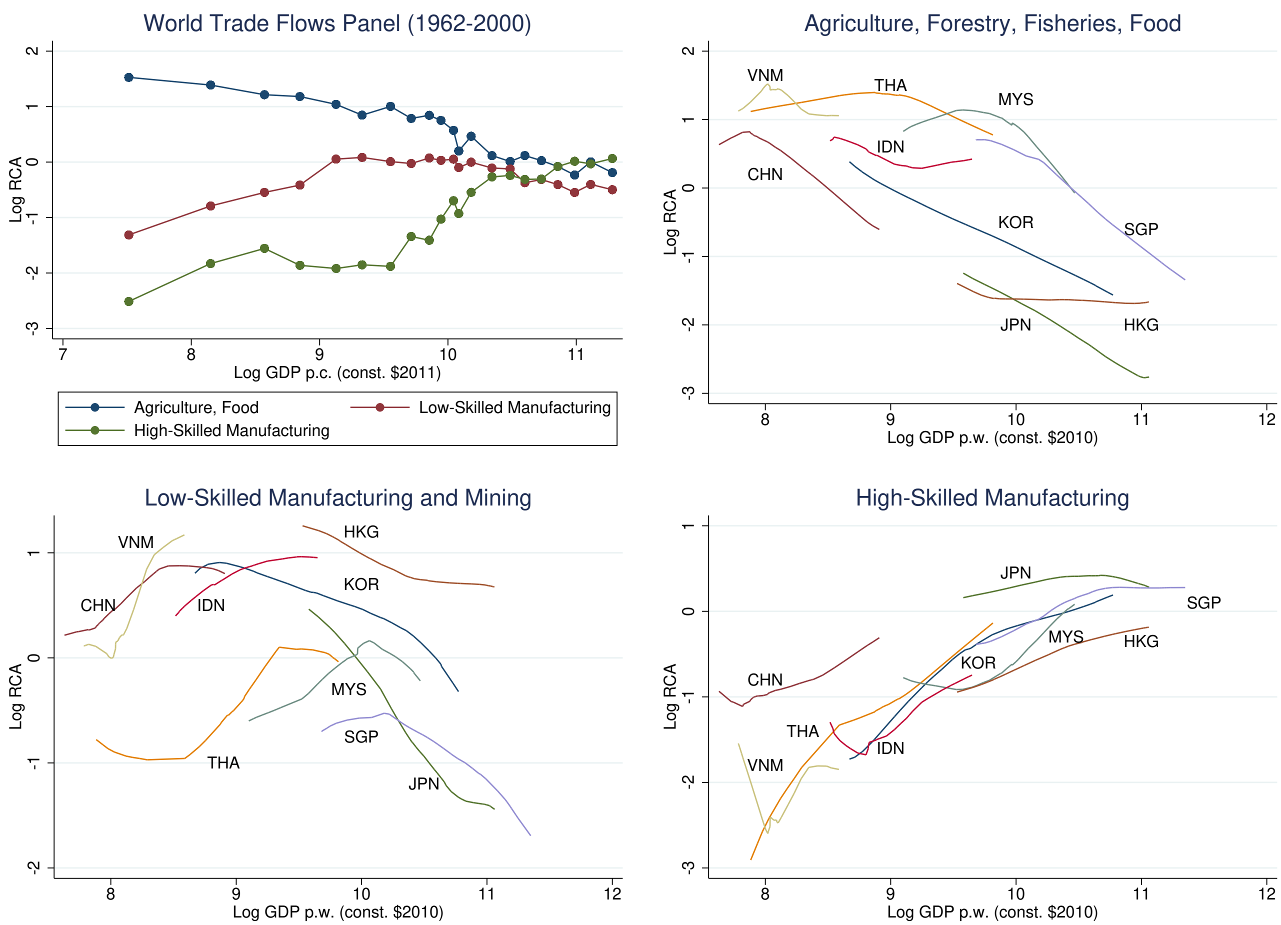
Notes: The left figure presents a binned scatterplot of countries' share of tradable employment for the three tradable clusters against log GDP p.w. for the IPUMS International Panel from 1970 to 2012. The right figures presents a similar binned scatterplot for the United States for each decade from 1850 to 2010. Employment data for the U.S. are based on micro-data from IPUMS USA censuses. Real GDP per worker (constant $2010) data for the cross-country sample are from Penn World Tables 9.0. Estimates of real GDP per capita (constant $2011) data for the U.S. are from the Maddison Project Database.

In a world without trade costs, constant returns to scale, and homogeneous sector-specific Cobb-Douglas preferences, RCA reflects relative sector-specific unit costs.[17] Figure 2 plots (log) RCA for the three clusters against GDP per worker. While poorer countries tend to be relatively more productive in agriculture and food, their RCA shifts towards low-skilled manufacturing and mining as they increase their aggregate productivity. In turn, their RCA in this cluster tends to peak and decline at the expense of higher RCA in high-skilled manufacturing. Through the lens of a gravity model, these patterns suggest that, as countries become richer, they tend to experience below average productivity growth in agriculture and food. At the same time, their productivity growth in high-skilled manufacturing tends to accelerate, while relative productivity growth in low-skilled manufacturing is hump-shaped.

In order to go beyond this cross-sectional pattern, I plot the evolution of RCA against GDP per capita for *within* fast-growing East Asian countries (Korea, China, Japan, Thailand, Malaysia, Indonesia, Singapore, and Vietnam). These plots are presented in Figure 2. Reassuringly, these patterns are very similar to the ones previously documented. Again, RCA is monotonically decreasing in income per worker for agriculture and food, hump-shaped for low-skilled manufacturing and mining, and monotonically increasing for highs-skilled manufacturing.

[17]See the definition of static equilibrium in section 3.1.4 and exporter fixed effects in gravity equation estimates (section 4.1.1). Appendix B contains details.

Figure 2: Structural Transformation of Comparative Advantage in Tradable Clusters



Notes: The upper left figure presents a binned scatterplot of countries' revealed comparative advantage for the three tradable clusters against log GDP p.w. for the World Trade Flows sample from 1970 to 2000. The other three figures presents series of revealed comparative advantage in the three clusters for fast-growing East Asian countries (Vietnam, China, Thailand, Indonesia, Malaysia, Korea, Japan, Singapore, and Hong Kong), smoothed using a lowess smoother. Real GDP per worker (constant $2010) data are from Penn World Tables 9.0.

2.2 Fact 2

Fact 2: *Comparative advantage exhibits convergence and tends to shift into occupationally similar sectors.*

In order to explore to what extent comparative advantage (or relative productivity) tends to spill over between industries, I need a sector-specific measure of 'related' comparative advantage in similar sectors, which in turn requires a notion of similarity. Given that sectors that are similar in skill intensity tend to have similar levels of RCA (Fact 1), I posit a simple production function in which a firm in sector k combines inputs $t_{n,t}^{a,k}$ from occupations (denoted by a) with different skill levels:

$$Q_{n,t}^{k} = \prod_{a=1}^{A} (t_{n,t}^{a,k})^{\zeta_a^k} \qquad ; \sum_{a=1}^{A} \zeta_a^k = 1 \tag{2}$$

where ζ_a^k is sector k's input intensity of occupation a, which has an empirical equivalent as the occupation a's share of wages or employment in sector k. For details on the occupational classification and data used, see section 5.

I can now define 'Revealed Occupational Advantage' as the share of exports attributed to an occupation a in country n relative to the global average:

$$ROA_{n,t}^{a} = \frac{\sum_{k=1}^{K} \zeta_a^k X_{n,t}^k / X_{n,t}}{\sum_{k=1}^{K} \zeta_a^k X_t^k / X_t} \tag{3}$$

In turn, I construct a sector's 'related' RCA as a Cobb-Douglas aggregate of a country's ROA terms, with a sector's occupation cost share as exponents. For example, if a country has a high RCA in chemicals and aircrafts then it will also have a high 'related RCA' in office machinery as these sectors all use high-skill occupations relatively intensively. Formally, 'related RCA' $RR_{n,t}^k$ of sector k in country n is defined as:

$$RR_{n,t}^{k} = \Pi_{a=1}^{A} (ROA_{n,t}^{a})^{\zeta_a^k} \tag{4}$$

The final estimation equation becomes:

$$\Delta \ln RCA_{n,t}^{k} = \beta_0 + \beta_1 \ln RCA_{n,t-1}^{k} + \beta_2 \ln RR_{n,t-1}^{k} + \delta_{n,k} + \delta_{n,t} + \delta_{k,t} + \epsilon_{n,t}^{k} \tag{5}$$

where $\Delta \ln RCA^k_{n,t}$ is a sector's log 10 year difference in RCA. $\delta_{n,k}$, $\delta_{n,t}$, and $\delta_{k,t}$ are country-sector, country-time and sector-time fixed effects, respectively, and $\epsilon^k_{n,t}$ is an error term.[18] I estimate 5 using OLS on the WTF panel.[19],[20]

Table 1 reports the associated regressions. In the first four specifications, the unconditional convergence coefficient on $\ln RCA^k_{n,t-1}$ is negative and significant around -.25, which is close to the average estimates in Levchenko and Zhang (2016). The coefficient on related RCA is positive, significant, and around .24 with or without including sector-year fixed effects. This indicates substantial inter-industry spillovers, as a 10 percent increase in initial related RCA is associated with a roughly 2.3 percent higher subsequent growth in RCA. However, this average masks substantial heterogeneity. In columns (2) and (4), I interact a sector's related RCA with a dummy for the cluster to which it belongs. Most of the average inter-industry spillovers are driven by high-skilled manufacturing sectors, for which the coefficient on related RCA edges around 1, implying a 10 percent higher subsequent RCA growth rate. At the same time, the coefficient on related RCA is close to zero for the other two low-skilled clusters.

2.3 Preliminary Conclusions

Taken together, these two motivating facts suggest that (i) economies become relatively more productive in skill-intensive tradable sectors as they get richer, (ii) sector-specific productivity -relative to the country mean- exhibits convergence over time, and (iii) producing in a given sector leads to (above average) productivity growth in occupationally similar sectors, and (iv) these inter-industry spillovers are mainly present in high-skilled manufacturing industries. [21]

[18]Under certain conditions, equation 5 corresponds to the estimating equation of endogenous changes in sector-specific unit costs in the model developed in section 3.2. See Appendix B for details.

[19]For details on sectors and countries covered, see Appendix D.

[20]I consider only country-year cells that contain at least 30 sectors and after dropping observations that are within the 0.1 % tails in terms of $\Delta \ln RCA^k_{n,t}$.

[21]Note that these four patterns may shed a light on a puzzle in the growth literature highlighted by Rodrik (2012), who documents that, even though aggregate labor productivity tends to exhibit extremely slow unconditional (cross-country) convergence, sector-specific labor productivity converges much faster. Heterogeneous inter-industry productivity spillovers may play a role here. If spillovers are stronger in high-skill intensive sectors -in which richer countries tend to have a comparative advantage- then poorer countries may catch up at the sector-level but not in the aggregate. I explore the role of inter-industry spillovers in accounting for cross-country convergence in more detail in section 7.1.

Table 1: Inter-Industry Spillovers of Revealed Comparative Advantage

	(1) $\Delta \ln RCA^k_{n,t}$	(2) $\Delta \ln RCA^k_{n,t}$	(3) $\Delta \ln RCA^k_{n,t}$	(4) $\Delta \ln RCA^k_{n,t}$	(5) $\Delta \ln RCA^k_{n,t}$	(6) $\Delta \ln RCA^k_{n,t}$
$\ln RCA^k_{n,t-1}$	-0.211***	-0.233***	-0.220***	-0.235***	-0.877***	-0.883***
	(0.00438)	(0.00475)	(0.0131)	(0.00493)	(0.0190)	(0.00858)
$\ln RR^k_{n,t-1}$	0.240***		0.245***		0.431***	
	(0.0200)		(0.0499)		(0.115)	
$HSM \cdot \ln RR^k_{n,t-1}$		0.986***		1.123***		1.218***
		(0.0712)		(0.0781)		(0.122)
$LSM \cdot \ln RR^k_{n,t-1}$		0.131**		0.0585		0.916***
		(0.0566)		(0.0621)		(0.107)
$AG \cdot \ln RR^k_{n,t-1}$		0.145***		0.145***		0.159***
		(0.0192)		(0.0191)		(0.0449)
Country-year FE	Y	Y	Y	Y	Y	Y
Sector-year FE	N	N	Y	Y	Y	Y
Country-sector FE	N	N	N	N	Y	Y
Observations	123502	123502	123502	123502	123450	123450
Adjusted R^2	0.359	0.366	0.385	0.392	0.720	0.720

Standard errors, clustered at country-year level, in parentheses
$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

Notes: This table reports estimates of different specifications of estimating equation 5. Columns (1) and (2) includes only country-year fixed effects, with and without interaction effects. Columns (3) and (4) add sector-year fixed effects. Columns (5) and (6) add country-sector fixed effects. Interaction effects include a dummy interacted with lagged related revealed comparative advantage (RR) for the three clusters of tradable sectors: High-Skilled Manufacturing (HSM), Low-Skilled Manufacturing and Mining (LSM) and Agriculture and Food (AG).

3 Theoretical Framework

The model developed in this section has two components. The static component entails a multi-country multi-sector GE model. The main difference with the canonical model of Caliendo and Parro (2015) is its production structure. Rather than combining capital and labor, firms employ different combinations of occupations. In this sense, the static part of the model is very similar to that of Lee (2015).

The dynamic component of the model endogenizes the evolution of an economy's aggregate occupational productivity levels. In particular, I model this type of productivity growth in the form of dynamic scale economies. Within a period, production is constant returns to scale, but over time, countries endogenously increase their productivity in different tasks through learning-by-doing or human capital spillovers.

The model is tractable to be able to perform counterfactuals. Nevertheless, estimating inter-industry productivity spillovers requires only four key assumptions: (i) bilateral trade takes a gravity form at the sectoral level[22], (ii) goods and factor markets are competitive, (iii) sector-specific Hicks-neutral TFP terms are orthogonal to occupation-specific cost shares, and (iv) agents do not internalize any of their effects on future productivity. The gravity equation and competitive market assumptions guarantee bilateral trade flows reflect effective unit costs. The last two assumptions ensure that inter-industry productivity spillovers reflect the mapping from initial export structure to sector-specific changes in effective unit costs.

3.1 Static Framework

3.1.1 Environment

The world consists of N countries indexed $n \in \mathbf{N} = \{1, ..., N\}$. In each country, there are K tradable sectors indexed $k \in \mathbf{K} = \{1, ..., K\}$. In turn, each sector is composed of a continuum of product varieties indexed $\omega_k \in \mathbf{\Omega} = \{1, ..., +\infty\}$. The production of a variety entails combining services from different types of occupations $a \in \mathbf{A} = \{1, ..., A\}$. Finally, in every country there is a continuum of households -measure $L_{n,t}$- that supply labor inelastically.

3.1.2 Demand

Households consume a bundle of sector aggregates $\{C^k_{n,t}\}^K_{k=1}$. Preferences are Cobb-Douglas with country- and time-specific weights $\alpha^k_{n,t}$:

$$U(\{C^k_{n,t}\}^K_{k=1}) = \prod_{k=1}^{K} (C^k_{n,t})^{\alpha^k_{n,t}} \qquad \sum_{k=1}^{K} \alpha^k_{n,t} = 1 \tag{6}$$

Households have two sources of income: wages, $w_{n,t}$ and deficits, $D_{n,t}/L_{n,t}$.[23] To maximize welfare, a typical household picks expenditure shares $\alpha^k_{n,t}$ s.t.

$$\alpha^k_{n,t} = \frac{P^k_{n,t} C^k_{n,t}}{w_{n,t} + D_{n,t}/L_{n,t}} \tag{7}$$

[22] In the model below I micro-found the gravity equation by using a multi-sector set-up of Eaton and Kortum (2002) as developed by Costinot et al. (2011). However, this specification is not necessary for any of the empirical results of the paper. Alternatively, one could use the supply side of several other models that deliver a gravity equation, such as those of Anderson and Van Wincoop (2003) or Krugman (1979).

[23] Trade deficits are necessary to exactly match observed data when computing equilibria in counterfactual changes. Throughout the paper, they serve as a source of exogenous income for households.

3.1.3 Production

In a given sector, productions entails combining services of different types of occupations. In the rest of the paper, I will refer to these services as *tasks*. There are three types of firms:

- **Task Producers** use labor $L^a_{n,t}$ to produce task services.
- **Variety Producers** combine task services to produce quantity $q^k_{n,t}(\omega_k)$ of variety ω_k in sector k of country n.
- **Sector Aggregators** combine varieties from the lowest cost producers of ω_k to produce the sector aggregate $Q^k_{n,t}$. These varieties can be imported from any country.

Task Producers

Tasks are indexed $a \in \mathbf{A} = \{1, ..., A\}$. The task production market is perfectly competitive and market prices of tasks are denoted by $p^a_{n,t}$. A firm in county n producing services of task a hires $L^a_{n,t}$ units of labor with mean task productivity $T^a_{n,t}$ at a market price $w^a_{n,t}$ per effective unit. A typical task producer solves the problem:

$$\max_{L^a_{n,t} \geq 0} p^a_{n,t} T^a_{n,t} L^a_{n,t} - w^a_{n,t} L^a_{n,t}$$

Variety Producers

The market for varieties is perfectly competitive. A firm in country n producing variety ω_k in sector k hires A different task inputs $\{t^a_{n,t}(\omega_k)\}^A_{a=1}$ to produce quantity $q^k_{n,t}(\omega_k)$. The TFP of a variety producer $z^k_{n,t}(\omega_k)$ is a random draw from a Frechet distribution with location and dispersion parameters $T^k_{n,t}$ and $\theta > 1$. The variety's production function is

$$q^k_{n,t}(\omega_k) = z^k_{n,t}(\omega_k) \prod_{a=1}^{A} (t^a_{n,t}(\omega_k))^{\zeta^k_a} \tag{8}$$

where factor shares ζ^k_a are uncorrelated with the sector-specific location parameter of TFP, $T^k_{n,t}$.[24] ζ^k_a are crucial parameters as they capture the similarity of production functions in any two given sectors, thereby governing the strength of inter-industry productivity spillovers. A typical variety producer solves the problem

[24]The assumption of independence between factor shares and sector-specific TFP ensures that a linear fitted relationship between sector-specific unit costs and factor shares reflects differences in relative task productivity levels. See also Malmberg (2017).

$$\max_{\{t^a_{n,t}(\omega_k)\geq 0\}^A_{a=1}} p^k_{n,t}(\omega_k)q^k_{n,t}(\omega_k) - \sum_{a=1}^A p^a_{n,t}t^a_{n,t}(\omega_k)$$

Sector Aggregators

The representative aggregator firm of sector k in country n combines varieties from the lowest cost producers of ω_k to produce the sector aggregate. Varieties can be imported from any country. The firm sells the sector aggregate to consumers and material producers in country n.

Aggregators face sector-specific trade costs that vary by importer-exporter pair and are denoted by $\tau^k_{nm,t}$ for importer n and exporter m. The trade costs take the usual iceberg form and satisfy the triangle inequality.

A typical aggregator solves the problem

$$\max_{\{q^k_{n,t}(\omega_k)\}_{\omega_k\in\Omega}} P^k_{n,t}Q^k_{n,t} - \int_0^1 p^k_{n,t}(\omega_k)q^k_{n,t}(\omega_k)$$
$$\text{s.t. } Q^k_{n,t} = [\int_0^1 (q^k_{n,t}(\omega_k))^{\frac{\xi-1}{\xi}} d\omega_k]^{\frac{\xi}{\xi-1}} \qquad ; \qquad \xi > 0$$

where $p^k_{n,t}(\omega_k)$ is the (unique) minimum price at which a firm in sector k producing variety ω_k can deliver that variety in country n, i.e. $p^k_{n,t}(\omega_k) = \min\{\frac{c^k_{i,t}(\omega_k)\tau^k_{ni,t}}{z^k_{i,t}(\omega_k)}; i = 1, ..., N\}$.

Households

Before being hired by a firm, households are homogeneous with respect to their task-specific productivity levels. Given task wages $\{w^a_{n,t}\}^A_{a=1}$ a household maximizes its income by sorting into a specific task a. This problem can be summarized as

$$\max_{\{\tilde{a}_a\}^A_{a=1}} \sum_{a=1}^A \tilde{a}_a w^a_{n,t}T^a_{n,t} \qquad \text{s.t. } \sum_{a=1}^A \tilde{a}_a = 1; \qquad \{\tilde{a}_a\}^A_{a=1} \in \{0,1\}^A$$

3.1.4 Equilibrium

Static Level Equilibrium

Given country-specific fundamentals, a static level equilibrium consists of a vector of prices

$\{w_{n,t}, \{P^k_{n,t}\}^K_{k=1}, \{w^a_{n,t}, p^a_{n,t}\}^A_{a=1}\}^N_{n=1}$ s.t.

- Task producers minimize unit costs:

$$p^a_{n,t} = w^a_{n,t} \tag{9}$$

- Variety producers minimize unit costs:[25]

  - $c^k_{n,t} = \Gamma_k \prod_{a=1}^{A} (p^a_{n,t})^{\zeta^k_a}$

- Aggregators source from lowest cost producers such that expenditure shares $\pi^k_{ni,t}$ and prices of sector aggregates $P^k_{n,t}$ equal:[26]

  - $P^k_{n,t} = \Lambda^k [\sum_{i=1}^{N} T^k_{i,t} (c^k_{i,t} \tau^k_{ni,t})^{-\theta}]^{-1/\theta}$
  - $\pi^k_{ni,t} = \frac{T^k_{i,t}[c^k_{i,t}\tau^k_{ni,t}]^{-\theta}}{\sum_{i'=1}^{N} T^k_{i',t}[c^k_{i',t}\tau^k_{ni',t}]^{-\theta}}$

- Households maximize income and utility:

$$w^a_{n,t} T^a_{n,t} = w^{a'}_{n,t} T^{a'}_{n,t} = w_{n,t} \quad \forall a, a' \in \mathbf{A} \tag{10}$$

$$\alpha^k_{n,t} = \frac{P^k_{n,t} C^k_{n,t}}{w_{n,t} + D_{n,t}/L_{n,t}} \tag{11}$$

- Trade is balanced for each country:

  - $\sum_{k=1}^{K} \sum_{i=1}^{N} \alpha^k_{n,t} (w_{n,t} L_{n,t} + D_{n,t}) \pi^k_{ni,t} = \sum_{k=1}^{K} \sum_{i=1}^{N} \alpha^k_{i,t} (w_{i,t} L_{i,t} + D_{i,t}) \pi^k_{in,t} + D_{n,t}$

- Goods and labor markets clear in each country

Static Counterfactual Equilibrium

Let $\{w_{n,t}, \{P^k_{n,t}\}_{k=1}^K, \{w^a_{n,t}, p^a_{n,t}\}_{a=1}^A\}_{n=1}^N$ denote an equilibrium under a set of country-specific fundamentals, and let $\{w'_{n,t}, \{(P^k_{n,t})'\}_{k=1}^K, \{(w^a_{n,t})', (p^a_{n,t})'\}_{a=1}^A\}_{n=1}^N$ denote an equilibrium under a different set of country-specific fundamentals. We can now define an equilibrium in relative changes, where a variable with a hat ($\hat{x}$) represents the relative change of that variable ($\hat{x} = x'/x$). A static counterfactual equilibrium consists of a vector of relative counterfactual prices $\{\hat{w}_{n,t}, \{\hat{P}^k_{n,t}\}_{k=1}^K, \{\hat{w}^a_{n,t}, \hat{p}^a_{n,t}\}_{a=1}^A\}$ s.t.

- $\hat{p}^a_{n,t} = \hat{w}^a_{n,t}$

- $\hat{c}^k_{n,t} = \prod_{a=1}^{A} (\hat{p}^a_{n,t})^{\zeta^k_a}$

- $\hat{P}^k_{n,t} = [\sum_{i=1}^{N} \pi^k_{ni,t} \hat{T}^k_{i,t} (\hat{c}^k_{i,t} \hat{\tau}^k_{ni,t})^{-\theta}]^{-1/\theta}$

- $\hat{\pi}^k_{ni,t} = \hat{T}^k_{i,t} [\frac{\hat{c}^k_{i,t} \hat{\tau}^k_{ni,t}}{\hat{P}^k_{n,t}}]^{-\theta}$

[25] Γ_k is a sector-specific constant. It does not play any role in this paper.
[26] Λ_k is a sector-specific constant. It does not play any role in this paper.

- $\hat{w}^a_{n,t}\hat{T}^a_{n,t} = \hat{w}^{a'}_{n,t}\hat{T}^{a'}_{n,t} = \hat{w}_{n,t} \quad \forall(a, a')$

- $\sum_{k=1}^{K}\sum_{i=1}^{N}\alpha^k_{n,t}(w_{n,t}L_{n,t}\hat{w}_{n,t} + D_{n,t})\pi^k_{ni,t}\hat{\pi}^k_{ni,t} = \sum_{k=1}^{K}\sum_{i=1}^{N}\alpha^k_{i,t}(w_{i,t}L_{i,t}\hat{w}_{i,t} + D_{i,t})\pi^k_{in,t}\hat{\pi}^k_{in,t} + D_{n,t}$

3.2 Dynamic Framework

3.2.1 Endogenous Task Productivity Growth

Task Production

The production of a task entails the completion of a continuum of *subtasks* $\omega_a \in [0,1]$.[27] A task producer hires a measure $L^a_{n,t}$ of ex ante homogeneous workers at the effective wage rate $w^a_{n,t}T^a_{n,t}$. After being hired, each worker is uniformly assigned to do one of the subtasks and produces this subtask at productivity $z_{n,t}(\omega_a)$. A worker's productivity $z_{n,t}(\omega_a)$ is drawn from a productivity distribution $G^a_{n,t}$ and represents the state-of-the-art technology or idea about how to produce subtask ω_a. Together, these workers produce a quantity $q^a_{n,t}$ of task a using a CES aggregator:

$$q^a_{n,t} = T^a_{n,t}L^a_{n,t} = [\int_0^1 (z^a_{n,t}(\omega_a))^{\frac{\chi-1}{\chi}}d\omega_a]^{\frac{\chi}{\chi-1}}L^a_{n,t} \qquad \chi > 0 \tag{12}$$

where $T^a_{n,t}$ captures the average productivity of a worker. χ is the elasticity of substitution between different subtasks.[28]

New Ideas

Within each time period, a worker assigned to subtask ω_a receives $n^a_{n,t} = n \cdot \tilde{n}^a_{n,t}$ new, random ideas with productivity z from exogenous distribution with CDF $H(z)$. This distribution has a Pareto right tail with exponent θ_H such that $\lim_{z\to\infty}(1 - H(z))/z^{-\theta_H} = 1$. Moreover, I assume that the initial knowledge frontier follows a Frechet distribution.[29]

Productivity Spillovers

Each worker combines an original random idea with insights from others. Every time a worker re-

[27] The concept of a *subtask* is analogous to a task as a variety is to a sector in Buera and Oberfield (2017). It is similar to the *trade* of a craftsman in De la Croix et al. (2017), who model historical labor productivity growth as 'learning on the shopfloor' through personal contact between a designated 'master' and an apprentice. The concept is not strictly necessary for any of the results in the paper but facilitates exposition.

[28] The value of χ is irrelevant for any of the empirical results as it affects only the absolute level, but not the relative level or growth of $T^a_{n,t}$.

[29] To satisfy Assumption 1 in Buera and Oberfield (2017), the *initial* frontier distribution of knowledge also needs to have a sufficiently thin right tail. This additional assumption is satisfied if the initial frontier of knowledge follows a Frechet distribution.

ceives random idea, it meets others with probability $p^a_{n,t} = p \cdot \tilde{p}^a_{n,t}$, so the number of successful meetings of a worker of type a follows a Binomial distribution with parameters $(n^a_{n,t}, p^a_{n,t})$. As $n \to \infty$ while $n \cdot p$ remains constant, this process converges to a Poisson distribution with an arrival rate of $\eta^a_{n,t} = n^a_{n,t} p^a_{n,t}$. When the two workers meet, they exchange ideas and potentially engage in technology adoption. I assume that this form of learning is external to any individual firm and/or worker.

If the worker producing variety ω_a chooses to adopt, the actual productivity of the new technology is $(z^a_{n,t}(\omega'_a))^\beta (z^a_{n,t}(H))^{1-\beta}$. $\beta \in [0,1)$ is an adoption parameter that captures the importance of ideas of others. A worker only adopts if the new technology is better than the old one, i.e. if $(z^a_{n,t}(\omega'_a))^\beta (z^a_{n,t}(H))^{1-\beta} > z^a_{n,t}(\omega_a)$.

Under these assumptions, the state-of-the-art productivity levels of a given variety ω_a are distributed Frechet (Buera and Oberfield, 2017) with CDF $F^a_{n,t} = exp(-\tilde{T}^a_{n,t} z^{-\theta_a})$, where $\theta_a = \frac{\theta_H}{1-\beta}$. The latter is assumed to be invariant across tasks. The location parameter $\tilde{T}^a_{n,t}$ of this distribution follows the law of motion:

$$\frac{\tilde{T}^a_{n,t}}{\tilde{T}^a_{n,t-1}} = n^a_{n,t} p^a_{n,t} \int_0^\infty x^{\beta\theta_a} dG^a_{n,t}(x) = n^a_{n,t} p^a_{n,t} \Gamma(1-\beta)(\tilde{T}^a_{n,t-1})^{\beta-1} \tag{13}$$

where $\Gamma(\cdot)$ is the Gamma function.

Expected task productivity, $T^a_{n,t}$ equals:

$$T^a_{n,t} = (\tilde{T}^a_{n,t})^{1/\theta_a} [\Gamma(1 - \frac{\chi-1}{\chi}\frac{1}{\theta_a})]^{\frac{\chi}{\chi-1}} \tag{14}$$

which follows the law of motion (in logs):

$$\Delta \ln T^a_{n,t} = \frac{1}{\theta_a}[\ln n^a_{n,t} p^a_{n,t} + \ln \Gamma(1-\beta) + (\beta - 1)\ln T^a_{n,t-1}] \tag{15}$$

where $\ln n^a_{n,t} p^a_{n,t}$ captures the arrival of new, successfully adopted ideas, $\ln \Gamma(1-\beta)$ captures an exogenous, time- and task-invariant component of productivity growth, and $(\beta - 1)\ln T^a_{n,t-1}$ captures a 'fishing-out' effect, as more productive ideas become harder to find when the knowledge frontier expands (as $\beta - 1 < 0$).

Dynamic Scale Economies

There is a long-standing literature in trade and growth examining the importance of dynamic scale economies for economic convergence and the dynamic welfare gains from trade (e.g. Krugman (1987), Grossman and Horn (1988), Young (1991), Stokey (1991)). In a large set of models the growth in productivity $T^x_{n,t}$ of a given sector or factor x takes the form:

$$\Delta \ln T^x_{n,t} = \beta_x + \tilde{\eta}_x \ln L^x_{n,t-1} + \phi \ln T^x_{n,t-1}; \qquad \tilde{\eta}_x > 0; \qquad \phi \leq 0 \tag{16}$$

where β_x is a constant, and $\phi \ln T^x_{n,t-1}$ captures convergence in productivity. $\tilde{\eta}_x \ln L^x_{n,t-1}$ reflect dynamic scale economies, i.e. dynamic increasing returns to the use of a production factor. The exact source of dynamic scale economies can differ depending on the setting, although most papers posit them either as a result of learning-by-doing (e.g. Krugman (1987), Lucas Jr (1988), Matsuyama (1992), Redding (1999), Mendoza (2010)) or human capital spillovers (e.g. Lucas Jr (1988), Stokey (1991), Lucas (2004), Lucas Jr (2015)).[30]

Consider the framework that generates the law of motion of task productivity growth, equation 15. Suppose the arrival rate of ideas is constant ($n^a_{n,t} = n \forall a, n, t$). Whether a meeting is successful (with probability $p^a_{n,t}$) depends on the share of workers engaged in the production of the task and task-specific learning spillovers. The latter manifest as increasing returns to scale in the production of task-specific knowledge. Specifically, the extent of learning spillovers depends on the required *team size* for a successful meeting, $\tilde{\eta}_a \geq 0$. I treat $\tilde{\eta}_a$ as a continuous variable in the rest of the paper.[31] In every time period, a worker of type a is randomly assigned to $\tilde{\eta}_a - 1$ other workers of the same type. The worker's meeting is successful if an only if all members of its team meet another worker of the same type, so $p^a_{n,t} = (L^a_{n,t}/L_{n,t})^{\tilde{\eta}_a}$, where $L^a_{n,t}/L_{n,t}$ is the share of workers in country n that are engaged in the production of task a.

I will now consider two extreme cases of these dynamic scale economies: pure learning-by-doing ($\beta = 0$) and pure human capital spillovers ($\beta \to 1$).

Pure Learning-by-doing

[30] A good example is the learning-by-doing model in Matsuyama (1992), later used by Mendoza (2010). If production is Cobb-Douglas, sector-specific TFP evolves according to $\Delta \ln T^k_{n,t} = \beta_k + \zeta \ln L^k_{n,t-1}$ where $\zeta \in (0,1)$ is the Cobb-Douglas exponent and $L^k_{n,t}$ the share of labor employed in sector k.

[31] The continuous interpretation is necessary in order to map the model to the data. Alternatively, one could interpret the estimated rate $\hat{\tilde{\eta}}_a$ in section IV as an average treatment effect of time- and/or country-dependent $\tilde{\eta}^n_{a,t}$.

If there is no diffusion of ideas between workers ($\beta = 0$), successfully arrived ideas for active workers are the only source of productivity growth. Any differences in task productivity growth between countries n and n' are driven by differences in the allocation of labor and initial task productivity, i.e.

$$\Delta \ln T^a_{n,t}/T^a_{n',t} = \frac{1}{\theta_a}[\tilde{\eta}_a \ln \frac{L^a_{n,t-1}/L^a_{n',t-1}}{L_{n,t-1}/L_{n',t-1}} + \ln T^a_{n,t-1}/T^a_{n',t-1}] \tag{17}$$

Pure Human Capital Spillovers

If active workers do not receive any new ideas ($\beta \to 1$), existing ideas from other workers are the only source of productivity growth to contribute meaningfully to any cross-country differences. As a consequence, any differences in task productivity growth between countries n and n' are approximately driven by differences in the allocation of labor only, i.e.

$$\Delta \ln T^a_{n,t}/T^a_{n',t} \approx \frac{1}{\theta_a}[\tilde{\eta}_a \ln \frac{L^a_{n,t-1}/L^a_{n',t-1}}{L_{n,t-1}/L_{n',t-1}}] \tag{18}$$

Combination of Mechanisms

In the rest of the paper, I do not take a stance on the relative importance of learning-by-doing or human capital spillovers, but posit the arrival rate of new ideas as:

$$\ln n^a_{n,t} p^a_{n,t} = \tilde{\eta}_a \ln L^a_{n,t-1}/L_{n,t-1} + \epsilon^a_{n,t} \tag{19}$$

where $\epsilon^a_{n,t}$ captures the arrival of new ideas independent from the scale of production, and $\tilde{\eta}_a$ is the elasticity of total new ideas with respect to the scale of production, $L^a_{n,t}$. As a consequence, the law of motion for task productivity growth now becomes:

$$\Delta \ln T^a_{n,t} = \frac{1}{\theta_a}[\ln \Gamma(1-\beta) + \tilde{\eta}_a \ln L^a_{n,t-1}/L_{n,t-1} + (\beta - 1)\ln T^a_{n,t-1} + \epsilon^a_{n,t}] \tag{20}$$

3.2.2 Equilibrium

Dynamic Level Equilibrium

Given country-specific fundamentals and initial task productivity levels $\{T^a_{n,t=1}\}^A_{a=1}$, a dynamic level equilibrium consists of a vector of prices

$\{\{w_{n,t}, \{P^k_{n,t}\}^K_{k=1}, \{w^a_{n,t}, p^a_{n,t}\}^A_{a=1}\}^N_{n=1}\}^T_{t=1}$ s.t.

- In each period $t = \tau$, given country-specific fundamentals and task productivity levels $\{T^a_{n,\tau}\}^A_{a=1}$, the price vector $\{w_{n,\tau}, \{P^k_{n,\tau}\}^K_{k=1}, \{w^a_{n,\tau}, p^a_{n,\tau}\}^A_{a=1}\}^N_{n=1}$ solves a static level equilibrium, as defined in section 3.1.4.

- Between two periods $t = \tau$ and $t = \tau - 1$, task productivity levels $\{\{T^a_{n,\tau}\}^A_{a=1}\}^T_{t=1}$ satisfy $\Delta \ln T^a_{n,t} = \frac{1}{\theta_a}[\ln \Gamma(1-\beta) + \tilde{\eta}_a \ln L^a_{n,t-1}/L_{n,t-1} + (\beta - 1)\ln T^a_{n,t-1} + \epsilon^a_{n,t}]$

Dynamic Counterfactual Equilibrium

A dynamic counterfactual equilibrium consists of a vector of relative counterfactual prices $\{\{\hat{w}_{n,t}, \{\hat{P}^k_{n,t}\}^K_{k=1}, \{\hat{w}^a_{n,t}, \hat{p}^a_{n,t}\}^A_{a=1}\}^T_{t=1}$ s.t.

- In each period $t = \tau$, given counterfactual task productivity levels $\{\{\hat{T}^a_{n,t}\}^A_{a=1}\}^T_{t=1}$, the price vector $\{\hat{w}_{n,t}, \{\hat{P}^k_{n,t}\}^K_{k=1}, \{\hat{w}^a_{n,t}, \hat{p}^a_{n,t}\}^A_{a=1}$ solves a static counterfactual equilibrium, as defined in 3.1.4.

- Between two periods $t = \tau$ and $t = \tau - 1$, counterfactual task productivity levels $\{\{\hat{T}^a_{n,\tau}\}^A_{a=1}\}^T_{t=1}$ satisfy

  $\hat{T}^a_{n,\tau} = [\hat{L}^a_{n,\tau-1}]^{\tilde{\eta}_a}(\hat{T}^a_{n,\tau-1})^{\beta-1}$

  $\hat{L}^a_{n,\tau-1} = \frac{\sum_{k=1}^K \zeta^k_a \sum_{i=1}^N (X^k_{in,\tau-1})'}{\sum_{k=1}^K \zeta^k_a \sum_{i=1}^N X^k_{in,\tau-1}} \frac{1}{\hat{w}_{n,\tau-1}}$

3.2.3 Balanced Growth

A simple balanced growth path exists in two cases. In both cases, the task-specific residual arrival rate $\epsilon^a_{n,t}$ must grow at an exponential rate, $\epsilon^a_{n,t} = \tilde{n}_0 \exp(\gamma^a_n t)$, to offset the fishing-out effect of a higher task productivity level (as $\theta_a(\beta - 1) < 0$). Task productivity $T^a_{n,t}$ grows at the rate $\frac{\gamma^a_n}{1-\beta}$.

In the first case, all countries are closed ($\tau^k_{ni,t} \to \infty \forall n \neq i$) and preferences and sector-specific productivity levels are constant over time. In this case, welfare grows at the country-specific rate $\frac{1}{1-\beta}\sum_{k=1}^K \alpha^k_n \sum_{a=1}^A \zeta^k_a \gamma^a_n$. A second balanced growth path exists in a symmetric world in which all countries are same in terms of fundamentals (preferences, trade costs, and productivity levels) but any degree of (symmetric) trade integration can exist. In this case, welfare grows at the general rate $\frac{1}{1-\beta}\sum_{k=1}^K \alpha^k \sum_{a=1}^A \zeta^k_a \gamma^a$.

In general, a balanced growth path does not exist if economies differ in terms of fundamentals and their is some degree of trade integration. However, a unique equilibrium path exists for any sequence of fundamentals as a sequence of static equilibria defined in section 3.1.4. These equilibria are connected by the law of motion of task productivity levels in equation 15. As firms and workers do not internalize any of the learning spillovers, there is no forward-looking behavior and the sequence of task productivity levels is solely determined by initial productivity levels and the sequence of fundamentals.

3.3 Welfare Implications

3.3.1 Static and Dynamic Gains from Trade

Counterfactual welfare in period t is given by

$$\ln \hat{w}_{n,t}/\hat{P}_{n,t} = -\sum_{k=1}^{K} \frac{\alpha_{n,t}^{k}}{\theta} \ln \hat{\pi}_{nn,t}^{k} + \sum_{k=1}^{K} \alpha_{n,t}^{k} \sum_{a=1}^{A} \zeta_{a}^{k} \tilde{\eta}_{a} \ln \hat{L}_{n,t-1}^{a} \tag{21}$$

This decomposition describes the welfare effects of integration as the product of two terms. The first term covers the usual static gains from trade (Arkolakis et al. (2012)): the more open -as measured by domestic expenditure shares- a country becomes (smaller $\hat{\pi}_{nn}^{k}$), the larger the welfare gains from trade. These gains are especially large if integration reduces a country's domestic expenditure shares more in sectors from which it consumes more (higher $\alpha_{n,t}^{k}$).

The second term is new and summarizes the dynamic effects from trade integration. In contrast to the first term, the dynamic term can contribute to lower welfare gains and could potentially lead to welfare losses if it is larger than the static gains. The direction of this effect depends on the changes in labor allocation at period $t = 1$. If the trade shock induces countries to shift labor into tasks ($\ln \hat{L}_{n,t-1}^{a} > 0$) with a high diffusion rate $\tilde{\eta}_{a}$, gains are higher. These gains are particularly elevated when labor reallocation leads to higher endogenous productivity growth in tasks that are used intensively (higher ζ_{k}^{a}) in sectors from which the country consumes more.

3.3.2 Planner Solution in a Closed Economy

Welfare in equation 21 is not necessarily optimized in the case of free trade nor autarky. To maximize welfare, a country must shift labor into sectors that use high spillover tasks intensively, while minimizing associated static welfare losses.

Consider a closed 2-period economy with K sectors and A tasks. Normalize $L_{n,t} = 1$. To optimize the sum of the static and dynamic welfare components in equation 21, a planner would solve the allocation of sector-specific task employment shares $\{\{L_{n,t}^{a,k}\}_{a=1}^{A}\}_{k=1}^{K}$ in two steps.

First, as task-specific labor from any sector are perfect substitutes in their contribution to future productivity (equation 15), the share of labor of task a allocated to sector k equals its relative contribution to current marginal utility, i.e.

$$L_{n,t}^{a,k} = \frac{\alpha_n^k \zeta_a^k}{\sum_{k'=1}^K \alpha_n^{k'} \zeta_a^{k'}} L_{n,t}^a \tag{22}$$

where $L_{n,t}^a$ is the share of total labor employed in task a. In turn, this share equals its relative contribution to the sum of discounted marginal utility over the two periods, i.e.

$$L_{n,t}^a = \frac{(1+\rho\tilde{\eta}_a)\sum_{k=1}^K \alpha_n^k \zeta_a^k}{\sum_{a'=1}^A (1+\rho\tilde{\eta}_{a'})\sum_{k'=1}^K \alpha_n^{k'} \zeta_{a'}^{k'}} \tag{23}$$

where $\rho \in (0,1)$ is a discount factor. In a decentralized equilibrium, on the other hand:

$$L_{n,t}^a = \frac{\sum_{k=1}^K \alpha_n^k \zeta_a^k}{\sum_{a'=1}^A \sum_{k'=1}^K \alpha_n^{k'} \zeta_{a'}^{k'}} \tag{24}$$

Note that the decentralized and planner equilibrium coincide if the strength of diffusion $\tilde{\eta}_a$ is the same across tasks, or when $\alpha_n^k \zeta_a^k$ is the same across sectors. In the end, whether the decentralized allocation is optimal depends on the extent to which workers and firms internalize learning spillovers. To facilitate the analysis, I assume an extreme case in which there is not internalization whatsoever. An interesting question for further research is how the model's predictions would change if one loosens this assumption.

3.3.3 Gains from Trade in a Small Open Economy

While the decentralized allocation is not necessarily efficient under trade (nor autarky), this does not imply that the gains from trade are negative for countries that have a comparative advantage in low spillover sectors. First, even if there are dynamic efficiency losses from specializing in these kinds of sectors, trade integration always features static efficiency gains through lower prices. Second, if trade integration gives a country access to a larger export market in high spillover sectors, it can achieve productivity gains by exporting in these sectors while achieving static efficiency gains from cheaper imports.

Consider an open economy that is small in the sense that it does not impact other countries' productivity levels, wages and prices. Preferences differ by country but are constant over time. Over two periods, welfare in counterfactual changes takes the form

$$\ln \hat{w}_{n,t}/\hat{P}_{n,t} + \rho \ln \hat{w}_{n,t+1}/\hat{P}_{n,t+1} = -\sum_{k=1}^{K}[\frac{\alpha_n^k}{\theta}\ln\hat{\pi}_{nn,t}^k + \rho\frac{\alpha_n^k}{\theta}\ln\hat{\pi}_{nn,t+1}^k] + \sum_{k=1}^{K}\alpha_n^k\sum_{a=1}^{A}\zeta_a^k\tilde{\eta}_a \ln\hat{L}_{n,t}^a \tag{25}$$

where $\rho \in (0,1)$ is a discount factor.

Suppose that a country's trade costs change by a factor τ that is common to all country-sector-pairs ($\tau^k_{ni,t} = \tau\tilde{\tau}^k_{ni,t}$). In the short-run, the change only impacts the static welfare gains from trade. Total differentiation of the short-run impacts in equation 25 gives

$$\frac{d\ln\frac{w_{n,t}}{P_{n,t}}}{d\tau} = -\sum^{K}\frac{\alpha^k_n}{\theta}\frac{\partial\ln\pi^k_{nn,t}}{\partial\tau} = -\frac{1}{\tau} + \frac{\partial\ln w_{n,t}}{\partial\tau}[1 - \sum_{k=1}^{K}\alpha^k_n\frac{\partial\ln P^k_{n,t}}{\partial w_{n,t}}] \tag{26}$$

where the first term is the direct effect of the change in trade costs on the price index and the second term captures the general equilibrium effect of the change on the country's wage. In the long-run (at $t+1$), the change in trade costs also affects the country's productivity:

$$\frac{d\ln\frac{w_{n,t+1}}{P_{n,t+1}}}{d\tau} = -\sum^{K}\alpha^k_n[\frac{1}{\theta}\frac{\partial\ln\pi^k_{nn,t+1}}{\partial\tau} - \sum_{a=1}^{A}\zeta^k_a\frac{\partial\ln T^a_{n,t+1}}{\partial\tau}] = \frac{\partial\ln w_{n,t+1}}{\partial\tau} - \sum_{k=1}^{K}\alpha^k_n\frac{\partial\ln P^k_{n,t}(\tau,\{\ln T^a_{n,t+1}\}^A_{a=1})}{\partial\tau} \tag{27}$$

which is equivalent to

$$-\frac{1}{\tau} + \frac{\partial\ln w_{n,t+1}}{\partial\tau}[1 - \sum_{k=1}^{K}\alpha^k_n\frac{\partial\ln P^k_{n,t+1}}{\partial w_{n,t+1}}] - \sum_{k=1}^{K}\alpha^k_n\sum_{a=1}^{A}\frac{\partial\ln P^k_{n,t}}{\partial\ln T^a_{n,t+1}}\frac{\partial\ln T^a_{n,t+1}}{\partial\tau} \tag{28}$$

where the first two terms are the short-term effects identified earlier, and the third term captures dynamic productivity effects of trade integration.

Dynamic scale economies affects welfare through $\frac{\partial\ln T^a_{n,t+1}}{\partial\tau}$. Unpacking this term further gives:

$$\frac{\partial\ln T^a_{n,t+1}}{\partial\tau} = \tilde{\eta}_a[\frac{\sum_{i=1}^{N} w_{i,t}\sum_{k=1}^{K}\alpha^k_{i,t}\zeta^k_a\frac{\partial\pi^k_{in,t}}{\partial\tau}}{L^a_{n,t}w_{n,t}} + \frac{\partial\ln w_{n,t}}{\partial\tau}[\frac{\partial\ln L^a_{n,t}w_{n,t}}{\partial\ln w_{n,t}} - 1]] \tag{29}$$

where the first term is the effect of reallocation of labor caused directly by the change in trade costs, and the second term captures the general equilibrium effect of the change on reallocation through a change in domestic income.

The first term reflects the effect of foreign demand on task productivity growth. If the change in the import share of foreign countries $\frac{\partial\pi^k_{in,t}}{\partial\tau}$ is stronger for richer ones with greater demand in sectors that use this particular task intensively, the effect on task productivity growth is stronger. As a result, if trade integration leads a country to export to countries that consume more in sectors that use high spillover tasks intensively than its own consumption share, the exporting country achieves higher productivity growth under trade than under autarky while it also benefits from lower import prices.

4 Estimation Strategy

4.1 Productivity Parameters

This section outlines the procedure for estimating and calibrating the following productivity parameters: the dispersion parameters of the Frechet distributions of task productivity (θ_a) and sectoral TFP (θ), the adoption parameter (β) that governs convergence of task productivity, the sectoral output elasticities of different tasks (ζ_a^k), and, ultimately, the diffusion parameters ($\tilde{\eta}_a$) that govern the extent of dynamic scale economies for different tasks.

I calibrate the dispersion parameters externally using estimates from the literature. Specifically, I set the trade elasticity θ to 4 (Simonovska and Waugh (2014)) and θ_a to 1.13 (Burstein et al. (2015)). Moreover, I calibrate ζ_a^k to the sector- and occupation-specific wage share of tradable sectors in the United States in 1970.[32]. This leaves the rest of this section to the estimation of β and $\tilde{\eta}_a$.

4.1.1 Comparative Advantage

Several international GE models -including the EK-style model outlined above- deliver a gravity equation of the form:

$$\ln \pi_{nm,t}^k = \delta_{m,t}^k + \mu_{n,t}^k - \theta \ln \tau_{nm,t}^k \tag{30}$$

where $\pi_{nm,t}^k$ is the import share of country n from country m in sector k. $\delta_{m,t}^k$ is an exporter-specific fixed effect in sector k, $\mu_{n,t}^k$ is an importer-specific fixed effect, and $\theta \ln \tau_{nm,t}^k$ covers the sector-specific effect of trade costs $\tau_{nm,t}^k$ between the two countries that affect the trade share with elasticity θ.

If $\tau_{ni,t}^k = \tau_{in,t}^k \; \forall n \neq i$ and $\tau_{nn',t}^k = 1 \; \forall n = n'$ (Head and Ries (2001)), one can recover trade costs using[33]

$$\tau_{ni,t}^k = [\frac{\pi_{ni,t}^k}{\pi_{nn,t}^k} \frac{\pi_{in,t}^k}{\pi_{ii,t}^k}]^{\frac{-1}{2\theta}} \tag{31}$$

In an Eaton-Kortum type model (e.g. Caliendo and Parro (2015)), the exporter- and importer-

[32]For details on occupational groups and micro-data used for wage sector- and occupation-specific wage shares, see section 5 and Appendix D

[33]I choose to specify trade costs symmetrically to be consistent with the counterfactual exercise in section 7.1. An alternative would be to specify trade costs as a sector- and year-specific log-linear function of distance variables (e.g. Levchenko and Zhang (2016), Bartelme et al. (2019)). Using this specification, estimated comparative advantage terms or spillover parameters are not qualitatively different.

specific fixed effects take the form

$$\delta^k_{m,t} = -\theta \ln c^k_{m,t}/\bar{c}^k_t + \ln T^k_{n,t}/\bar{T}^k_t \tag{32}$$

$$\mu^k_{n,t} = \ln \Phi^k_{n,t}/\bar{\Phi}^k_{n,t} \tag{33}$$

where a bar over a variable refers to its global (unweighted) mean. The exporter-specific fixed effect thus captures *effective* unit costs of country m in sector k, which reflect the country's comparative advantage in that sector.[34] The importer-specific fixed effect captures the 'multilateral resistance' in sector k of country n such that $\Phi^k_{n,t} = (\sum_{i=1}^N T^k_{i,t}(c^k_{i,t}\tau^k_{ni,t})^{-\theta})^{-1}$. Hanson et al. (2015), following Eaton et al. (2012), recast this gravity equation to allow for zero trade flows by assuming that in each industry-country pair only a finite number of firms make productivity draws. As a result, equation 30 holds only in expectation:

$$\mathbb{E}[\pi^k_{nm,t}] = \frac{exp[\delta^k_{m,t} - \theta \ln \tau^k_{nm,t}]}{exp[\mu^k_{n,t}]} \tag{34}$$

Combining the gravity and unit cost equations, and expressing them relative to the global mean yields an estimating equation

$$\ln \mathbb{E}[\pi^k_{nm,t}] = \underbrace{\ln T^k_{m,t}/\bar{T}^k_t - \theta \ln c^k_{m,t}/\bar{c}^k_t}_{\text{exporter fixed effect } \delta^k_{m,t}} \quad \underbrace{+\Phi^k_{n,t}/\bar{\Phi}^k_{n,t}}_{\text{importer fixed effect } \mu^k_{n,t}} \quad -\frac{1}{2}\ln \frac{\pi^k_{ni,t}}{\pi^k_{nn,t}}\frac{\pi^k_{in,t}}{\pi^k_{ii,t}} + \nu^k_{nm,t} \tag{35}$$

where $\nu^k_{nm,t}$ is a mean-zero misspecification term. I estimate equation 35 separately for each sector and year under the constraint that the exporter and importer fixed effects each sum up to zero. I use both log-linear OLS and PPML (Silva and Tenreyro, 2006). [35]

4.1.2 Spillovers

Changes in a country's sector-specific *effective* unit costs $\tilde{c}^k_{n,t}$ can be expressed as

$$\Delta \ln \tilde{c}^k_{n,t} = \Delta \ln c^k_{n,t} - \Delta \ln T^k_{n,t} \tag{36}$$

[34] Note that in a world without trade costs ($\tau^k_{ni,t} = 1 \forall n, i \in N$), the exporter fixed effects are a measure of revealed comparative advantage (RCA), i.e. for any two countries n and m and any two sectors k and k', $\ln \frac{RCA^k_{n,t}/RCA^{k'}_{n,t}}{RCA^k_{m,t}/RCA^{k'}_{m,t}} = \frac{\delta^k_{n,t}/\delta^{k'}_{n,t}}{\delta^k_{m,t}/\delta^{k'}_{m,t}}$. See also Appendix section B.

[35] The correlation between the estimated fixed effects of these two methods is always higher than 0.99. In the rest of the paper I use the OLS estimates whenever referring to results or computations based on these fixed effects

Using the definition of unit costs and arbitrage in the labor market gives

$$\Delta \ln \tilde{c}^{k}_{n,t} = \Delta \ln w_{n,t} - \sum_{a=1}^{A} \zeta^{k}_{a} \Delta \ln T^{a}_{n,t} - \Delta \ln T^{k}_{n,t} \tag{37}$$

In the endogenous growth model outlined above, we can express the growth of the task productivity level $T^{a}_{n,t}$ in log changes as

$$\Delta \ln T^{a}_{n,t} = \beta_0 + \frac{1}{\theta_a} \tilde{\eta}_a \ln L^{a}_{n,t-1} + (\beta - 1) \ln T^{a}_{n,t} + \epsilon^{a}_{n,t} \tag{38}$$

where β_0 is a constant, $\eta^{a}_{n,t}$ is a diffusion parameter that differs by task, country and time. $\epsilon^{a}_{n,t}$ is a shock specific to task a in country n at time t. Plugging this expression into equation 37 on the right-hand-side, and the definition of the exporter fixed effect on the left-hand-side, while expressing all to the global unweighted mean, yields an estimating equation:

$$\frac{1}{\theta} \Delta \delta^{k}_{n,t} = \underbrace{-\beta_0}_{\text{constant}} - \frac{1}{\theta_a} \sum_{a=1}^{A} \tilde{\eta}_a \zeta^{k}_{a} \ln L^{a}_{n,t-1} / L_{n,t-1} + (\beta - 1) \frac{1}{\theta} \delta^{k}_{n,t-1} + \gamma_{n,t} + \tilde{\epsilon}^{k}_{n,t} \tag{39}$$

where $\gamma_{n,t}$ is a fixed effect that captures $\Delta \ln w_{n,t} + (1-\beta) \ln w_{n,t-1}$, and $\tilde{\epsilon}^{k}_{n,t}$ is a an error term capturing $\sum_{a=1}^{A} \zeta^{k}_{a} \epsilon^{a}_{n,t} - \Delta \ln T^{k}_{n,t} + (1-\beta) \ln T^{k}_{n,t-1}$.[36] The only unknown param of interest are $\tilde{\eta}_a$, and β. $\frac{1}{\theta} \Delta \delta^{k}_{n,t}$ and $\frac{1}{\theta} \delta^{k}_{n,t-1}$ can be constructed using a value of θ and gravity estimates. I first estimate equation 39 for 10 year periods using OLS.

This naive estimation method raises endogeneity issues, however. A potential concern could be that producers in fast-growing sectors preemptively increase production in period $t-1$, anticipating productivity growth between t and $t-1$. Such anticipatory behavior would generate a correlation between $\zeta^{k}_{a} L^{a}_{n,t-1}$ and $\zeta^{k}_{a} \epsilon^{a}_{n,t}$ or between $\zeta^{k}_{a} L^{a}_{n,t-1}$ and $\Delta \ln T^{k}_{n,t}$. To circumvent these kind of supply side concerns, I rely on foreign demand shocks that generate variation in the task employment share $L^{a}_{n,t} / L_{n,t}$.

Note that the task employment share has a model-implied equivalent in the weighted average of exports, i.e.

$$L^{a}_{n,t} / L_{n,t} = \frac{\sum_{k=1}^{K} \zeta^{k}_{a} \sum_{n'=1}^{N} X^{k}_{n'n,t}}{\sum_{k=1}^{K} \sum_{n'=1}^{N} X^{k}_{n'n,t}} \tag{40}$$

Using the gravity equation in section 9, exports of country n in sector k can be expressed as (relative

[36] Note that under the assumption that both $T^{k}_{n,t}$ and $\epsilon^{a}_{n,t}$ are orthogonal to ζ^{k}_{a} the regression coefficient on $\zeta^{k}_{a} \ln \frac{L^{a}_{n,t-1}}{L_{n,t-1}}$ etersyields consistent estimates of $\frac{1}{\theta_a} \tilde{\eta}_a$ using OLS.

to the global mean):

$$\sum_{n' \neq n}^{N} X_{n'n,t}^{k} = \delta_{n,t}^{k} \cdot \underbrace{\sum_{n' \neq n}^{N} E_{n',t}^{k} \mu_{n',t}^{k} (\tau_{n'n,t}^{k})^{-\theta}}_{FMA_{n,t}^{k}} \tag{41}$$

where $\delta_{n,t}^{k}$ captures effective unit costs relative to the global mean and $E_{n',t}^{k}$ is total expenditure of country n' in sector k. While the exporter fixed effect reflects the effect of supply side factors in country n on its exports, the second term captures foreign demand. I will refer to this sum of foreign demand factors as Foreign Market Access (FMA) (Bartelme et al. (2019)).

I can now construct a synthetic measure of task employment share that is only driven by demand shocks. Removing supply side variation by setting effective unit costs to the global mean:

$$(L_{n,t}^{a}/L_{n,t})^{FMA} = \frac{\sum_{k=1}^{K} \zeta_{a}^{k} \cdot FMA_{n,t}^{k}}{\sum_{k=1}^{K} FMA_{n,t}^{k}} \tag{42}$$

I also estimate equation 39 using this demand shock driven measure of task employment. Finally, I run IV 2SLS using $(L_{n,t}^{a}/L_{n,t})^{FMA}$ as instruments for $L_{n,t}^{a}/L_{n,t}$.

4.2 Demand Parameters

On the demand side, I need to estimate preference parameters $\alpha_{n,t}^{k}$ in order to perform counterfactuals and construct measures of welfare. I do this by calibrating $\alpha_{n,t}^{k}$ as a country's expenditure share in sector k at time t, i.e.

$$\alpha_{n,t}^{k} = \frac{\sum_{i=1}^{N} X_{ni,t}^{k}}{\sum_{k=1}^{K} \sum_{i=1}^{N} X_{ni,t}^{k}} \tag{43}$$

5 Data

This section briefly describes data sources and implementation strategy. See Appendix D for details on steps taken.

5.1 Occupations

A challenge for the estimation of the parameters governing task productivity growth is that there are potentially hundreds of occupations and thus potentially hundreds of parameters that can be estimated using only limited variation in the trade data. To reduce the number of estimable parameters, I assign occupations into four groups based on the task content of their work.[37]

[37] Although there are some standard classifications that assign occupations to broad groups, these tend to be based on the sectors in which occupations are mainly active, and not the occupations task content. As a result, these classifications do a poor job capturing occupational linkages between sectors. The International Standard Classification Occupations ISCO-

I use data on tasks ('Work Activities') in O*NET to assign each occupation in the BLS Standard Occupational Classification (SOC) to an occupational group, which I call task groups. First, I reduce the task space from 41 to 5 tasks by assigning each task to one of five groups (Table A1): (i) information-intensive tasks (e.g. "Analyzing Data or Information"), (ii) planning-intensive tasks (e.g. "Performing Administrative Activities"), (iii) equipment-intensive tasks (e.g. "Inspecting Equipment, Structures or Material"), (iv) mechanical tasks (e.g. "Performing General Physical Activities"), and (v) contact tasks (e.g. "Establishing and Maintaining Interpersonal Relationships").

Next, I normalize each occupations' score for a task ('task score') and rank all occupations according to each task score. Finally, I assign an occupation to the task for which it has the highest rank. Table A2 shows the five highest ranked occupations and sectors (by share of total wages) for each of the information, planning, equipment and mechanical tasks. In the subsequent empirical analysis, I focus on these four non-contact tasks.[38]

5.2 Productivity Parameters

Estimation of comparative advantage, and, ultimately, spillover parameters requires data on (i) bilateral sectoral trade flows $X^k_{ni,t}$, and (ii) task-level sectoral wage shares ζ^k_a, (iii) as well as estimates of task employment shares $L^a_{n,t}/L_{n,t}$.

Data on bilateral sectoral trade flows are from the World Trade Flows (WTF) database developed by Feenstra et al. (2005). These cover UN COMTRADE bilateral trade between country pairs at the disaggregated four digit SITC2 level for the years 1962-2000. I aggregate goods to the level of industries from the 1950 Census Bureau industrial classification system to be able to calibrate task-level sectoral wage shares. Table A3 in the Appendix contains the corresponding list of sectors. The rest of my procedure follows Hanson et al. (2015), leaving me with 87 countries and 61 tradable sectors. See Appendix D for details.

Micro-data on sector- and occupation-specific wages are from the IPUMS USA 1970 Census. I consider only wage income and consider both part-time and full-time employment. I then calculate the wage share as total wages paid to an occupational group in a sector as a share of total wages paid in that same sector.

08, for example, assigns all agricultural workers to one of eight groups, and most service and sales workers to another. The BLS Standard Occupational Classification (SOC) assigns almost all occupations to its major groups based on sector, for example, Healthcare Support Occupations and Farming, Fishing, and Forestry Occupations. Moreover, SOC's highest level of aggregation includes 23 major groups, without an obvious method of clustering these into smaller groups.

[38] An alternative method for classifying would be to assign shares of working time of each occupation to tasks. Unfortunately, O*NET contains only ordinal data on the relative importance of tasks for a given occupation.

I consider two measures of task employment shares $L^a_{n,t}/L_{n,t}$. As I lack domestic expenditure data at a detailed sector level, I use only export data to construct shares. First, I construct a share based on reported exports, i.e.

$$L^a_{n,t}/L_{n,t} = \frac{\sum_{k=1}^{K} \zeta^k_a \sum_{n' \neq n}^{N} X^k_{n'n,t}}{\sum_{k=1}^{K} \zeta^k_a \sum_{n' \neq n}^{N} X^k_{n'n,t}} \tag{44}$$

Second, I construct shares based on estimated foreign market access (equation 42).

6 Results

6.1 Productivity

6.1.1 Effective Unit Costs

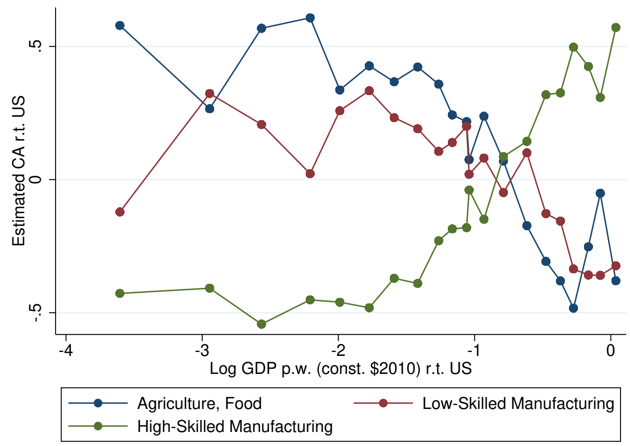
Figure 3 shows a binned scatterplot with estimates of countries' comparative advantage (or inverse effective unit costs) in the three tradable clusters plotted against GDP per worker, where both are expressed relative to the United States. I present these inverse effective unit cost terms as a weighted average (by exports) of the exporter fixed effects in equation 35. In line with the evidence presented in section 2, poorer countries tend to have lower effective unit costs in agriculture, which increases relative to the U.S. as they become more productive. Comparative advantage in low-skilled manufacturing and mining is hump-shaped in GDP per worker, increasing for poorer countries but declining for advanced economies. In contrast, effective unit costs in high-skilled manufacturing are relatively flat for the poorest economies in the sample but decrease steeply as countries catch up to the frontier.

6.1.2 Spillovers

Table 2 presents the estimation results for spillovers from estimating equation 39. Column (1) and (2) report estimates using exports- and FMA-based task employment shares, and column (3) reports estimates of an IV 2SLS procedure with the FMA-based shares as an instruments for the exports-based shares.

There is considerable and significant heterogeneity in the coefficients of spillover parameters $\tilde{\eta}_a$ of different tasks. For all specifications, the point estimates of the spillover parameter is highest for planning tasks (1.2 to 5.1) and also large for information tasks (0.5 to 0.7). These contrast with estimated spillovers for equipment (0.2 to 0.6) and mechanical tasks (0.1 to 0.3). Hence overall, estimated spillovers are higher for tasks generally performed by high-skilled labor than for those performed more often by low-skilled labor.

Figure 3: Estimated Comparative Advantage (Inverse Effective Unit Costs) and GDP per worker r.t. U.S.



Notes: This figure presents a binned scatterplot of countries' estimated comparative for the three tradable clusters against log GDP p.w. for the World Trade Flows sample from 1970 to 2000. These inverse effective unit cost terms are a country's weighted average (by exports) of exporter fixed effects in a cluster as estimated in equation 35. Real GDP per worker (constant $2010) data are from Penn World Tables 9.0.

Another apparent feature of the results is the robust and substantially negative estimate of the convergence parameter, $\beta - 1$. It is relatively precisely estimated around -.45, indicating that, over a 10 year period, comparative advantage at one tenth of the global frontier catches up to that same frontier by about 11 percent per year. Through the lens of the model in section 3.2, an 0.55 estimate of β suggests a roughly equal importance of learning-by-doing forces and human capital spillovers. It is only slightly lower than the calibrated estimate of 0.6 in Buera and Oberfield (2017).

In the rest of the paper, I will use the estimates in column (2) of Table 2 to perform quantitative exercises. A first implication of the heterogeneity in spillovers concerns how they aggregate to the sector level. Producing in sectors that use high-skill planning and information tasks intensively, has a larger positive effect on aggregate productivity because spillovers are higher in these high-skill tasks. Table A5 in the Appendix reports the relative effect of allocating labor to sectors on aggregate productivity. In general, inter-industry spillovers are highest in technologically advanced sectors (e.g. electrical and optical equipment, chemicals) at intermediate levels for low-skilled manufacturing sectors (e.g. textiles, furniture, toys) and mining, and lowest in agriculture. See section E.1 in the Appendix for details.

Table 2: Estimated Spillovers

	(1) Exports	(2) Foreign demand shocks	(3) IV 2SLS
η_{plan}	1.202***	1.842***	5.066 ***
	(0.181)	(0.466)	(0.448)
η_{info}	0.731***	0.724***	0.528***
	(0.0431)	(0.121)	(0.0642)
η_{equip}	0.238***	0.629**	0.118**
	(0.0337)	(0.110)	(0.0385)
η_{mech}	0.142***	0.164**	0.350**
	(0.0194)	(0.0491)	(0.0263)
$\beta - 1$	-0.467***	-0.449***	-0.476***
	(0.00903)	(0.00893)	(0.00611)
Country-year FE	Y	Y	Y
Observations	91626	91626	91626
Adjusted R^2	0.464	0.455	

Standard errors in parentheses, clustered at country-year level.
2SLS uses 1000 bootstrap replications to compute standard errors.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table reports estimates of different specifications of estimating equation 39. All specifications include country-year fixed effects. Column (1) reports estimates using task employment shares based on export data (equation 44). Column (2) reports estimates using task employment shares based on foreign market access estimates (equation 42). Column (3) reports estimates for an IV 2SLS procedure with employment shares from Column (2) as instruments for those in Column (1).

6.2 Model Fit

6.2.1 Sectoral Productivity Growth

I will now assess the extent to which the model can account for measured changes in sectoral unit costs. Using the gravity estimates from 35, we can express the change in log unit costs from 1970 to 2000 relative to the (unweighed) global mean as:

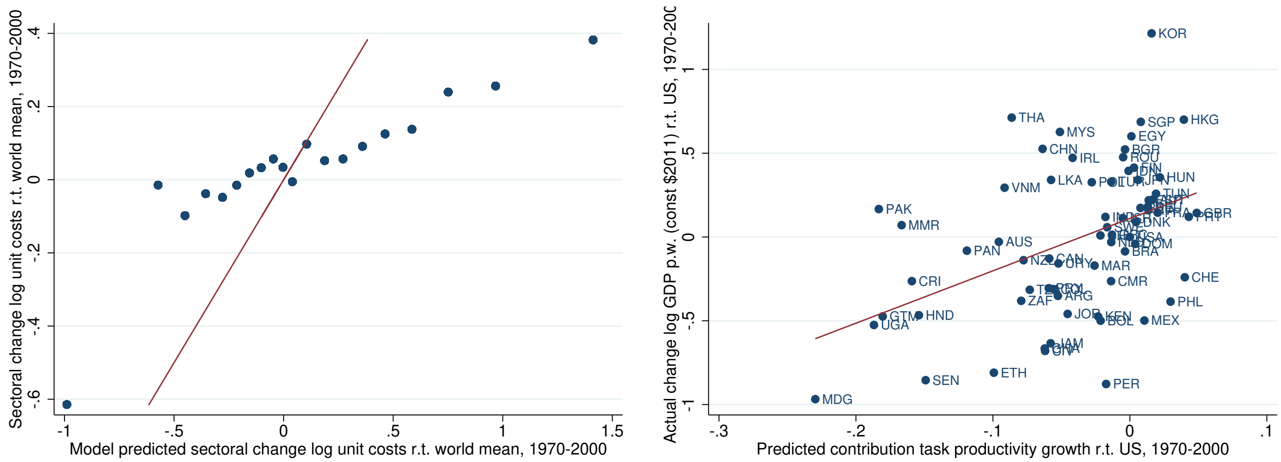
$$\sum_{t=1980}^{2000} \Delta \ln \frac{c_{n,t}^k}{\bar{c}_t^k} = \sum_{t=1971}^{2000} [\Delta \ln \frac{w_{n,t}}{\bar{w}_t} - \Delta \ln \frac{T_{n,t}^k}{\bar{T}_{n,t}^k} - \frac{1}{\theta_a} \sum_{a=1}^{A} (\zeta_a^k \tilde{\eta}_a \ln \frac{L_{n,t-1}^a}{\bar{L}_{n,t-1}^a} + \epsilon_{n,t}^a - \bar{\epsilon}_{n,t}^a) + (\beta - 1) \ln \frac{c_{n,t-1}^k}{\bar{c}_{n,t-1}^k}] \tag{45}$$

where bars refer to variables expressed in terms of the global mean. Out of the five sources of relative changes in unit costs (wages, sectoral TFP, spillovers, convergence, and residual country-specific growth) I can construct an estimate of the contribution of spillovers and convergence using estimates of $\tilde{\eta}_a$, β, $L_{n,t-1}^a$ and $c_{n,t}^k$. Formally, I construct 'sector-level' accumulated spillovers as:

$$\sum_{t=1980}^{2000} [\tfrac{1}{\theta_a} \sum_{a=1}^{A} (\zeta_a^k \tilde{\eta}_a \ln \tfrac{L_{n,t-1}^a}{\bar{L}_{n,t-1}^a} + (\beta - 1) \ln \tfrac{c_{n,t-1}^k}{\bar{c}_{n,t-1}^k}]$$

Figure 4 shows a binned scatterplot of these accumulated spillovers against estimated relative changes

Figure 4: Model Predicted Accumulated Spillovers and Actual Sectoral and Aggregate Productivity Growth



Notes: The left figure plots changes in estimated sector-level effective unit costs between 1970 and 2000 (equation 35) against sector-level accumulated spillovers $\sum_{t=1980}^{2000}[\frac{1}{\theta_a}\sum_{a=1}^{A}(\zeta_a^k\tilde{\eta}_a \ln \frac{L^a_{n,t-1}}{\bar{L}^a_{n,t-1}} + (\beta-1)\ln\frac{c^k_{n,t-1}}{\bar{c}^k_{n,t-1}}]$ predicted by the model. Both are expressed relative to the (unweighted) global mean in each sector. The right figure plots changes in real GDP p.w. (national prices) between 1970 and 2000 against aggregate accumulated spillovers $\sum_{t=1980}^{2000}\theta^k_{US,t-1}\sum_{a=1}^{A}[\frac{1}{\theta_a}\sum_{a=1}^{A}(\zeta^k_a\tilde{\eta}_a\ln\frac{L^a_{n,t-1}}{L^a_{US,t-1}}]$ predicted by the model.

in effective unit costs, $\sum_{t=1971}^{2000}\Delta\ln\frac{c^k_{n,t}}{\bar{c}^k_t}$. The model performs well in this regard. Indeed, on average the model predicts about 23 % of the variation in measured relative changes in unit costs for the entire sample. Quantitatively, the model predicted accumulated spillovers are on average somewhat more extreme.

6.2.2 Aggregate Productivity Growth

Aggregate labor productivity $y_{n,t}$ is the weighted average of value added labor productivity $y^k_{n,t}$ in individual sectors:

$$y_{n,t} = \sum_{k=1}^{K} L^k_{n,t} y^k_{n,t} \tag{46}$$

where $L^k_{n,t}$ is a sector's employment share. Up to a first order, aggregate labor productivity growth can be expressed as (Rodrik, 2011):

$$\Delta \ln y_{n,t} \approx \sum_{k=1}^{K}\theta^k_{n,t-1}\sum_{a=1}^{A}\zeta^k_a\Delta\ln T^a_{n,t} + \sum_{k=1}^{K}\theta^k_{n,t-1}[\Delta\ln P^k_{n,t} + \Delta\ln T^k_{n,t}] + \sum_{k=1}^{K}\frac{y^k_{n,t-1}}{y_{n,t-1}}\Delta L^k_{n,t} \tag{47}$$

where $\theta^k_{n,t-1}$ is the value added share of sector k in period $t-1$. Plugging in the evolution task productivity growth and ignoring the second reallocation term:

$$\Delta \ln y_{n,t} \approx \sum_{k=1}^{K} \theta^k_{n,t-1} \sum_{a=1}^{A} \zeta^k_a \tilde{\eta}_a \ln L^a_{n,t-1} + \sum_{k=1}^{K} \theta^k_{n,t-1} [\Delta \ln P^k_{n,t} + \Delta \ln \tilde{T}^k_{n,t} + \sum_{a=1}^{A} \zeta^k_a [\beta_0 + \phi \ln T^a_{n,t-1} + \epsilon^a_{n,t}] \tag{48}$$

Similar to the sector-level case, I can now construct 'aggregate' accumulated spillovers. Aggregating sectors using United States value added shares and expressing task productivity growth relative to the U.S. gives a measure of these spillovers:[39]

$\sum_{t=1980}^{2000} \theta^k_{US,t-1} \sum_{a=1}^{A} [\frac{1}{\theta_a} \sum_{a=1}^{A} (\zeta^k_a \tilde{\eta}_a \ln \frac{L^a_{n,t-1}}{L^a_{US,t-1}}]$

Figure 4 plots these accumulated spillovers against changes in real GDP per worker (at national prices) between 1970 and 2000. Again, the model performs well in this regard. On average the model predicts about 22 % of the variation in real GDP per worker. Quantitatively, however, the model predicted contribution of spillovers to aggregate productivity growth is smaller than the data.

7 Quantitative Implications

7.1 Inter-Industry Spillovers and Economic Convergence

What is the role of inter-industry spillovers in accounting for cross-country convergence in aggregate productivity? I explore this counterfactual by setting $\tilde{\eta}_a = 0$ for all tasks, shutting down the effect of dynamic scale economies on productivity growth. Between two periods $t = \tau$ and $t = \tau - 1$, counterfactual task productivity levels $\{\{\hat{T}^a_{n,\tau}\}^A_{a=1}\}^T_{t=1}$ now satisfy:

$$\hat{T}^a_{n,\tau} = [L^a_{n,\tau-1}]^{-\tilde{\eta}_a} (\hat{T}^a_{n,\tau-1})^{\beta-1} \tag{49}$$

Countries that allocate labor to high-skill intensive sectors thus experience a relative reduction in their productivity growth as spillovers tend to be higher in those sectors. I simulate counterfactual changes for the World Trade Flows panel for the period 1970-2000, with the counterfactual dynamic

[39] In order to compare aggregate accumulated spillovers across countries, it is necessary to use a common aggregator across sectors, in this case the value added share in the U.S. Doing so will depress the explanatory power of the model, since this aggregation captures only differences in aggregate productivity growth driven by differences in spillovers *within* sectors. It does not capture cross-country differences in sectoral value added shares interacted with high or low average spillovers. I therefore interpret the estimated explanatory power of the model as a lower bound.

equilibrium defined in section 3.2.2.

The counterfactual change in welfare $U_{n,t}$ (real GDP at PPP) per worker can then be expressed in two ways. First, if nominal incomes are deflated using international prices, it is simply the weighted geometric average of changes in sector-specific prices:

$$\Delta \ln \hat{U}_{n,t} = \ln \hat{w}_{n,t} - \sum_{k=1}^{K} \alpha_{n,t}^{k} \ln \hat{P}_{n,t}^{k} \tag{50}$$

Second, if real GDP is measured using prices of a domestically produced bundle:

$$\Delta \ln \hat{U}_{n,t} = \ln \hat{w}_{n,t} + \sum_{k=1}^{K} \alpha_{n,t}^{k} \sum_{a=1}^{A} \zeta_{a}^{k} \ln \hat{T}_{n,t}^{a} \tag{51}$$

I show the importance of spillovers for counterfactual convergence using both measures. While the first is a more accurate measure of welfare, the second is a better reflection of changes in productivity.

I perform an unconditional (beta) convergence regression for 1970-2000 of counterfactual real GDP per worker growth on real GDP per worker in 1970. Table 3 summarizes these regressions. After accounting for the effect of spillovers, the convergence coefficient for unconditional convergence turns robustly negative. While there is no unconditional cross-country convergence in aggregate productivity (column 3),[40] counterfactual changes in aggregate productivity are significantly higher for countries that were initially poorer in 1970. With an international price deflator (column 1), a country at one tenth of the frontier in 1970 grows 0.39 percentage points per year faster in a counterfactual without spillovers. Using prices of a domestically produced bundle, this difference increases to 1.23 percentage points per year. Putting these numbers into perspective, in the same sample countries experienced *divergence* in real GDP per worker over the 1970-2000 period, with a typical country at one tenth of the frontier growing 0.43 percentage points slower than the frontier.

Figures 5(a)-(b) highlights these effects of spillovers on cross-country convergence. Shutting down spillovers increases real GDP growth relative to the frontier (the United States) for poorer countries in Sub-Saharan Africa (e.g. Ethiopia, Tanzania, Madagascar, Uganda) but lowers growth for some Eastern European and East Asian fast-growing countries (e.g. Romania, Korea, Hong Kong). At the same time, in the counterfactuals growth is slower in Western European countries (e.g. France, Italy, Denmark, Sweden) that catch up to the United States during this period. These countries export rel-

[40] See also Rodrik (2012).

Table 3: Counterfactual Convergence of Real GDP per worker (1970-2000)

	(1) International prices	(2) Domestic prices	(3) Actual $\ln y_{n,2000} - \ln y_{n,1970}$
$\ln y_{n,1970}$	-0.0488***	-0.154***	0.0544
	(0.00619)	(0.0390)	(0.0573)
Constant	-0.0578***	0.0356	0.166**
	(0.0113)	(0.0600)	(0.0800)
Observations	67	67	67
Adjusted R^2	0.451	0.145	-0.004

Robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table reports convergence regressions for counterfactual changes in real GDP per worker between 1970 and 2000 on real GDP per worker (PPP) in 1970. Column (1) uses the counterfactual change in welfare based on international prices (equation 50) as a measure of changes in GDP per worker whereas column (2) uses the change in welfare based on prices of a domestically produced bundle of goods (equation 51). Column (3) reports a convergence regression with actual changes real GDP per worker as the dependent variable. In all cases, real GDP per worker data (PPP at constant $2010) are from Penn World Tables 9.0. The sample includes all countries in the World Trade Flow sample but excludes oil exporters (Ecuador, Norway, Algeria, Venezuela, Iran, Kuwait, Libya, Nigeria, Oman, Saudi Arabia, Syria and Trinidad & Tobago).

atively more in skill intensive sectors. All in all, relatively faster growth for initially poorer countries turns divergence in the data into convergence in the counterfactual. Convergence is stronger when deflating GDP using domestic prices, which are a more direct reflection of endogenous changes in productivity.

7.2 Dynamic Gains from Trade and Initial Comparative Advantage

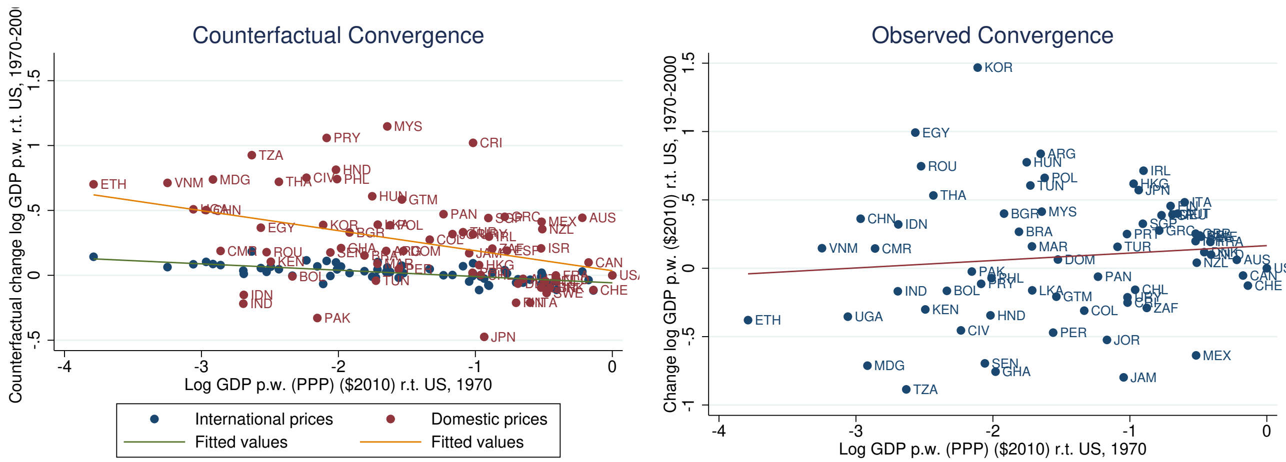
How do inter-industry spillovers affect the dynamic gains from trade? What is the role of initial comparative advantage in mediating these dynamic gains? I examine these questions by exploring a series of counterfactuals in which I keep one country's (symmetric) trade costs remain at the 1970 level, and construct the ensuing dynamic counterfactual equilibrium from 1970 to 2000. This equilibrium is summarized in section 3.2.2. Remember that the gains from trade in 2000 are summarized by

$$\ln \hat{w}_{n,t}/\hat{P}_{n,t} = -\sum_{k=1}^{K} \frac{\alpha_{n,t}^{k}}{\theta} \ln \hat{\pi}_{nn,t}^{k} + \sum_{k=1}^{K} \alpha_{n,t}^{k} \sum_{a=1}^{A} \zeta_{a}^{k} \ln \hat{T}_{n,t}^{a} \tag{52}$$

where the first term covers the standard static gains from trade (Arkolakis et al., 2012), and the second term covers the dynamic gains from trade.

Figure 6(a) plots these two types of gains against each other for the given sample of countries. Countries with larger static gains (mainly fast-growing developing countries) tend to experience slightly larger dynamic gains, although this relationship is weak. In most countries, dynamic gains of trade are substantial and equal 5 percent on average, which is roughly 1/3 of the average static gains. There

Figure 5: Counterfactual and Observed Convergence of real GDP per worker (PPP)



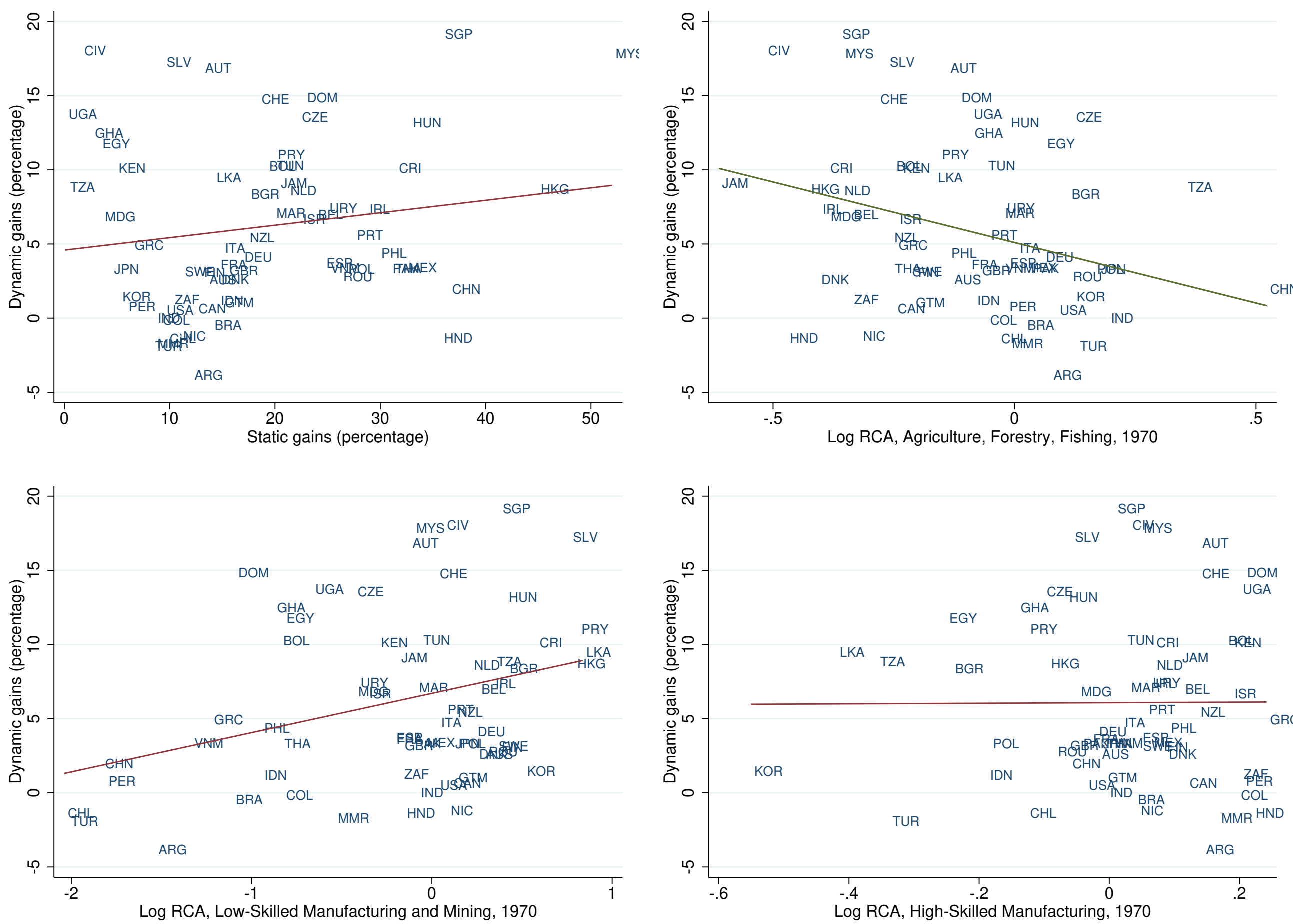
Notes: The left figure presents a scatterplot with associated linear fit of counterfactual changes in welfare between 1970 and 2000 against actual real GDP per worker in 1970. Blue dots and green fit line refer to counterfactual welfare changes using an international price bundle (equation 50). Red dots and orange fit line refer to counterfactual welfare changes using a price bundle of domestically produced goods (equation 51). All variables are expressed relative to the United States. For both figures, real GDP per worker (PPP, constant $2010) are from Penn World Tables 9.0.

exists considerable heterogeneity across countries in terms of the dynamic gains from trade. Several countries have negative estimated dynamic gains, indicating that they shift labor into sectors with lower spillovers when trade barriers decrease during the period studied.

To what extent are these differences explained by initial underlying comparative advantage? Figure 6(b)-(d) plots dynamic gains against countries' revealed comparative advantage in 1970, for each of the three clusters defined in section 2. Countries with a comparative advantage in agriculture, such as Argentina, United States, and Brazil, tend to have lower dynamic gains, which is not surprising given that estimated spillovers are low in this cluster. At the same time, estimated gains are generally higher in countries with a comparative advantage in low-skilled manufacturing, while they are roughly flat with respect to comparative advantage in high-skilled manufacturing.

There are at least two reasons why countries with initial comparative advantage in low-skilled manufacturing have higher estimated dynamic gains than those with a comparative advantage in high-skilled manufacturing. First, the reduction in trade barriers since the 1970s has been smaller in advanced economies that tend to specialize in high skill intensive exports relative to developing economies. Second, due to non-homothetic preferences, trade barriers tend to restrict the reallocation of labor towards manufacturing in developing economies (Tombe, 2015), while richer countries tend to consume and export skill intensive products (Caron et al., 2014). Both of these mechanisms amplify the trade-induced reallocation of labor towards sectors with higher spillovers more in developing countries with an initial comparative advantage in low-skilled manufacturing.

Figure 6: Dynamic Gains from Trade and Initial Comparative Advantage



Notes: All four figures plot a country's counterfactual dynamic gains from trade (second term in equation 52) for each country, in a counterfactual dynamic equilibrium (section 3.2.2) in which the country's inferred trade costs remain at their 1970 levels. The upper left figure plots countries' dynamic gains against the static gains (first term in equation 52). The other three figures plot countries' dynamic gains against the revealed comparative advantage in the three clusters defined in section 2: agriculture (upper left), low-skilled manufacturing and mining (bottom left), and high-skilled manufacturing (bottom right).

8 Conclusions

Developing economies that catch up to the global economic frontier tend to produce more skill-intensive products as they grow. This paper aims to quantify the role of inter-industry productivity spillovers in this catch-up process. Through the lens of a general equilibrium, multi-sector trade model featuring occupation-specific dynamic scale economies, heterogeneous inter-industry spillovers are important for understanding two stylized facts in the growth literature.

First, the model implies that heterogeneous spillovers can account for the lack of cross-country convergence in aggregate productivity (Rodrik, 2012) if dynamic scale economies are stronger for high-skilled occupation, leading to stronger productivity spillovers for countries that produce relatively more in high-skilled intensive sectors. Indeed, the estimates in this paper suggest that dynamic scale economies are substantial in high-skill intensive production but negligible in low-skill intensive production. As a consequence, countries farther away from the global economic frontier would experience faster catch-up growth in the absence of inter-industry productivity spillovers.

Second, the model suggest heterogeneous inter-industry spillovers are important for understanding why some countries (mostly East Asian and Eastern European) have been able to catch up to the frontier in the last five decades. Through the lens of the model, exporting relatively more complex, skill-intensive products has a positive effect on subsequent economic growth (Hausmann et al. (2007); Hidalgo and Hausmann (2009)) because it leads to higher future productivity in sectors in which a country is initially noncompetitive. In this sense, the findings in this paper mirror those of Hanson (2017), who documents that labor-abundant East Asian countries with an initial comparative advantage in low-skilled manufacturing tend to climb a ladder of complex industries as they become more productive, whereas these patterns are not present in resource abundant Latin American countries.

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References

Alvarez, F. E., Buera, F. J., and Lucas Jr, R. E. (2013). Idea flows, economic growth, and trade. Technical report.

Anderson, J. E. and Van Wincoop, E. (2003). Gravity with gravitas: a solution to the border puzzle. *American economic review*, 93(1):170–192.

Arkolakis, C., Costinot, A., and Rodríguez-Clare, A. (2012). New trade models, same old gains? *American Economic Review*, 102(1):94–130.

Atkin, D. (2016). Endogenous skill acquisition and export manufacturing in mexico. *American Economic Review*, 106(8):2046–85.

Bahar, D., Rosenow, S., Stein, E., and Wagner, R. (2019). Export take-offs and acceleration: Unpacking cross-sector linkages in the evolution of comparative advantage. *World Development*, 117:48–60.

Bajona, C. and Kehoe, T. J. (2010). Trade, growth, and convergence in a dynamic heckscher-ohlin model. *Review of Economic Dynamics*, 13(3):487–513.

Bartelme, D., Lan, T., and Levchenko, A. (2019). Specialization, market access and medium-term growth.

Basco, S. and Mestieri, M. (2019). The world income distribution: the effects of international unbundling of production. *Journal of Economic Growth*, pages 1–33.

Blanchard, E. J. and Olney, W. W. (2017). Globalization and human capital investment: Export composition drives educational attainment. *Journal of International Economics*, 106:165–183.

Buera, F. J., Kaboski, J. P., and Rogerson, R. (2015). Skill biased structural change. Technical report, National Bureau of Economic Research.

Buera, F. J. and Oberfield, E. (2017). The global diffusion of ideas. Technical report.

Burstein, A., Morales, E., and Vogel, J. (2015). Accounting for changes in between-group inequality. Technical report, National Bureau of Economic Research.

Cai, J. and Li, N. (2012). Growth through intersectoral knowledge linkages. In *Econometric Society Winter Meeting, Chicago, January*, pages 6–8.

Cai, J. and Li, N. (2015). Innovation allocation, knowledge composition and long-run growth.

Cai, J. and Stoyanov, A. (2016). Population aging and comparative advantage. *Journal of International Economics*, 102:1–21.

Caliendo, L. and Parro, F. (2015). Estimates of the trade and welfare effects of nafta. *The Review of Economic Studies*, 82(1):1–44.

Caron, J., Fally, T., and Markusen, J. R. (2014). International trade puzzles: A solution linking production and preferences. *The Quarterly Journal of Economics*, 129(3):1501–1552.

Caselli, F. (2016). *Technology Differences Over Space and Time*. Princeton University Press.

Caselli, F., Coleman, I. I., and John, W. (2006). The world technology frontier. *American Economic Review*, 96(3):499–522.

Chor, D. (2010). Unpacking sources of comparative advantage: A quantitative approach. *Journal of International Economics*, 82(2):152–167.

Ciccone, A. and Papaioannou, E. (2009). Human capital, the structure of production, and growth. *The Review of Economics and Statistics*, 91(1):66–82.

Costinot, A., Donaldson, D., and Komunjer, I. (2011). What goods do countries trade? a quantitative exploration of ricardo's ideas. *The Review of economic studies*, 79(2):581–608.

Daruich, D., Easterly, W., and Reshef, A. (2019). The surprising instability of export specializations. *Journal of Development Economics*, 137:36–65.

De la Croix, D., Doepke, M., and Mokyr, J. (2017). Clans, guilds, and markets: Apprenticeship institutions and growth in the preindustrial economy. *The Quarterly Journal of Economics*, 133(1):1–70.

Dekle, R., Eaton, J., and Kortum, S. (2007). Unbalanced trade. *American Economic Review*, 97(2):351–355.

Deng, L. (2016). Specialization dynamics, convergence, and idea flows.

Duernecker, G. and Herrendorf, B. (2016). Structural transformation of occupation employment. Technical report.

Eaton, J. and Kortum, S. (2001). Technology, trade, and growth: A unified framework. *European economic review*, 45(4-6):742–755.

Eaton, J. and Kortum, S. (2002). Technology, geography, and trade. *Econometrica*, 70(5):1741–1779.

Eaton, J., Kortum, S. S., and Sotelo, S. (2012). International trade: Linking micro and macro. Technical report.

Eicher, T. S. and Kuenzel, D. J. (2016). The elusive effects of trade on growth: Export diversity and economic take-off. *Canadian Journal of Economics/Revue canadienne d'économique*, 49(1):264–295.

Feenstra, R. C. (1996). Trade and uneven growth. *Journal of Development Economics*, 49(1):229–256.

Feenstra, R. C., Lipsey, R. E., Deng, H., Ma, A. C., and Mo, H. (2005). World trade flows: 1962-2000. Technical report.

Fiszbein, M. (2017). Agricultural diversity, structural change and long-run development: Evidence from the us. Technical report.

Galor, O. and Mountford, A. (2006). Trade and the great divergence: the family connection. *American Economic Review*, 96(2):299–303.

Galor, O. and Mountford, A. (2008). Trading population for productivity: theory and evidence. *The Review of economic studies*, 75(4):1143–1179.

Grossman, G. M. and Horn, H. (1988). Infant-industry protection reconsidered: the case of informational barriers to entry. *The Quarterly Journal of Economics*, 103(4):767–787.

Hanson, G. H. (2017). What do we really know about offshoring? industries and countries in global production sharing.

Hanson, G. H., Lind, N., and Muendler, M.-A. (2015). The dynamics of comparative advantage. Technical report, National bureau of economic research.

Hanson, G. H., Lind, N., and Muendler, M.-A. (2018). The dynamics of comparative advantage.

Hausmann, R. and Hidalgo, C. A. (2011). The network structure of economic output. *Journal of Economic Growth*, 16(4):309–342.

Hausmann, R., Hwang, J., and Rodrik, D. (2007). What you export matters. *Journal of economic growth*, 12(1):1–25.

Head, K. and Ries, J. (2001). Increasing returns versus national product differentiation as an explanation for the pattern of us-canada trade. *American Economic Review*, 91(4):858–876.

Hidalgo, C. A. and Hausmann, R. (2009). The building blocks of economic complexity. *Proceedings of the national academy of sciences*, 106(26):10570–10575.

Hidalgo, C. A., Klinger, B., Barabási, A.-L., and Hausmann, R. (2007). The product space conditions the development of nations. *Science*, 317(5837):482–487.

Johnson, P. and Papageorgiou, C. (2019). What remains of cross-country convergence? *Journal of Economic Literature*.

Johnson, W. (2017). Economic growth and the evolution of comparative advantage in an occupation-based network of industries.

Jones, B. F. (2014). The human capital stock: a generalized approach. *American Economic Review*, 104(11):3752–77.

Kongsamut, P., Rebelo, S., and Xie, D. (2001). Beyond balanced growth. *The Review of Economic Studies*, 68(4):869–882.

Krugman, P. (1981). Trade, accumulation, and uneven development. *Journal of Development Economics*, 8(2):149–161.

Krugman, P. (1987). The narrow moving band, the dutch disease, and the competitive consequences of mrs. thatcher: Notes on trade in the presence of dynamic scale economies. *Journal of development Economics*, 27(1-2):41–55.

Krugman, P. R. (1979). Increasing returns, monopolistic competition, and international trade. *Journal of international Economics*, 9(4):469–479.

Lagakos, D., Moll, B., Porzio, T., Qian, N., and Schoellman, T. (2018). Life cycle wage growth across countries. *Journal of Political Economy*, 126(2):797–849.

Leamer, E. E. (1984). *Sources of international comparative advantage: Theory and evidence*. MIT press Cambridge, MA.

Lee, E. (2015). Trade, inequality, and the endogenous sorting of heterogeneous workers. Technical report.

Levchenko, A. A. and Zhang, J. (2016). The evolution of comparative advantage: Measurement and welfare implications. *Journal of Monetary Economics*, 78:96–111.

Lucas, Jr, R. E. (2004). Life earnings and rural-urban migration. *Journal of political economy*, 112(S1):S29–S59.

Lucas Jr, R. E. (1988). On the mechanics of economic development. *Journal of monetary economics*, 22(1):3–42.

Lucas Jr, R. E. (2015). Human capital and growth. *American Economic Review*, 105(5):85–88.

Malmberg, H. (2017). Human capital and development accounting revisited. *mimeo Institute for International Economic Studies*.

Marshall, A. (1890). Principles of economics macmillan. *London (8th ed. Published in 1920)*.

Matsuyama, K. (1992). Agricultural productivity, comparative advantage, and economic growth. *Journal of economic theory*, 58(2):317–334.

Matsuyama, K. (2019). Engel's law in the global economy: Demand-induced patterns of structural change, innovation, and trade. *Econometrica*, 87(2):497–528.

Mendoza, R. U. (2010). Trade-induced learning and industrial catch-up. *The Economic Journal*, 120(546):F313–F350.

Morrow, P. M. and Trefler, D. (2014). Hov and the factor bias of technology. Technical report.

Morrow, P. M. and Trefler, D. (2015). Identification, hov, and factor biased technology.

Morrow, P. M. and Trefler, D. (2017). Endowments, skill-biased technology, and factor prices: A unified approach to trade. Technical report.

Ngai, L. R. and Pissarides, C. A. (2007). Structural change in a multisector model of growth. *American economic review*, 97(1):429–443.

Nunn, N. and Trefler, D. (2014). Domestic institutions as a source of comparative advantage. In *Handbook of international economics*, volume 4, pages 263–315. Elsevier.

O'Rourke, K. H., Rahman, A., and Taylor, A. M. (2019). Trade, technology, and the great divergence. Technical report, National Bureau of Economic Research.

Perla, J., Tonetti, C., and Waugh, M. E. (2015). Equilibrium technology diffusion, trade, and growth. Technical report.

Prebisch, R. (1959). Commercial policy in the underdeveloped countries. *The American Economic Review*, 49(2):251–273.

Redding, S. (1999). Dynamic comparative advantage and the welfare effects of trade. *Oxford economic papers*, 51(1):15–39.

Rodrik, D. (2006). What's so special about china's exports? *China & World Economy*, 14(5):1–19.

Rodrik, D. (2011). The future of economic convergence. Technical report.

Rodrik, D. (2012). Unconditional convergence in manufacturing. *The Quarterly Journal of Economics*, 128(1):165–204.

Romalis, J. (2004). Factor proportions and the structure of commodity trade. *American Economic Review*, 94(1):67–97.

Rossi, F. (2017). The relative efficiency of skilled labor across countries: Measurement and interpretation.

Sampson, T. (2015). Dynamic selection: an idea flows theory of entry, trade, and growth. *The Quarterly Journal of Economics*, 131(1):315–380.

Santacreu, A. M. (2015). Innovation, diffusion, and trade: Theory and measurement. *Journal of Monetary Economics*, 75:1–20.

Schott, P. K. (2008). The relative sophistication of chinese exports. *Economic policy*, 23(53):6–49.

Shikher, S. (2017). The impact of educated labor on technology adoption and comparative advantage.

Silva, J. M. C. S. and Tenreyro, S. (2006). The log of gravity. *The Review of Economics and statistics*, 88(4):641–658.

Simonovska, I. and Waugh, M. E. (2014). The elasticity of trade: Estimates and evidence. *Journal of international Economics*, 92(1):34–50.

Somale, M. (2017). Comparative advantage in innovation and production.

Stokey, N. L. (1991). Human capital, product quality, and growth. *The Quarterly Journal of Economics*, 106(2):587–616.

Tombe, T. (2015). The missing food problem: Trade, agriculture, and international productivity differences. *American Economic Journal: Macroeconomics*, 7(3):226–58.

Trefler, D. (1993). International factor price differences: Leontief was right! *Journal of political Economy*, 101(6):961–987.

Trefler, D. (1995). The case of the missing trade and other mysteries. *The American Economic Review*, pages 1029–1046.

Van der Ploeg, F. (2011). Natural resources: curse or blessing? *Journal of Economic Literature*, 49(2):366–420.

Whang, U. (2017). Structural transformation and comparative advantage: Implications for small open economies. *The World Economy*, 40(4):743–763.

Young, A. (1991). Learning by doing and the dynamic effects of international trade. *The Quarterly Journal of Economics*, 106(2):369–405.

Catch-Up Growth and Inter-Industry Productivity Spillovers

Online Appendix

Marijn Bolhuis

A Motivating Facts: Additional Material

This section presents additional material on Fact 1 in section 2 in the form of three different sets of figures. The first set of figures plots a binned scatterplot countries' share of tradable employment in a given sector against its (log) GDP p.w. (const. $2010) for all countries in the IPUMS International sample over the period 1970-2012. The second set of figures plots the United States share of tradable employment in a given sector against its (log) GDP p.c. (const. $2011) in the IPUMS USA sample over the period 1850-2010. The third set of figures plots a binned scatterplot of countries' (log) revealed comparative advantage (RCA) in a given sector against its (log) GDP p.w. (const $2010) in the World Trade Flows sample over the period 1962-2000.

Figure A1: (1) Binned Scatterplots Employment vs. GDP p.w. (IPUMS International, 1970-2012)

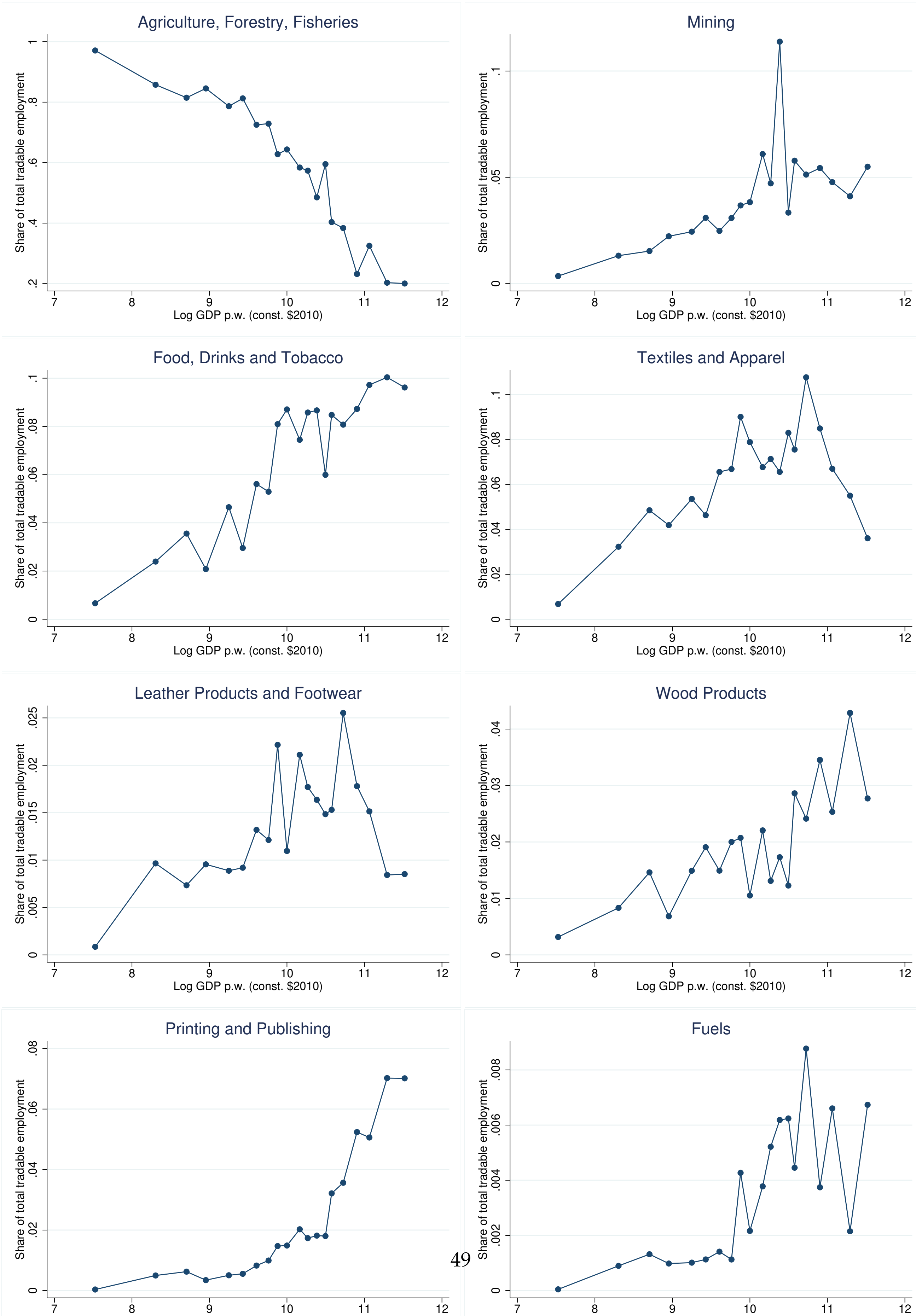


Figure A2: (2) Binned Scatterplots Employment vs. GDP p.w. (IPUMS International, 1970-2012)

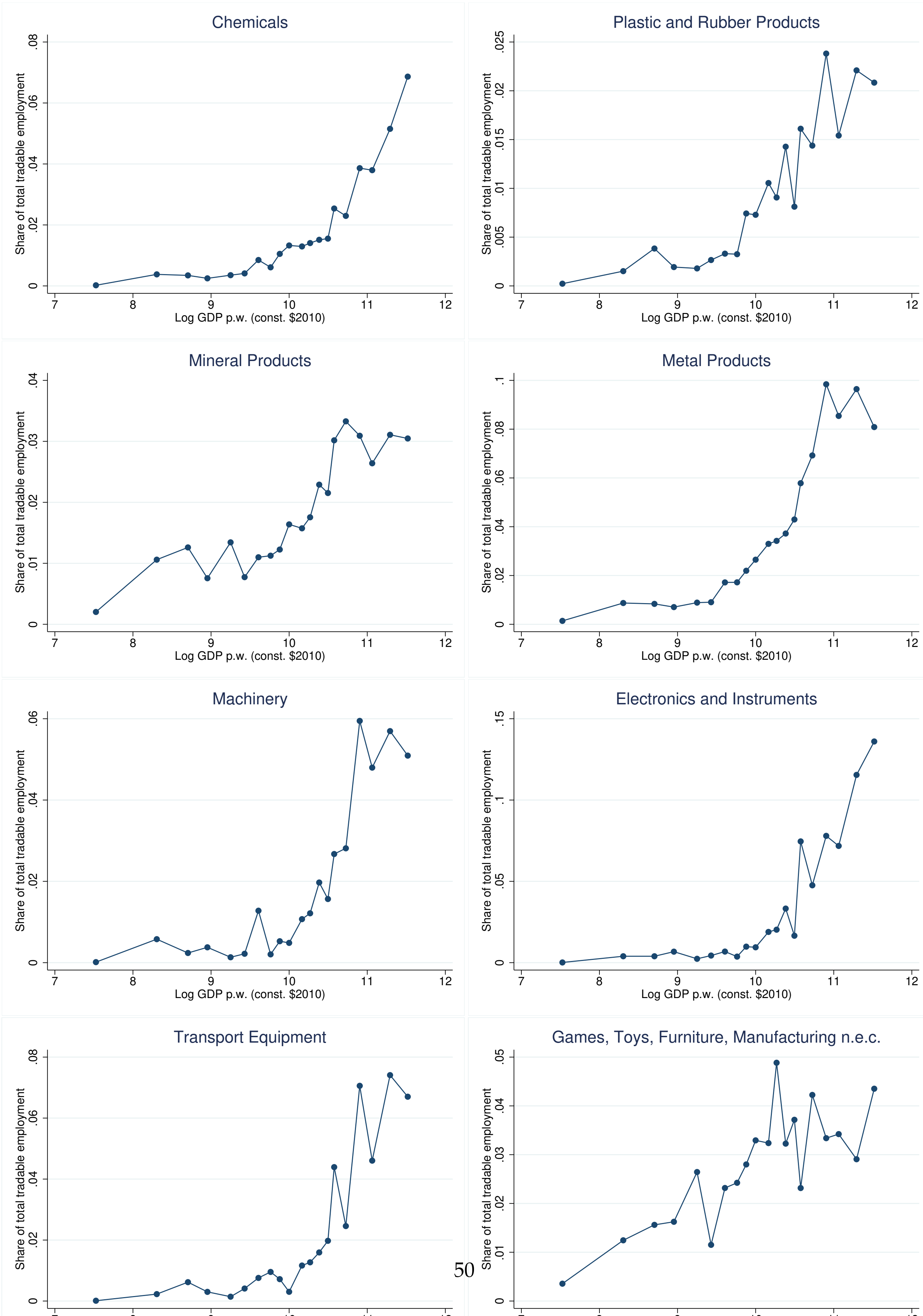


Figure A3: (1) Binned Scatterplots Employment vs. GDP p.w. (IPUMS USA), 1850-2010)

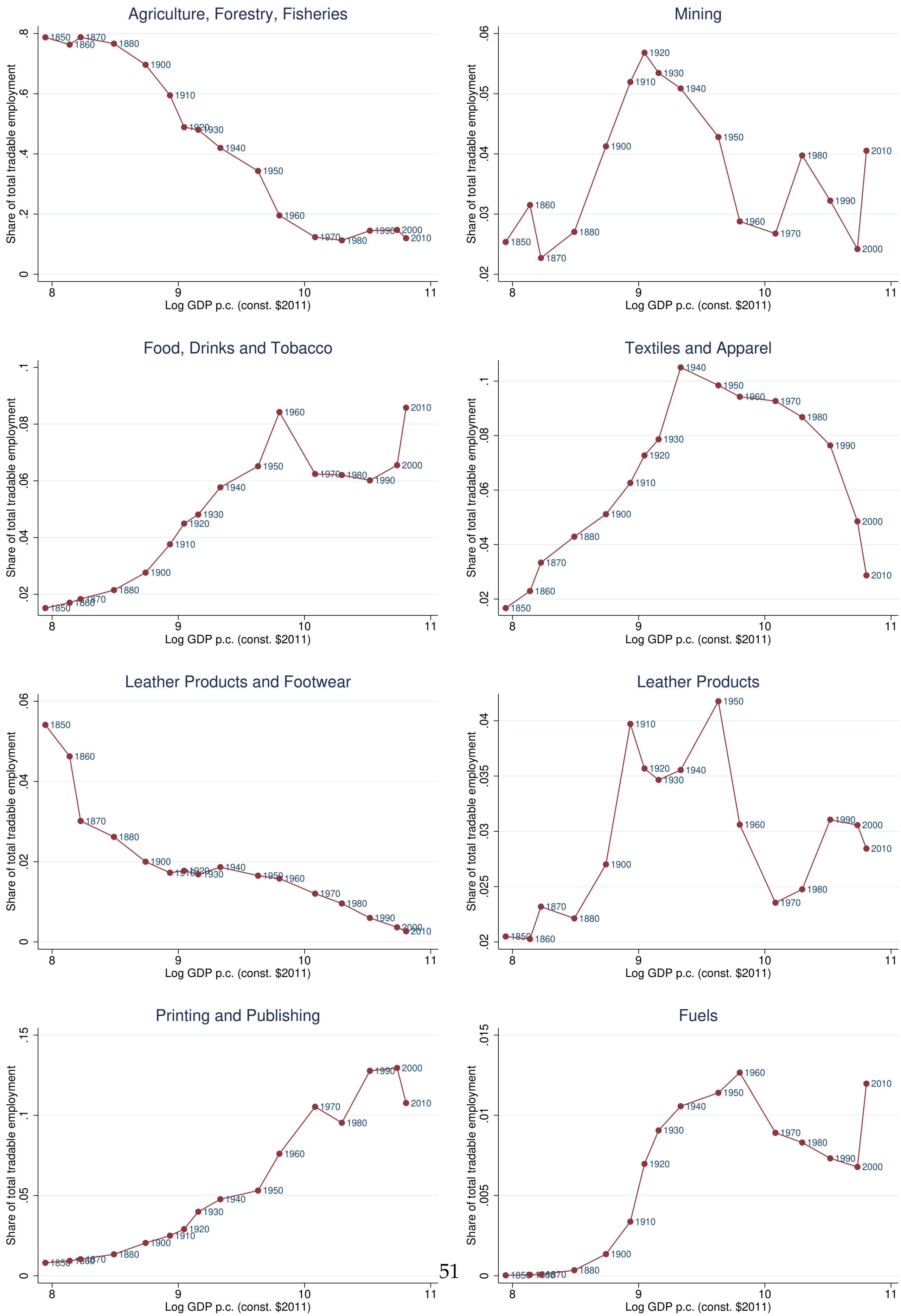


Figure A4: (2) Binned Scatterplots Employment vs. GDP p.w. (IPUMS USA), 1850-2010)

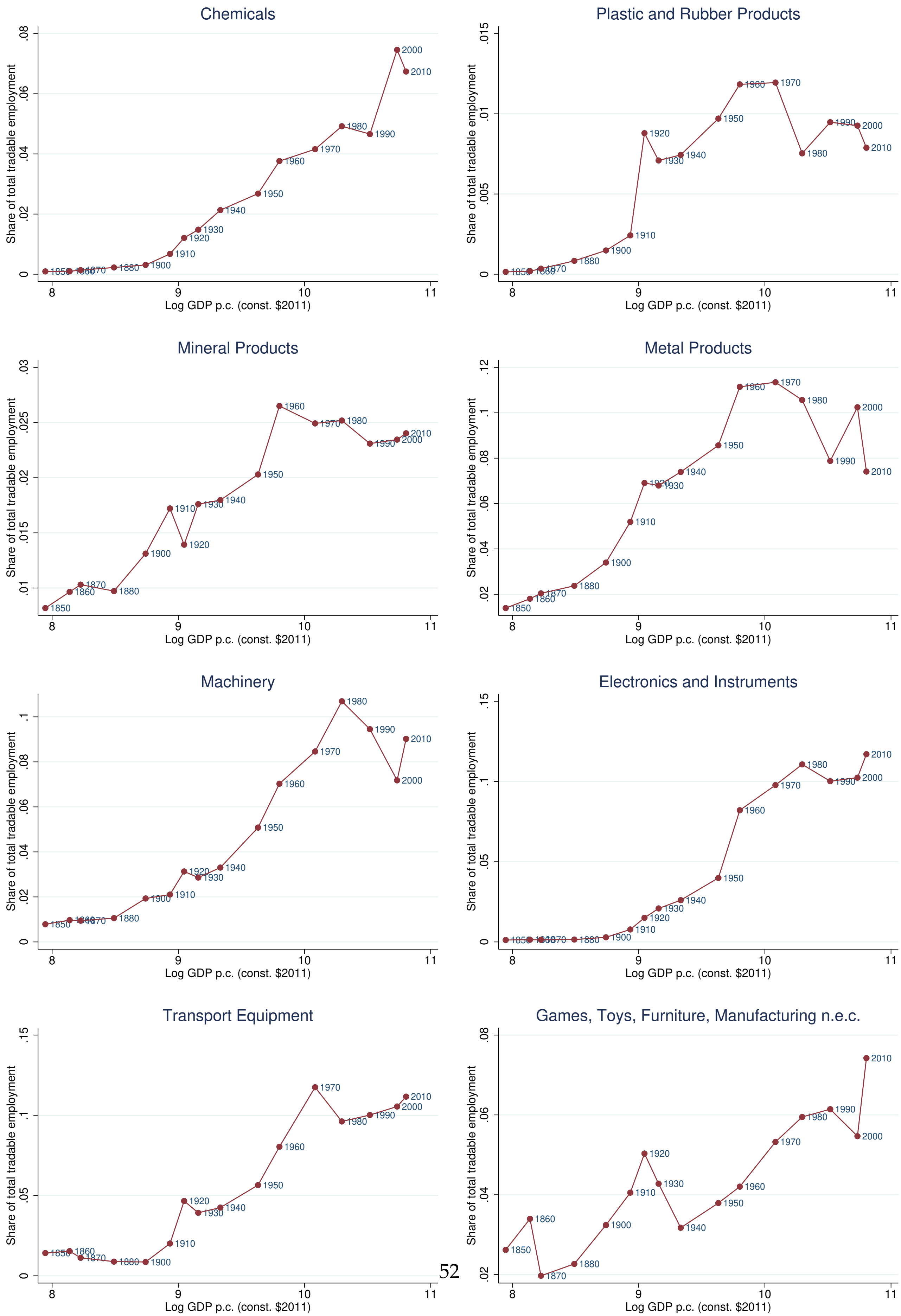


Figure A5: (1) Binned Scatterplots RCA vs. GDP p.w. (World Trade Flows), 1962-2000)

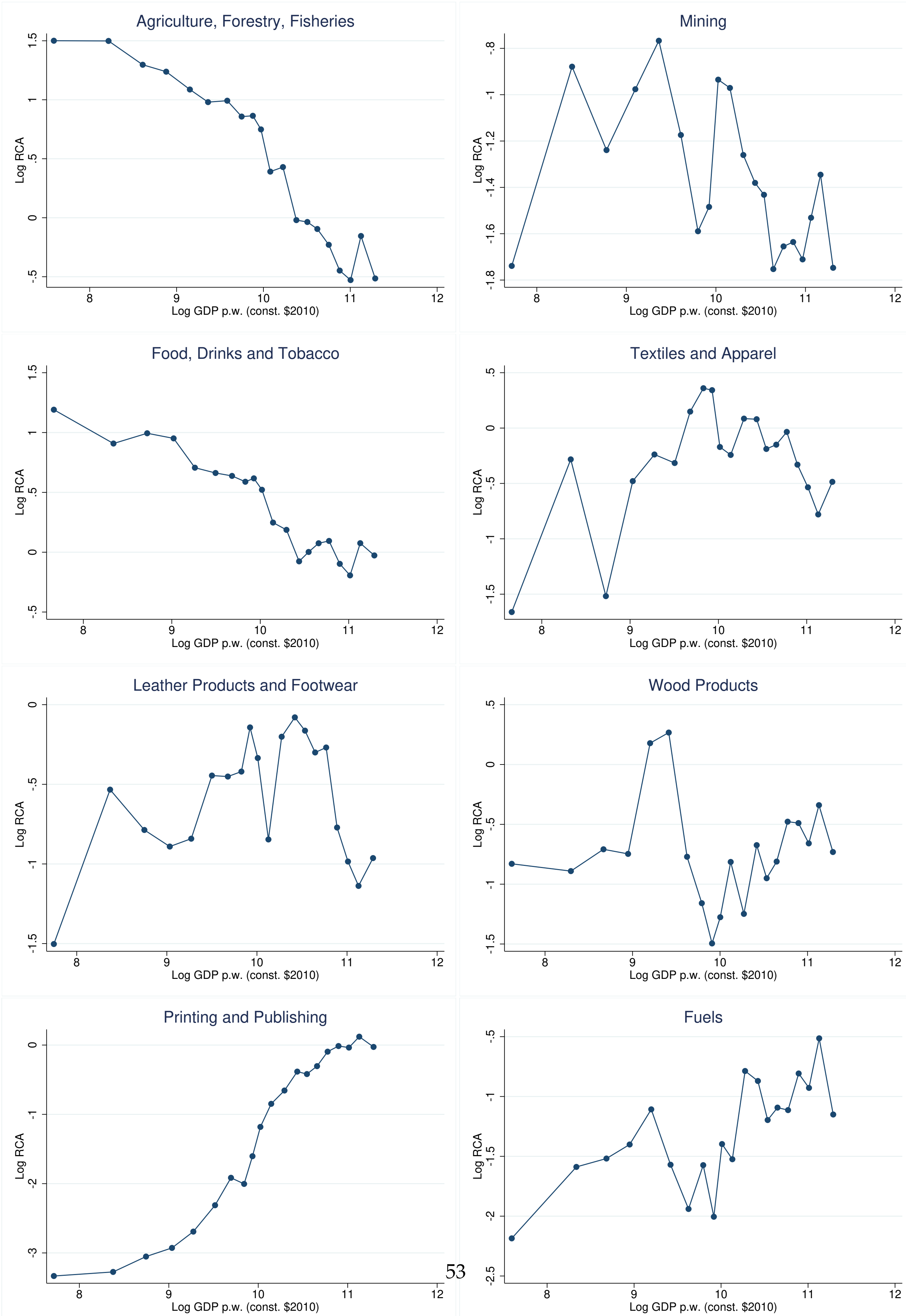
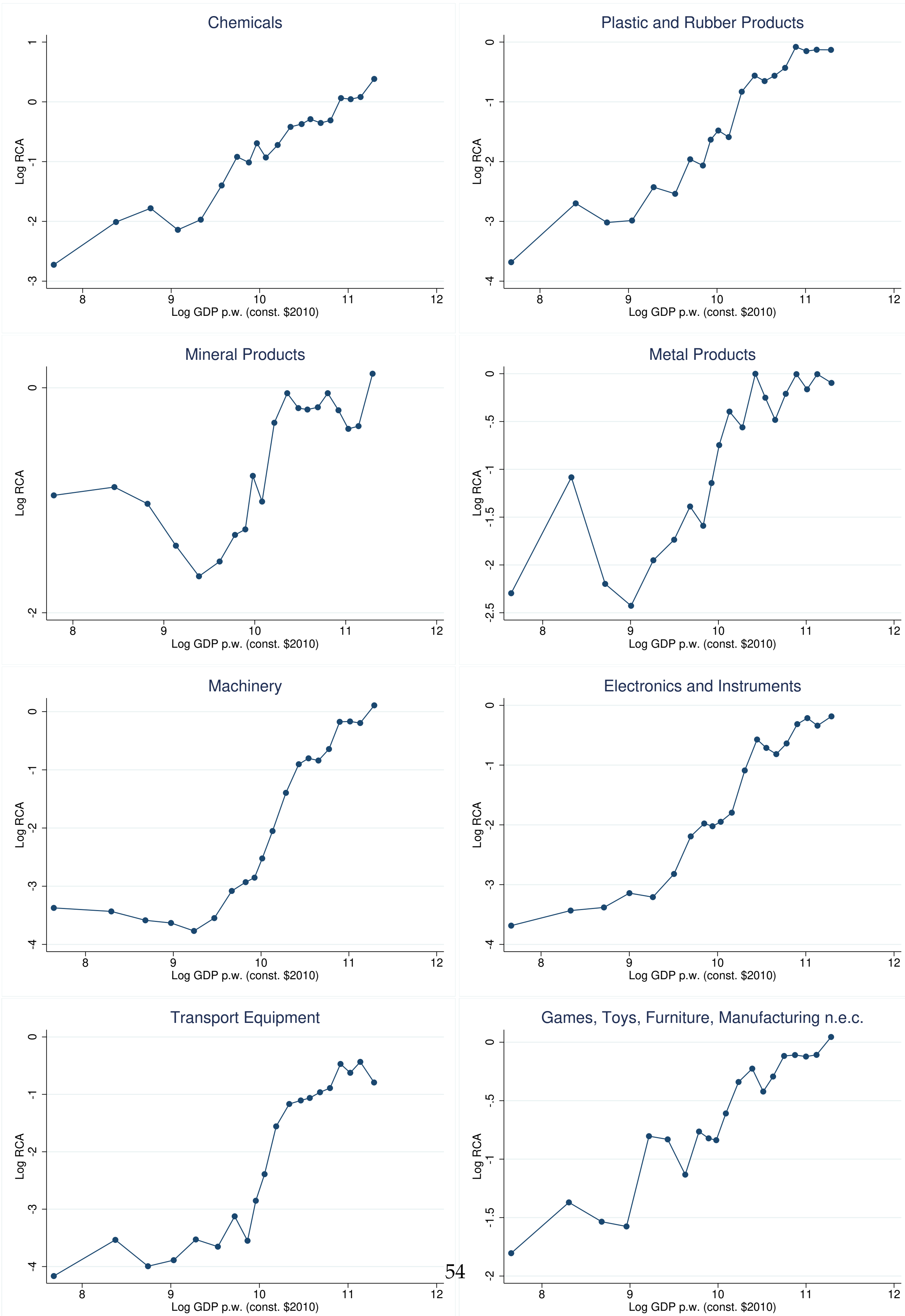


Figure A6: (2) Binned Scatterplots RCA vs. GDP p.w. (World Trade Flows), 1962-2000)



B Motivating Facts: Relationship Between RCA and Theoretical Framework

- **Claim 1:** Differences in RCA reflect differences in sector-specific effective unit costs
  - Assume no trade costs ($\tau^k_{nn',t} = 1 \forall n, n', t, k$), and constant sector-specific Cobb-Douglas preferences ($X^k_{n,t}/(I_{n,t}L_{n,t}) = \alpha_k \forall n, t$) .
  - Using

    $Y^k_{n,t} = \alpha_k \sum_{n=1}^{N} I_{n,t}L_{n,t} \sum_{n'=1}^{N} \pi^k_{n'n,t}$ and $\pi^k_{n'n,t} = T^k_{n,t}(c^k_{n,t}P^k_{n,t}/\Lambda_k)^{-\theta}$

    express relative RCA as a function of relative sector-specific effective unit costs:

    $$\frac{RCA^k_{n,t}/RCA^{k'}_{n,t}}{RCA^k_{m,t}/RCA^{k'}_{m,t}} = \frac{(T^k_{n,t}/T^{k'}_{n,t})(c^k_{n,t}/c^{k'}_{n,t})^{-\theta}}{(T^k_{m,t}/T^{k'}_{m,t})(c^k_{m,t}/c^{k'}_{m,t})^{-\theta}}$$

    Given that exporter fixed effects from the gravity equation equal

    $$\delta^k_{m,t} = -\theta \ln c^k_{m,t}/c^k_{US,t} + \ln T^k_{n,t}/T^k_{US,t}$$

    relative RCA also correspond to relative exporter fixed effects (in logs):

    $$\ln \frac{RCA^k_{n,t}/RCA^{k'}_{n,t}}{RCA^k_{US,t}/RCA^{k'}_{US,t}} = \frac{\delta^k_{n,t}/\delta^{k'}_{n,t}}{\delta^k_{m,t}/\delta^{k'}_{m,t}}.$$

- **Claim 2:** Estimating equation 5 in section 2 corresponds to the sector-level version of dynamic scale economies in equation 20 (section 3.2)
  - In addition, to assuming no trade costs and constant sector-specific Cobb-Douglas preferences, assume sector-specific TFP terms are constant over time (e.g. $T^k_{n,t} = 1 \forall n, t, k$) and there are no deficits ($D_{n,t} = 0$). Express log changes in RCA as
    * $\Delta \ln RCA^k_{n,t} = \Delta \ln X^k_{n,t} - \Delta \ln X_{n,t} - \Delta \ln X^k_t + \Delta \ln X_t$

    where the last three terms will be captured by country-time and sector-time fixed effects. Inserting the previous expression for $X^k_{n,t}$
    * $\Delta \ln RCA^k_{n,t} = -\theta \Delta \ln c^k_{n,t} - \Delta \ln X_{n,t} - \Delta \ln X^k_t + 2\Delta \ln X_t - \theta \Delta \ln P^k_t$

    where the sectoral price index does not have a country-specific subscript as it is the same across countries. Using the definition of unit costs:
    * $\Delta \ln RCA^k_{n,t} = \theta \sum_{a=1}^{A} \zeta^k_a \Delta \ln T^a_{n,t} - \theta \Delta \ln w_{n,t} - \Delta \ln X_{n,t} - \Delta \ln X^k_t + 2\Delta \ln X_t - \theta \Delta \ln P^k_t$

    Using endogenous task productivity growth ($\Delta \ln T^a_{n,t} = \beta_0 + \tilde{\eta}_a \ln L^a_{n,t-1} + (\beta - 1) \ln T^a_{n,t-1} + \epsilon^a_{n,t}$ with $\theta_a \approx 1$):
    * $\Delta \ln RCA^k_{n,t} = \theta[\beta_0 + (1-\beta) \ln c^k_{n,t-1} + \sum_{a=1}^{A} \zeta^k_a \tilde{\eta}_a \ln L^a_{n,t-1}] + \theta[(\beta - 1) \ln w_{n,t-1} + \sum_{a=1}^{A} \zeta^k_a \eta^a_{n,t}] - \theta \Delta \ln w_{n,t} - \Delta \ln X_{n,t} - \Delta \ln X^k_t + 2\Delta \ln X_t - \theta \Delta \ln P^k_t$

    Inserting relationship between unit costs and revealed comparative advantage used earlier gives:
    * $\Delta \ln RCA^k_{n,t} = \theta \beta_0 - (1-\beta) \ln RCA^k_{n,t-1} + \theta \sum_{a=1}^{A} \zeta^k_a \tilde{\eta}_a \ln L^a_{n,t-1} + \theta[(\beta - 1) \ln w_{n,t-1} + \sum_{a=1}^{A} \zeta^k_a \eta^a_{n,t}] - \theta \Delta \ln w_{n,t} - \Delta \ln X_{n,t} - \Delta \ln X^k_t + 2\Delta \ln X_t - \theta \Delta \ln P^k_t + \frac{(1-\beta)}{\theta}[\ln \alpha_k + \ln X_{t-1} + \theta \ln \Lambda_k - \theta \ln P^k_{t-1}]$
  - If the diffusion parameter $\tilde{\eta}_a$ is constant across tasks, substituting in the definition of related RCA $RR^k_{n,t}$ yields
    * $\Delta \ln RCA^k_{n,t} = \theta \beta_0 - (1-\beta) \ln RCA^k_{n,t-1} + \theta \tilde{\eta} \ln RR^k_{n,t-1} + \theta[(\beta - 1) \ln w_{n,t-1} + \sum_{a=1}^{A} \zeta^k_a \eta^a_{n,t}] - \theta \Delta \ln w_{n,t} - \Delta \ln X_{n,t} - \Delta \ln X^k_t + 2\Delta \ln X_t - \theta \Delta \ln P^k_t + \frac{(1-\beta)}{\theta}[\ln \alpha_k + \ln X_{t-1} + \theta \ln \Lambda_k - \theta \ln P^k_{t-1}] + \theta \sum_{a=1}^{A} \frac{\zeta^k_a X^k_t}{X_t}$
  - Finally, rearranging yields the estimating equation 5 in section 2

* $\Delta \ln RCA^k_{n,t} = \frac{\theta}{\theta_a} \ln \Gamma(1-\beta) - (1-\beta) \ln RCA^k_{n,t-1} + \theta \tilde{\eta} \ln RR^k_{n,t-1} + \delta_{n,t} + \delta^k_n + \delta^k_t + \epsilon^k_{n,t}$

– where the country-time fixed effect $\delta_{n,t}$ captures $\theta(\beta-1)\ln w_{n,t-1} - \theta \Delta \ln w_{n,t} - \Delta \ln X_{n,t}$, the country-sector fixed effect δ^k_n captures $\frac{(1-\beta)}{\theta} \ln \alpha_k + (1-\beta) \ln \Lambda_k$, and the sector-time fixed effect δ^k_t captures $-\Delta \ln X^k_t + 2\Delta \ln X_t - \theta \Delta \ln P^k_t \frac{(1-\beta)}{\theta} \ln X_{t-1} - (1-\beta) \ln P^k_{t-1} + \theta \sum_{a=1}^{A} \frac{\zeta^k_a X^k_t}{X_t}$.

C Estimation Strategy: Algorithms

Algorithm for Computing Static Counterfactual Equilibrium

Given $\hat{\tau}^k_{ni,t}$, $\hat{T}^k_{n,t}$,

1. Guess $\hat{w}_{n,t}$
    - compute (in this order) $\hat{w}^a_{n,t}$, $\hat{p}^a_{n,t}$, $\hat{c}^k_{n,t}$, $\hat{P}^k_{n,t}$, $\hat{\pi}^k_{ni,t}$
    - compute imports and exports
    - if counterfactual trade balance differs from deficit, go back to (1) and adjust guess of $\hat{w}_{n,t}$
2. Iterate until trade balance has converged to deficit for all countries

D Data: Details

Table A1: Work Activities O*NET and their assigned task categories.

Task description	**Category**
Getting Information	Information
Identifying Objects, Actions, and Events	Information
Estimating the Quantifiable Characteristics of Products, Events, or Information	Information
Judging the Qualities of Things, Services, or People	Information
Processing Information	Information
Evaluating Information to Determine Compliance with Standards	Information
Analyzing Data or Information	Information
Making Decisions and Solving Problems	Information
Thinking Creatively	Information
Updating and Using Relevant Knowledge	Information
Interacting With Computers	Information
Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment	Information
Documenting/Recording Information	Information
Interpreting the Meaning of Information for Others	Information
Provide Consultation and Advice to Others	Information
Developing Objectives and Strategies	Planning
Scheduling Work and Activities	Planning
Organizing, Planning, and Prioritizing Work	Planning
Performing Administrative Activities	Planning
Performing General Physical Activities	Physical
Handling and Moving Objects	Physical
Operating Vehicles, Mechanized Devices, or Equipment	Physical
Controlling Machines and Processes	Equipment
Repairing and Maintaining Mechanical Equipment	Equipment
Repairing and Maintaining Electronic Equipment	Equipment
Monitor Processes, Materials, or Surroundings	Equipment
Inspecting Equipment, Structures, or Material	Equipment
Communicating with Supervisors, Peers, or Subordinates	Contact
Communicating with Persons Outside Organization	Contact
Establishing and Maintaining Interpersonal Relationships	Contact
Assisting and Caring for Others	Contact
Selling or Influencing Others	Contact
Resolving Conflicts and Negotiating with Others	Contact
Performing for or Working Directly with the Public	Contact
Coordinating the Work and Activities of Others	Contact
Developing and Building Teams	Contact
Training and Teaching Others	Contact
Guiding, Directing, and Motivating Subordinates	Contact
Coaching and Developing Others	Contact
Staffing Organizational Units	Contact
Monitoring and Controlling Resources	Contact

Table A2: Top 5 occupations and sectors, by task. Occupations are ranked by their normalized task score. Sectors are ranked by the share of wages paid to occupations assigned to a task.

Task	Top 5 occupations (1970 census)	Top 5 sectors (1970 census)
Information	Physicists	Office and store machines and devices
	Aeronautical engineers	Aircraft and parts
	Chemical engineers	Drugs and medicines
	Mining engineers	Photographic equipment and supplies
	Draftsmen	Forestry
Planning	Authors	Miscellaneous food industries
	Electrotypers and stereotypers	Drugs and medicines
	Hucksters and peddlers	Printing, publishing and allied industries
	Newsboys	Paints, varnishes and related products
	Advertising agents and salesmen	Professional equipment and supplies
Equipment	Furnacemen, smeltermen and pourers	Knitting mills
	Heaters (metal)	Apparel and accessories
	Motion picture projectionists	Footwear
	Oilers and greasers	Coal mining
	Pressmen and plate printers	Miscellaneous fabricated textile products
Mechanical	Fishermen and oystermen	Agriculture
	Glaziers	Fisheries
	Mail carriers	Logging
	Plumbers and pipe fitters	Dairy products
	Welders and flame cutters	Bakery products

D.1 Bilateral Trade Flows

Data on bilateral sectoral trade flows are from the World Trade Flows (WTF) database developed by Feenstra et al. (2005). These cover bilateral trade between country pairs at the disaggregated four digit SITC2 level for the years 1962-2000. I aggregate goods to the level of industries from the 1950 Census Bureau industrial classification system. Table XXX shows the corresponding list of sectors. In the rest of the procedure, I follow Hanson et al. (2018). I create a balanced panel of countries by maintaining as single units countries that split up or unite (Czech Republic, Russia, Yugoslavia, Germany, Yemen) and restrict the analysis to countries that form a connected set to be able to identify importer and exporter fixed effects (Abowd et al., 2002). This leaves me with 87 countries and 59 (tradable) sectors.

The WTF database does not contain information on the consumption of domestically produced goods, 'self trade' $X^k_{nn,t}$. However, to be able to perform counterfactuals and calibrate expenditure shares, estimates of self-trade are necessary. As a result, I need to infer self trade at the country-industry level to compute industry-level expenditure. Hanson et al. (2018) show that, if a country's log trade costs have a common additively separable component and there are no internal trade costs, $\tau^k_{nn,t} = 1$, a country's self trade in sector k as a share of total self trade is given by

$$\frac{X^k_{nn,t}}{\sum_{k'=1}^{K} X^{k'}_{nn,t}} = \frac{\exp(\kappa^k_{n,t} + \tilde{\mu}^k_{n,t})}{\sum_{k'=1}^{K} \exp(\kappa^{k'}_{n,t} + \tilde{\mu}^{k'}_{n,t})} \tag{53}$$

where $\kappa^k_{n,t}$ and $\tilde{\mu}^k_{n,t}$ are a country's fixed effects estimates from the gravity equation estimation in section XXX.

One can then use use production data in tradable sectors to infer aggregate self trade as the difference between aggregate production $Y_{n,t}$ and exports:

$$\sum_{k=1}^{K} X^k_{nn,t} = Y_{n,t} - \sum_{k=1}^{K} \sum_{n' \neq n} X^k_{n'n,t} \tag{54}$$

As some trade costs differ systematically across sectors, using aggregate production data to infer self trade using this method leads to substantial measurement error in the self trade estimates. I therefore deviate from Hanson et al. (2018) by assuming trade costs have a common additively separable *sector-level* component, and use estimates of sector-level production data to

Table A3: List of tradable sectors in US Census 1950 classification.

Sector	Sector (2)
Agriculture	Photographic equipment and supplies
Own farm	Watches, clocks, and clockwork-operated devices
Forestry	Meat products
Fisheries	Dairy products
Hunting	Canning and preserving fruits, vegetables, and seafoods
Metal mining	Grain-mill products
Coal mining	Bakery products
Crude petroleum and natural gas extraction	Confectionery and related products
Nonmetallic mining and quarrying, except fuel	Beverage industries
Logging	Miscellaneous food preparations and kindred products
Sawmills, planing mills, and mill work	Tobacco manufactures
Miscellaneous wood products	Knitting mills
Furniture and fixtures	Dyeing and finishing textiles, except knit goods
Glass and glass products	Carpets, rugs, and other floor coverings
Cement, concrete, gypsum and plaster products	Yarn, thread, and fabric mills
Structural clay products	Miscellaneous textile mill products
Pottery and related products	Apparel and accessories
Miscellaneous nonmetallic mineral and stone products	Miscellaneous fabricated textile products
Blast furnaces, steel works, and rolling mills	Pulp, paper, and paperboard mills
Other primary iron and steel industries	Paperboard containers and boxes
Primary nonferrous industries	Miscellaneous paper and pulp products
Fabricated steel products	Printing, publishing, and allied industries
Fabricated nonferrous metal products	Synthetic fibers
Not specified metal industries	Drugs and medicines
Agricultural machinery and tractors	Paints, varnishes, and related products
Office and store machines and devices	Miscellaneous chemicals and allied products
Miscellaneous machinery	Petroleum refining
Electrical machinery, equipment, and supplies	Miscellaneous petroleum and coal products
Motor vehicles and motor vehicle equipment	Rubber products
Aircraft and parts	Leather: tanned, curried, and finished
Ship and boat building and repairing	Footwear, except rubber
Railroad and miscellaneous transportation equipment	Leather products, except footwear
Professional equipment and supplies	

Table A4: List of tradable sectors in WIOD classification.

ISIC rev.3 code	Industry name
A-B	Agriculture, hunting, forestry and fishing
C/E	Mining and quarrying / Electricity, gas and water supply
D15-16	Food, beverages and tobacco
D17-18	Textiles and textile products
D19	Leather, leather products and footwear
D20	Wood and products of wood and cork
D21-22	Pulp, paper, printing and publishing
D23	Coke, refined petroleum and nuclear fuel
D24	Chemicals and chemical products
D25	Rubber and plastics
D26	Other non-metallic minerals
D27-28	Basic metals and fabricated metals
D29	Machinery, not elsewhere classified
D30-33	Electrical and optical equipment
D34-35	Transport equipment
D36-37	Manufacturing, not elsewhere classified; recyling

estimate self trade at the *industry* level.

I classify sectors according to the World Input Output Database (Table XXX). I take value added production data for primary sectors and manufacturing from UN National Accounts. This leaves me with obtaining estimates of value added *shares* of manufacturing subsectors, for which I use production data from UNIDO INDSTAT 2.0. Along the way, to obtain estimates for country-sector-year cells with missing data, I extrapolate from non-missing observations by projecting variables onto log GDP per capita (Penn World Tables 9.0) and a time trend.

One cannot simply combine the WTF and production data from national accounts because the former are in terms of gross output and the latter in terms of value added. As gross output production data are not widely available, I convert any estimates of value added production data into gross output using yearly sector-level estimates from Korea KLEMS.

Finally, I estimate industry-level self trade as the product of equations 53 and 54. Doing so requires importer and exporter fixed effects for all industry-country-year cells, however. As not all countries import and/or export in all industries, I estimate synthetic fixed effects by extrapolating from non-missing observations by projecting fixed effects onto log GDP per capita and a time trend.

D.2 Occupations (O*NET)

I use detailed occupation-level information to assign occupations to subgroups (task groups). The Occupational Information Network (O*NET) is my primary source for information on the standardized work characteristics of occupations and sectors. Its O*NET database contains hundreds of standardized occupation-specific descriptors on almost 1,000 occupations that cover the entire U.S. economy. In particular, the database provides information on "Work Activities", which "(...) *summarize the kinds of tasks that may be performed across multiple occupations.*" As such, it provides a standardized set of tasks that are comparable across occupations and sectors.

Each descriptor in O*NET is associated with at least one scale, which are standardized to a score ranging from 0 to 100. The values of these scores are the average response of survey participants that work in a specific occupation. The database contains two scales for Work Activities: Importance and Level. The Importance scale "(...) *indicates the degree of importance a particular descriptor is to the occupation.*" The Level scale "(...) *indicates the degree, or point along a continuum, to which a particular descriptor is required or needed to perform the occupation.*." I choose to work with the Level scale. In total, O*NET contains data on 41 standardized work activities, which are summarized in Table A1.

E Results

E.1 Spillovers at the Sector-Level

To illustrate how differences in diffusion parameters at the task level translate into differences at the sector-level, I construct a measure that captures the effect of moving labor into a certain sector on global aggregate GDP relative to other sectors. Denote the effect of moving all labor into sector k on productivity in sector $\tilde{k}$ by $\Delta \ln \tilde{y}^{\tilde{k}}_{n,t}$. The effect on aggregate GDP is then given by

$$\sum_{\tilde{k}=1}^{K} \theta^{\tilde{k}}_t \Delta \ln \tilde{y}^{\tilde{k}}_{n,t} \tag{55}$$

where $\theta^{\tilde{k}}_t$ is the share of global exports accounted for by sector $\tilde{k}$. Substituting in dynamic scale economies when all labor is in sector k:

$$\sum_{\tilde{k}=1}^{K} \theta^{\tilde{k}}_t \sum_{a=1}^{A} \zeta^{\tilde{k}}_a \tilde{\eta}_a \ln L^{a,k}_{n,t} \tag{56}$$

Lastly, I express this measure of spillovers relative to a benchmark sector, agriculture (denoted by AB), which has the lowest extent of spillovers due to its intensive use mechanical occupations. The final measure of spillovers is thus

$$\sum_{\tilde{k}=1}^{K} \theta^{\tilde{k}}_t \sum_{a=1}^{A} \zeta^{\tilde{k}}_a \tilde{\eta}_a (\ln L^{a,k}_{n,t} - L^{a,AB}_{n,t}) \tag{57}$$

The estimated magnitude of this measure of sector-specific spillovers are summarized in Table A5. Spillovers tend to be highest as a result of allocating labor to sectors that use high-skilled occupations intensively, such as electrical and optical equipment, chemicals and fuels.

Table A5: Spillovers by Tradable Sector r.t. Agriculture (WIOD classification)

Subsector	**Spillover**
Agriculture, hunting, forestry and fishing (A & B)	0
Mining and quarrying (C)	0.84
Food, beverages and tobacco (D15-16)	0.90
Textiles and textile products (D17-18)	0.88
Leather, leather products and footwear (D19)	0.88
Wood and products of wood and cork (D20)	0.71
Pulp, paper, printing and publishing (D21-22)	0.97
Coke, refined petroleum and nuclear fuel (D23)	0.95
Chemicals and chemical products (D24)	0.98
Rubber and plastics (D25)	0.92
Other non-metallic minerals (D26)	0.87
Basic metals and fabricated metals (D27-28)	0.91
Machinery, not elsewhere classified (D29)	0.93
Electrical and optical equipment (D30-33)	0.96
Transport equipment (D34-35)	0.86
Manufacturing, not elsewhere classified; recyling (D36-37)	0.94

Notes: This table reports the magnitude of spillovers by tradable sector relative to the agricultural sector, taken as the unweighed mean over the years 1970-2000 in the World Trade Flows sample. Relative spillovers are defined as in equation 57. Table uses WIOD classification of sectors, which roughly corresponds to a 2-digit ISIC classification.