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WP 13-14R

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Abstract

We study the impact of intersectoral and interregional trade linkages in propagating disaggregated productivity changes to the rest of the economy. Using U.S. regional and industry data, we obtain the aggregate, regional and sectoral elasticities of measured TFP, GDP, and employment to regional and sectoral productivity changes. We find that the elasticities vary significantly depending on the sectors and regions affected, and are importantly determined by the spatial structure of the economy. We use our calibrated model to perform a variety of counterfactual exercises including several specific studies of the aggregate and disaggregate effects of shocks to productivity and infrastructure. The specific episodes we study include the boom in California's computer industry, the productivity boom in North Dakota associated with the shale oil boom, the disruptions in New York's finance and real state industries in the 2008 crisis, as well as the effect of the destruction of infrastructure in Louisiana following hurricane Katrina.

1. INTRODUCTION

Fluctuations in aggregate economic activity result from a wide variety of disaggregated phenomena. These phenomena can reflect underlying changes that are sectoral in nature, such as process or product innovations, or regional in nature, such as natural disasters or changes in local regulations. In other cases, fundamental productivity changes are actually specific to a sector and a location: a large corporate bankruptcy or bailout. The heterogeneity of these potential changes in productivity at the sectoral and regional levels implies that the particular sectoral and regional composition of an economy is essential in determining their aggregate impact. That is, regional trade, the presence of local factors such as land and structures, regional migration, as well as input-output relationships between sectors, all determine the impact of a disaggregated sectoral

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or regional productivity change on aggregate outcomes. In this paper, we present a model of the sectoral and regional composition of the U.S. economy and use it to measure the elasticity of aggregate measured productivity, output, and welfare, to disaggregated fundamental productivity and infrastructure changes.

The major part of research in macroeconomics has traditionally emphasized aggregate disturbances as sources of aggregate changes.[1] Exceptions to this approach were Long and Plosser (1983), and Horvath (1998, 2000) who posited that because of input-output linkages, productivity disturbances at the level of an individual sector would propagate throughout the economy in a way that led to notable aggregate movements.[2] More recently, a series of papers has characterized and verified empirically the condition under which sector and firm level disturbances can have aggregate consequences.[3] Notably, Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012) characterize the conditions under which the network structure of production linkages effectively amplifies the impact of microeconomic shocks,[4] while empirically, Foerster, Sarte, and Watson (2011) find support for sectoral shocks as determinants of aggregate effects.

We follow this strand of the literature, but note that to this point, the literature studying the aggregate implications of disaggregated productivity disturbances has largely abstracted from the regional composition of sectoral activity. A decomposition of the productivity changes experienced by the U.S. economy between 2002 and 2007 (or 2007 to 2012) into a local, a sectoral, and a residual component reveals that such an abstraction is unjustified. We find that the regional component is at least as important as the sectoral component, if not more, and that the residual component –which includes local sectoral shocks– is important as well. Hence, motivated by these findings, we build on the empirical evidence from Acemoglu, et al. (2015) and Acemoglu, Akcigit, and Kerr (2015), that production networks amplify regional-local shocks, and contribute to this literature by integrating sectoral production linkages with those that arise by way of inter-regional linkages. The resulting framework allows for the analysis, by way of region-specific production structures where inputs are traded across regions, of more granular disturbances that may vary at the level of a sector within a region. Regional considerations, therefore, become key in explaining the aggregate, sectoral, and regional effects of microeconomic disturbances.

The distribution of sectoral production across regions in the U.S. is far from uniform. Blanchard and Katz (1992), and more recently Fogli, Hill and Perri (2012), provide empirical evidence that factors related to geography, such as labor mobility across states, matter importantly for macroeconomic adjustments to disturbances. Furthermore, because inputs must be traded across space when production varies geographically, trade costs also play a role in determining macroeconomic allocations and welfare, consistent with the findings of Fernald (1999), and Duranton, Morrow, and Turner (2014), on the economic relevance of road networks. How then do geographical considerations play out in determining the effects of disaggregated productivity changes? What are the associated key mechanisms and what is their quantitative importance? We take up these issues and use our findings to analyze the aggregate consequences of variety of recent specific shocks to the U.S. economy.

The fact that different regions of the U.S. differ significantly in what they produce has two important implications. First, to the degree that economic activity involves a complex network of interactions between

[1] This emphasis, for example, permeates the large Real Business Cycles literature that followed the seminal work of Kydland and Prescott (1982).

[2] See also Jovanovic (1987) who shows that strategic interactions among firms or sectors can lead micro disturbances to resemble aggregate factors.

[3] Even absent of network effects, Gabaix (2011) shows that granular disturbances do not necessarily average out when the size distribution of firms or sectors is sufficiently fat-tailed. Carvalho and Gabaix (2013) find that idiosyncratic shocks can account for large swings in macroeconomic volatility, as exemplified by the "great moderation" and its recent undoing.

[4] Oberfield (2013) provides a theoretical foundation for such a network structure.

sectors, these interactions take place over potentially large distances by way of regional trade, but trading across distances is costly.[5] Second, since sectoral production has to take place physically in some location, it is then influenced by a wide range of changing circumstances in that location, from changes in policies affecting the local regulatory environment or business taxes to natural disasters. Added to these regional considerations is that some factors of production are fixed locally and unevenly distributed across space, such as land and structures, while others are highly mobile, such as labor.[6]

To study how these different aspects of economic geography influence the effects of disaggregated productivity disturbances, we develop a quantitative model of the U.S. economy broken down by regions and sectors. In each sector and region, there are two factors of production, labor and a composite factor comprising land and structures. As emphasized by Blanchard and Katz (1992), labor is allowed to move across both regions and sectors. Land and structures can be used by any sector but are fixed locally. Sectors are interconnected by way of input-output linkages but, in contrast to Long and Plosser (1983) and its ensuing literature, shipping materials to sectors located in other regions is costly in a way that varies with distance. Using data on pairwise trade flows across states by industry, as well as other regional and industry data, we calibrate the model and explore the regional, sectoral, and aggregate effects of disaggregated productivity changes. Specifically, for a given productivity change located within a particular sector and region, the model delivers the effects of this change on all sectors and regions in the economy.

We find that disaggregated productivity changes can have different aggregate implications depending on the regions and sectors affected. These effects arise in part by way of endogenous changes in the pattern of regional trade through a selection effect that determines what types of goods are produced in which regions. They also arise by way of labor migration towards regions that become more productive. When such migration takes place, the inflow of workers strains local fixed factors in those regions and, therefore, mitigates the direct effects of any productivity increases.[7] For example, the aggregate GDP elasticity of a regional fundamental productivity increase in Florida is 0.89.[8] In contrast, the aggregate GDP elasticity of a regional fundamental productivity increase in New York state, which is of comparable employment size relative to aggregate employment (6.1% versus 6.2%, respectively), is 1.6. Thus, the effects of disaggregated productivity changes depend in complex ways on the details of which sectors and regions are affected, and how these are linked through input-output and trade relationships to other sectors and regions.

These spatial effects impact significantly the magnitude of the aggregate elasticity of sectoral shocks; for example, failure to account for regional trade understates the aggregate GDP elasticity of an increase in productivity in the Petroleum and Coal industry – the most spatially concentrated industry in the U.S. economy– by about 10% but overstates it by 19% in the Transportation Equipment industry – an industry that exhibits much less spatial concentration. Ultimately, regional trade linkages, and the fact that materials produced in one region are potentially used as inputs far away, are essential in propagating productivity changes spatially and across sectors. We emphasize this point, and the use of the elasticities we present, through several specific applications. We start by studying the impact of the TFP gains in the Computers and Electronics industry in California, over the period 2002-2007; an example of a region and industry

[5] We find that eliminating U.S. regional trading costs associated with distance would result in aggregate TFP gains of approximately 50 percent, and in aggregate GDP gains on the order of 126 percent (see Appendix A.7).

[6] See Kennan and Walker (2011) for a recent detailed empirical study of migration across U.S. states.

[7] In very extreme cases, regional productivity increases can even have negative effects on aggregate GDP (although welfare effects are always positive). In our calibration this happens only for Hawaii (See Figure 8f).

[8] To highlight the mechanisms at play, aggregate elasticities throughout the paper are normalized to abstract from effects arising simply from variations in state size. Thus, in a model without sectoral or trade linkages, the elasticity of aggregate TFP with respect to a productivity change in a given state will be one for all states, rather than simply reflecting that state's weight in production.

specific productivity increase in a tradable industry. To study a regional shock that affects all sectors, we study the increases in productivity across industries in North Dakota associated with the shale oil boom. We also study the disruptions in the Finance and Real State industries in New York during the 2008 economic crisis; an example of a negative productivity shock to a nontradable industry. In a final application, we go beyond productivity changes and study the effect of the destruction in structures created by hurricane Katrina in Louisiana. This last case provides a novel, as far as we know, general equilibrium evaluation of the economic costs of this event.

Our framework builds on Eaton and Kortum (2002), and the growing international trade literature that extends their model to multiple sectors.[9] The geographic nature of our problem, namely the presence of labor mobility, local fixed factors, and heterogeneous productivities, introduce a different set of mechanisms through which changes in fundamental productivity affect production across sectors and space relative to most studies in the literature.

The rest of the paper is organized as follows. The next subsection describes the composition of U.S. economic activity. We make use of maps and figures to show how economic activity varies across U.S. states and sectors. Section 2 presents the quantitative model. Section 3 describes in detail how to compute and aggregate measures of TFP, GDP, and welfare across different states and sectors, and shows how these measures relate to fundamental productivity changes. Section 4 describes the data, shows how to carry out counterfactuals, and how to calibrate the model to 50 U.S. states and 26 sectors. Section 5 quantifies the effects of different disaggregated fundamental productivity changes. In particular, we measure the elasticity of aggregate productivity and output to sectoral, regional, as well as sector and region specific productivity changes. Section 6 presents several applications of these results to specific events. Section 7 concludes.

1.1 The Composition of U.S. Economic Activity

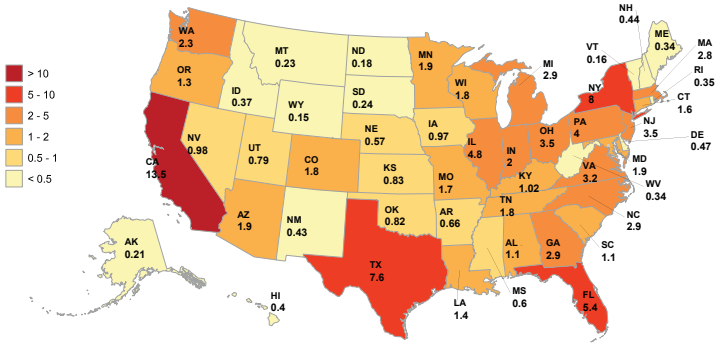
Throughout the paper, we break down the U.S. economy into 50 U.S. states and 26 sectors pertaining to the year 2007, our benchmark year. We motivate and describe in detail this particular breakdown in Section 4. As shown in Figure 1a, shares of GDP vary greatly across states. In part, these differences stem from differences in geographic size. However, as Figure 1a makes clear, differences in geographic size are not large enough to explain observed regional differences in GDP. New York state's share of GDP, for example, is slightly larger than Texas' even though its geographic area is several times smaller. The remaining differences cannot be explained by any mobile factor such as labor, equipment, or other material inputs, since those just follow other local characteristics. In fact, as illustrated in Figure 1b, the distribution of employment across states, although not identical to that of GDP, matches it fairly closely. Why then do some regions produce so much more than others and attract many more workers? The basic approach in this paper argues that three local characteristics, namely total factor productivity, local factors, and access to products in other states, are essential to the answer. Specifically, we postulate that changes to total factor productivity (TFP) that are sectoral and regional in nature, or specific to an individual sector within a region, are fundamental to understanding local and sectoral output changes. Furthermore, these changes have aggregate effects that

[9] For instance Caliendo and Parro (2015), Caselli, et al. (2012), Costinot, Donaldson, and Komunjer, (2012), Levchenko and Zhang, (2012), and Tombe and Zhu, (2015). Eaton and Kortum (2012) and Costinot and Rodriguez-Clare (2013) present surveys of recent quantitative extensions of the Ricardian model of trade. Our paper relates closely to Finicelli, Pagano, and Sbracia (2013) where they emphasize the selection effects in the Ricardian model. From a more regional perspective, two related papers, Redding (2012) and Allen and Arkolakis (2013), study the implications of labor mobility for the welfare gains of trade, but abstract from studying the role of sectoral linkages or from presenting a quantitative assessment of the effects of disaggregated fundamental productivity changes on U.S. aggregate measures of TFP, GDP, or welfare.

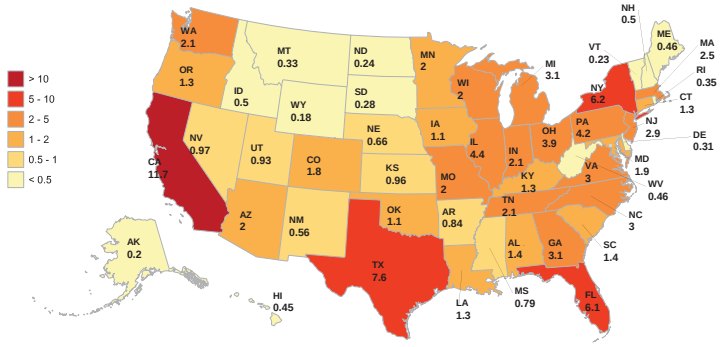
are determined by their geographic and sectoral distribution.

FIG. 1. Distribution of economic activity in the U.S.

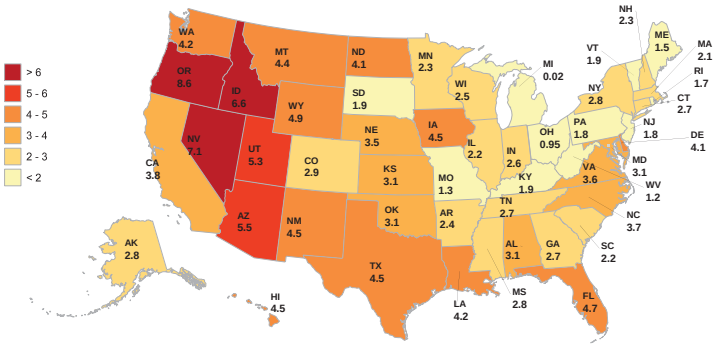
a: Share of GDP by region (%, 2007)



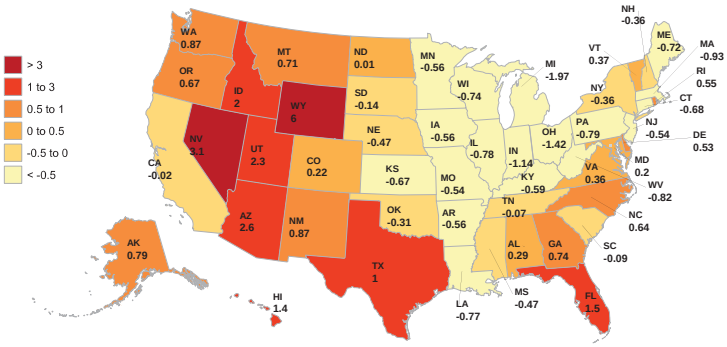
b: Share of Employment by region (%, 2007)



c: Change in GDP (%, 2002 to 2007)



d: Change in Employment shares (%, 2002 to 2007)



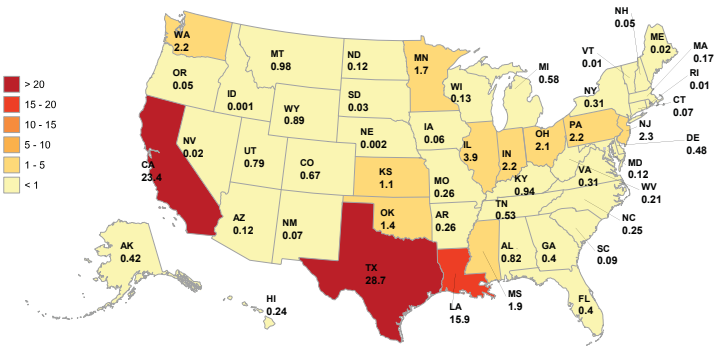
One initial indication that different regions indeed experience different circumstances is presented in Figure 1c, which plots average annualized percentage changes in regional GDP across states for the period 2002-2007 (Section 4 describes in detail the disaggregated data and calculations that underlie aggregate regional changes in GDP). The figure shows that annualized GDP growth rates vary across states in dramatic ways; from 7.1 percent in Nevada, to 0.02 percent in Michigan. Of course, some of these changes reflect changes in employment levels. Nevada's employment relative to aggregate U.S. employment grew by 3.1 percent during this period while that of Michigan declined by -1.97 percent. Figure 1d indicates that employment shares also vary substantially over time, although somewhat less than GDP. The latter observation supports the view that labor is a mobile factor, driven by changes in fundamentals, such as productivity.

While our discussion thus far has underscored overall economic activity across states, one may also consider particular sectors. Doing so immediately reveals that the sectoral distribution of economic activity also varies greatly across space. An extreme example is given by the Petroleum and Coal industry in Figure 2a. This industry is mainly concentrated in only 3 states, namely California, Louisiana, and Texas[10]. In contrast,

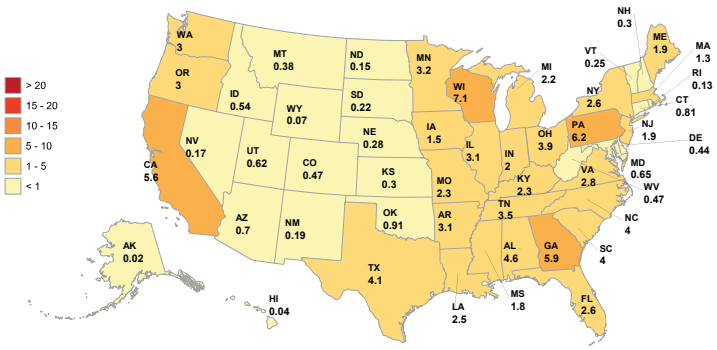
[10] The Petroleum and Coal Products Manufacturing sector in our data is the NAICS 324 sector. Namely, it is based on the transformation of crude petroleum and coal into usable products, and not the extraction of crude petroleum and coal. Therefore, it mainly captures petroleum refining, coal products and produce products, such as asphalt coatings and petroleum lubricating oils.

Fig. 2. Sectoral concentration across regions (shares, 2007)

a: Petroleum and Coal



b: Wood and Paper



c: Health Care

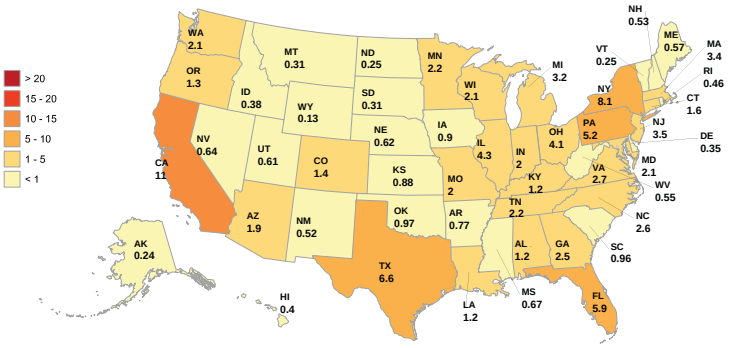
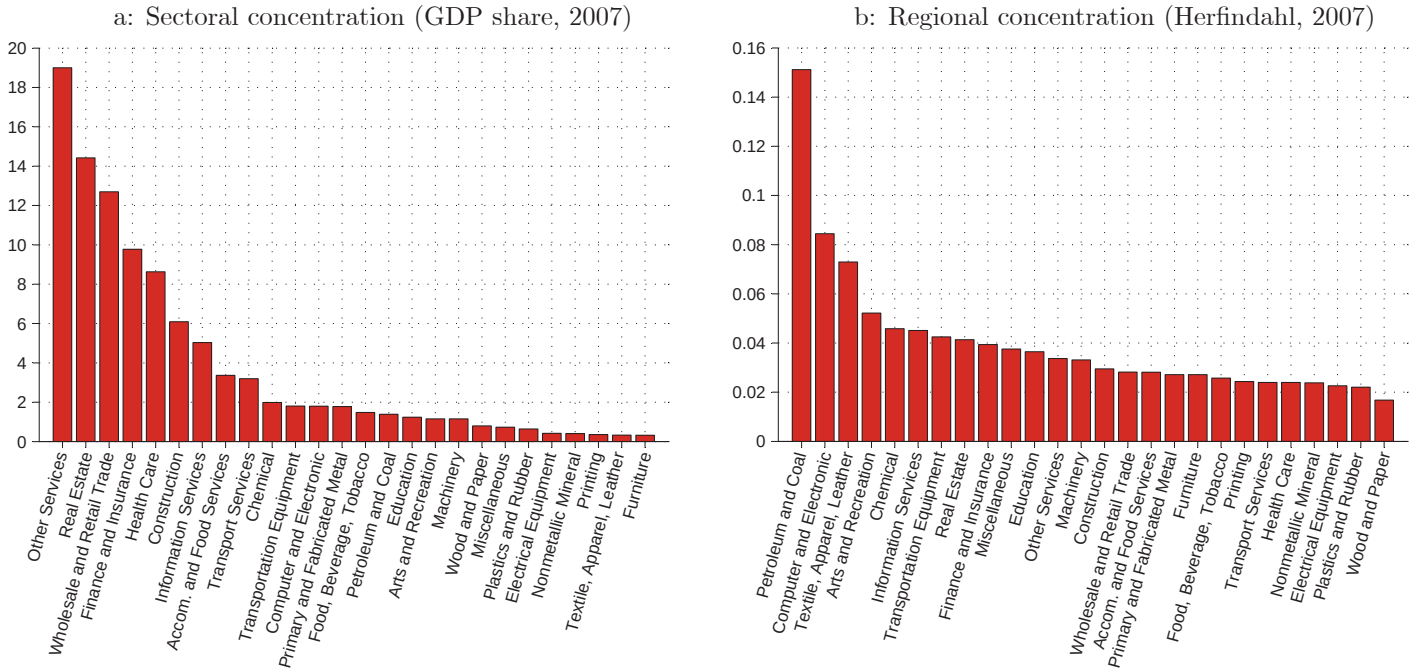


Figure 2b presents GDP shares in the Wood and Paper industry, the most uniformly dispersed industry in our sample. Figure 2c displays GDP shares in the Health Care industry, the least concentrated service industry in our sample. Economic activity in this industry is also much more uniformly dispersed than Computers and Electronics, but a bit more concentrated in the largest states than Wood and Paper. The geographic concentration of industries may, of course, be explained in terms of differences in local productivity or access to essential materials. In this paper, these sources of variation are reflected in individual industry shares across states. For now, we simply make the point that variations in local conditions are large, and that they are far from uniform across industries.

Figure 3a shows the sectoral concentration of economic activity while Figure 3b presents the Herfindahl index of GDP concentration across states for each industry in our study. Differences in the spatial distribution of economic activity for different sectors imply that sectoral disturbances of similar magnitudes will affect regions very differently and, therefore, that their aggregate impact will vary as well. Hence, to assess the implications of technological changes in different sectors, one needs to be cognizant of how these changes are filtered through the regional economy. Studying this process and its quantitative implications is the main purpose of this paper.

An important channel through which the geographic distribution of economic activity, and its breakdown

Fig. 3. Economic activity across sectors in the U.S.



across sectors, affects the impact of changes in total factor productivity relates to interregional trade. Trade implies that disturbances to a particular location will affect prices in other locations and thus consumption and, through input-output linkages, production in other locations. This channel has been studied widely with respect to trade across countries but much less with respect to trade across regions within a country. That is, we know little about the propagation of local productivity changes across regions within a country through the channel of interregional trade, when we take into account that people move across states. This is perhaps surprising given that trade is considerably more important within than across countries. Table 1 presents U.S. imports and exports as a percentage of GDP in 2007. Overall, trade across regions amounts to about two thirds of the economy and it is more than twice as large as international trade. This evidence underscores the need to incorporate regional trade in the analysis of the effects of productivity changes, as we do here.

Table 1. Importance of Regional Trade

U.S. trade as a share of GDP (%, 2007)			
	Exports	Imports	Total
International trade	11.9	17.0	28.9
Interregional trade	33.4	33.4	66.8

Source: World Development indicators and CFS

While interregional trade and input-output linkages have the potential to amplify and propagate technological changes, they do not generate them. Furthermore, if all disturbances were only aggregate in nature, regional and sectoral channels would play no role in explaining aggregate changes.

We now proceed to present some data which we have manipulated to represent variables that have a

clear counterpart in the model we propose in the next section. The first of those is measured total factor productivity (TFP). Figure 4a shows that annualized changes in sectoral measured TFP vary dramatically across sectors, from 14 percent per year in the Computer and Electronics industry to a decline in measured productivity of more than 2 percent in Construction. We describe in detail the data and assumptions needed to arrive at disaggregated measures of productivity by sector and region in Section 4. In that section, we underscore the distinction between fundamental productivity and the calculation of measured productivity that includes the effect of trade and sectoral linkages. In fact, the structure of the model driving our analysis helps precisely in understanding how changes in fundamental productivity affect measured productivity.[11]

Fig. 4. Sectoral measured TFP of the U.S. economy from 2002 to 2007

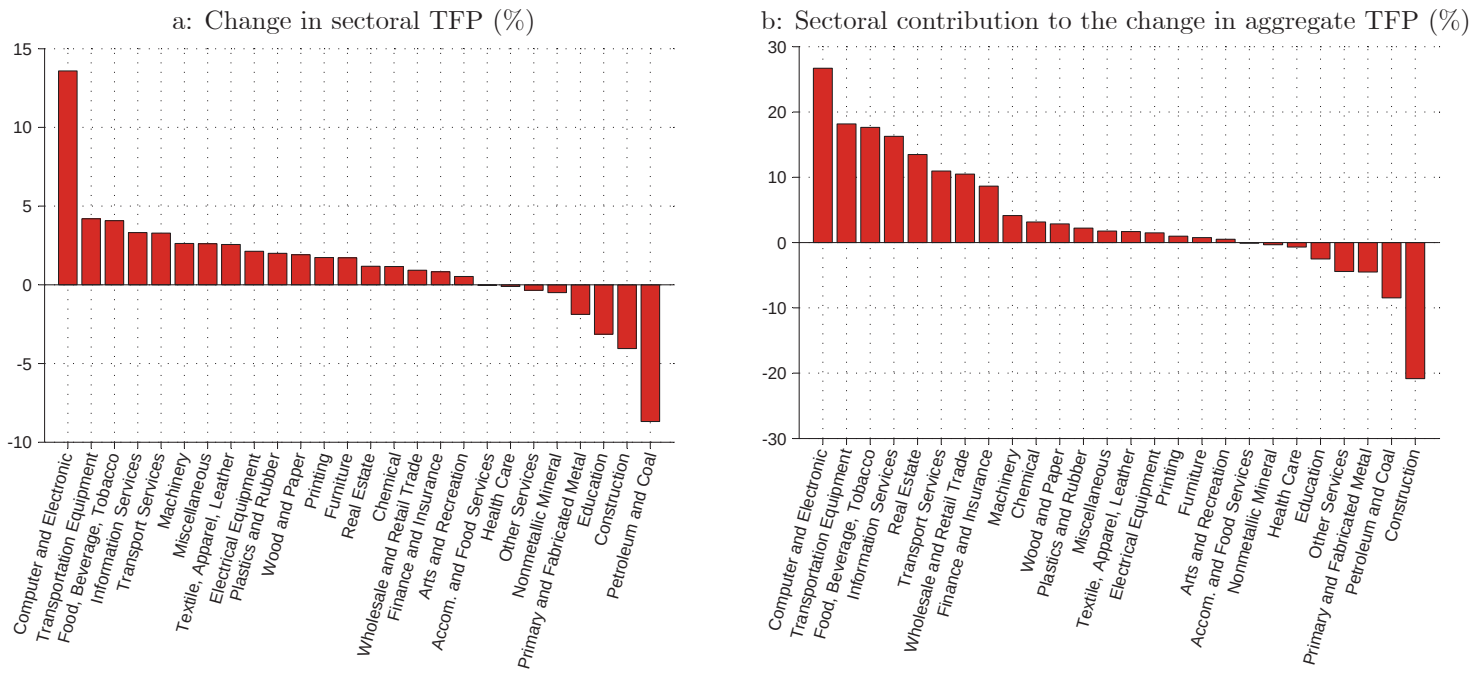


Figure 4b presents the contribution of sectoral changes in measured TFP to aggregate TFP changes. The distinction between Figures 4a and 4b reflects the importance or weight of different sectors in aggregate productivity. Once more, the heterogeneity across sectors is surprising. Moreover, this heterogeneity implies that changes in a particular sector will have very distinct effects on aggregate productivity, even conditional on the size of the changes.

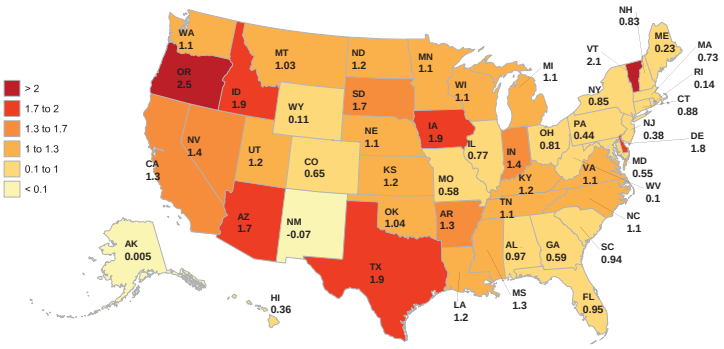
Variations in TFP across sectors have received considerable attention in the macroeconomics literature (see Foerster et al., 2011, Gabaix, 2011, and Acemoglu, et al., 2012, among others). In contrast, this literature has paid virtually no attention to the regional composition of TFP changes. Figures 5a and b shows that this lack of attention is potentially misguided. Changes in measured TFP vary widely across regions. Furthermore, the contribution of regional changes in measured TFP to variations in aggregate TFP is also very large. The difference between Figures 5a and 5b reflects the weight of different states in aggregate productivity.

[11] Regional measures of TFP at the state level are not directly available from a statistical agency. As explained in Section 4, our calculations of disaggregated TFP changes rely on other information directly observable by region and sector, such as value added or gross output, as well as on unobserved information inferred using equilibrium relationships consistent with the model presented in Section 2. Importantly, our measures of disaggregated TFP changes sum up to the aggregate TFP change for the same period directly available from the OECD productivity database.

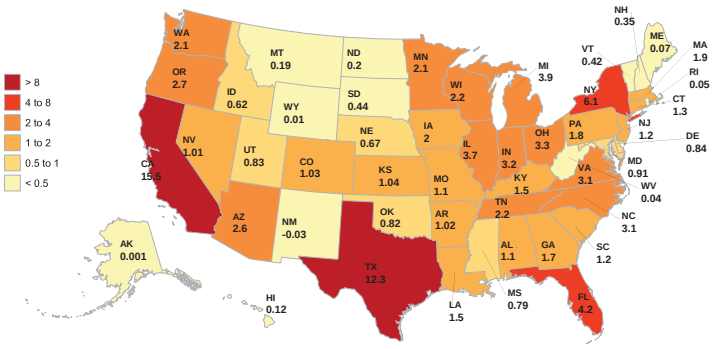
The change in TFP over the period 2002-2007 was 1.4 percent per year in Nevada but 1.1 percent in Michigan. These differences in TFP experiences naturally contributed to differences in employment and GDP changes in those states. More generally, variations across states result in part from sectoral productivity changes as well as changes in the distribution of sectors across space which, as we have argued, is far from uniform. However, even if all the variation in Figures 5a and b were ultimately traced back to sectoral changes, their uneven regional composition would influence their impact on trade and, ultimately, aggregate TFP.

Fig. 5. Regional measured TFP of the U.S. economy from 2002 to 2007

a: Change in TFP by regions (%)

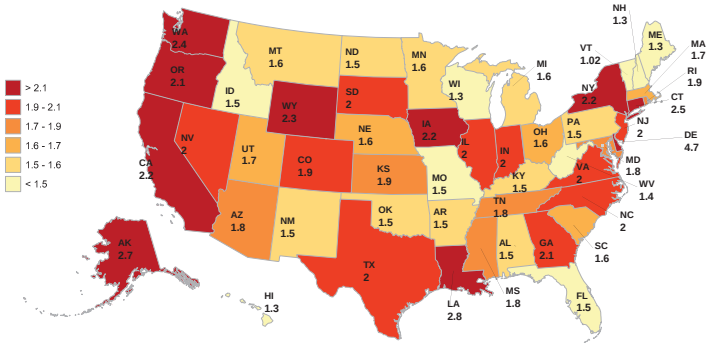


b: Regional contribution to the change in aggregate TFP (%)



One of the key economic determinants of income across regions is the stock of land and structures. To our knowledge, there is no direct measure of this variable. However, as we explain in detail in Section 4, we can use the equilibrium conditions from our model to infer the regional distribution of income from land and structures across U.S. states. Figure 6 shows that per capita income from land and structures in 2007 U.S. dollars varies considerably across states. The range varies from a low of 10,200 and 13,000 dollars per capita for the case of Vermont and Wisconsin respectively, to a high of 47,000 dollars in Delaware. We will argue that this regional dispersion of land and structures across regions in the U.S. is central to understanding the aggregate effects of disaggregated fundamental productivity changes.

Fig. 6. Per capita regional rent from land and structures (10,000 of 2007 U.S. dollars)



We conclude this section with an evaluation of the relative importance of regional and sectoral changes in TFP for the aggregate economy. To do so, we follow Koren and Tenreyro (2007)'s methodology to decompose measured TFP into a regional, a sectoral, and a regional-sectoral component. The results for measured TFP changes from 2002 to 2007 are presented in Table 2. The regional component accounts for 28.9% of the changes in measured TFP, while the sectoral component accounts for 21.1% of the variation and the region-sector component for the remaining 50%. In Appendix A.5, we describe in detail the methodology, as well as all the data and steps needed to perform the decomposition. We also show that the results for measured TFP changes between 2007 and 2012 are similar.[12] In all cases we find that regional productivity changes, either for all sectors or for specific sectors, account for more than three fourths of the variation in measured TFP. These results underscore the importance of regional shocks and the relevance of measuring their impact on regional and aggregate outcomes. The mapping between TFP changes at the local level and their impact on aggregate outcomes depends on the spatial characteristics of the economy; in particular its local factor endowments and its trade and input-output networks. The next section proposes a macroeconomic framework with spatial detail to quantify these relationships.

Table 2. Importance of Regional and Sectoral TFP Changes

Variation in measured TFP changes for 2002-2007 explained by	
Regional component	28.9%
Sectoral component	21.1%
Residual	50.0%

Table shows Sobol's Sensitivity index. See Appendix A.5 for further details.

2. THE MODEL

Our goal is to produce a quantitative model of the U.S. economy disaggregated across regions and sectors. For this purpose, we develop a static two factor model with N regions and J sectors. We denote a particular region by $n \in \{1, ..., N\}$ (or i), and a particular sector by $j \in \{1, ..., J\}$ (or k). The economy has two factors, labor and a composite factor comprising land and structures. Labor can freely move across regions and sectors. Land and structures, H_n, are a fixed endowment of each region but can be used by any sector. We denote total population size by L, and the population in each region by L_n. A given sector may be either tradable, in which case goods from that sector may be traded at a cost across regions, or non-tradable. Throughout the paper, we abstract from international trade and other international economic interactions.

2.1 Consumers

Agents in each location $n \in \{1, ..., N\}$ order consumption baskets according to Cobb-Douglas preferences given by

$$U(C_n) = \prod_{j=1}^{J} (c_n^j)^{\alpha^j} \quad \text{where} \sum_{j=1}^{J} \alpha^j = 1,$$

with shares α^j, over their consumption of final domestic goods c_n^j, bought at prices P_n^j, in all sectors $j \in \{1, ..., J\}$.

[12] In Appendix A.5 we also present the results where instead of using measured TFP we use fundamental TFP, a model-based concept of productivity that represents production efficiency in the production of value added in the absence of trade and selection effects. The results are again similar. Please refer to Table A5.1 in Appendix A.5 to see the results.

Agents move freely across regions. In equilibrium, households are indifferent between living in any region. Hence,

$$U = \frac{I_n}{P_n} \quad \text{for all } n \in \{1, ..., N\}, \tag{1}$$

where I_n is income earned by agents residing in region n, $P_n = \prod_{j=1}^{J} \left(P_n^j/\alpha^j\right)^{\alpha^j}$ is the ideal price index in region n, and U is determined in equilibrium. All prices are denoted in terms of a numéraire which we choose to be the price of aggregate output in the U.S.

2.2 Asset Holdings and Regional Deficits

A quantitative model of the U.S. economy should accommodate the large observed regional trade imbalances.[13] We model imbalances in our framework by determining the asset holdings of agents in each location. We assume that local factors are partly owned by local governments that redistribute their rents to local residents. The remaining share of local factors is aggregated in a national portfolio that is owned by all residents.

We assume that a fraction $\iota_n \in [0, 1]$ of the rents to the local factor go into the national portfolio of local assets. All residents hold an equal number of shares in the national portfolio and so receive the same proportion of its returns. The remaining share, $(1 - \iota_n)$, of local factors is owned by the local government in region n. The returns to this fraction of the local factors is distributed lump-sum to all local residents. This ownership structure of local factors result in a model that is flexible enough (through the determination of ι_n) to match almost exactly observed trade imbalances across states (see Section 4). It allows individuals living in certain states to receive higher returns from local factors but avoids the complications of individual wealth effects, and the resulting heterogeneity across individuals, that result from individual ownership of local assets. We refer to $1 - \iota_n$ as the share of local rents from land and structures.

The income of an agent residing in region n is therefore

$$I_n = w_n + \chi + (1 - \iota_n) \frac{r_n H_n}{L_n},$$

where w_n is the wage and r_n is the rental rate of structures and land, and $r_n H_n / L_n$, is the per capita income from renting land and structures to firms in region n. The term χ represents the return per person from the national portfolio of land and structures from all regions. In particular,

$$\chi = \frac{\sum_{i=1}^{N} \iota_i r_i H_i}{\sum_{i=1}^{N} L_i}.$$

The remittances by region n to the national portfolio are given by $\iota_n r_n H_n$. Hence, the difference between the remittances and the income in region n, generates imbalances given by

$$\Upsilon_n \equiv \iota_n r_n H_n - \chi L_n.$$

The excess of income generated by these imbalances in region n is spent by agents in local goods. The

[13] The international trade literature usually abstracts from modelling trade imbalances across countries, either by assuming that trade is balanced, or by assuming these imbalances are constant. The U.S. economy presents substantial trade imbalances across regions. For instance, Florida and Texas had trade deficits of about US 40 billion in 2007, while Wisconsin and Indiana have surpluses of about the same magnitude. Here we propose a practical way to deal with these imbalances in a static model.

magnitude of these imbalances will change in our model with changes in fundamental productivity, as they will impact the wages and the rental rate of structures. Increases in fundamental productivity in region n relative to the U.S. economy will increase the remittances sent to the national portfolio relative to the transfers from it; thus, increasing the likelihood of surpluses in region n, Υ_n. Note that if $\iota_n < 1$, so part of the rents from local assets are owned and redistributed by the local government, the competitive equilibrium is not efficient. The reason is that agents do not internalize the effect of their migration decisions on the local rents distributed to other agents.[14]

2.2 Technology

Technology in our model follows closely Eaton and Kortum (2002). Sectoral final goods are used for consumption and as material inputs into the production of intermediate goods in all industries. In each sector, final goods are produced using a continuum of varieties of intermediate goods in that sector. We refer to the intermediate goods used in the production of final goods as 'intermediates,' and to the final goods used as inputs in the production of intermediate goods as 'materials.'

2.2.1 Intermediate Goods

Representative firms, in each region n and sector j, produce a continuum of varieties of intermediate goods that differ in their *idiosyncratic* productivity level, z_n^j. In each region and sector, this productivity level is a random draw from a Fréchet distribution with shape parameter θ^j and location parameter 1. Note that θ^j varies only across sectors. We assume that all draws are independent across goods, sectors, and regions. The productivity of all firms producing varieties in a region-sector pair (n, j) is also determined by a deterministic productivity level, T_n^j, specific to that region and sector. We refer to T_n^j as fundamental productivity. The production function for a variety associated with idiosyncratic productivity z_n^j in (n, j) is given by

$$q_n^j(z_n^j) = z_n^j \left[T_n^j \left[h_n^j(z_n^j) \right]^{\beta_n} \left[l_n^j(z_n^j) \right]^{(1-\beta_n)} \right]^{\gamma_n^j} \prod_{k=1}^{J} \left[M_n^{jk}(z_n^j) \right]^{\gamma_n^{jk}}, \tag{2}$$

where $h_n^j(\cdot)$ and $l_n^j(\cdot)$ denote the demand for structures and labor respectively[15], $M_n^{jk}(\cdot)$ is the demand for final material inputs by firms in sector j from sector k (variables representing final goods are denoted with capital letters), $\gamma_n^{jk} \geqslant 0$ is the share of sector j goods spent on materials from sector k, and $\gamma_n^j \geqslant 0$ is the share of value added in gross output. We assume that the production function has constant returns to scale, namely that $\sum_{k=1}^{J} \gamma_n^{jk} = 1 - \gamma_n^j$.[16] Observe that we specified the technology in (2) such that T_n^j scales value added and not gross output. This implies that an increase in T_n^j, for all j and n, has a proportional effect

[14] An alternative option is to allow some immobile agents in each state to own state-specific shares of a national portfolio that includes all the rents of the immobile factor (namely $\chi = \sum_i r_i H_i$). As long as these shares sum to one, and the rentiers cannot move, such a model is as tractable as the one we propose in the main text. We have computed our main results with this alternative model and find similar results. For example, the correlation of the elasticities of aggregate TFP and real GDP to regional fundamental productivity changes between the model we propose and this alternative model is 95.2% and 95.1%, respectively. Ultimately, although not particular important given these numbers, the choice between having some local distribution of rents, or some immobile agents that own all the shares in the national portfolio, involves choosing between similar, albeit perhaps not ideal, simplifying assumptions.

[15] Our model will not ignore capital, as most static models do. We take a longer view of the economy and treat capital as materials (after all, capital is just a type of intermediate, which depreciates slowly). When we take the model to the data we are careful in accounting for capital in this particular way.

[16] In order to avoid a cumbersome notation, we decided to define the sectoral share of goods spent on materials from other sectors inclusive of the share of value added. Namely, $\gamma_n^{jk} = \left(1 - \gamma_n^j\right) \tilde{\gamma}_n^{jk}$, where $\sum_{k=1}^{J} \tilde{\gamma}_n^{jk} = 1$.

on aggregate real GDP (of course, this normalization only has consequences conditional on a calibration of the model).

Let x_n^j denote the cost of the input bundle needed to produce intermediate good varieties in (n, j). Then

$$x_n^j = B_n^j \left[r_n^{\beta_n} w_n^{1-\beta_n}\right]^{\gamma_n^j} \prod_{k=1}^{J} \left[P_n^k\right]^{\gamma_n^{jk}}, \tag{3}$$

where $B_n^j = \left[\gamma_n^j \left(1-\beta_n\right)^{(1-\beta_n)} \beta_n^{\beta_n}\right]^{-\gamma_n^j} \prod_{k=1}^{J} \left[\gamma_n^{jk}\right]^{-\gamma_n^{jk}}$. The unit cost of an intermediate good with idiosyncratic draw z_n^j in region-sector pair (n, j) is then given by $x_n^j \Big/ \left(z_n^j \left[T_n^j\right]^{\gamma_n^j}\right)$. Firms located in region n and operating in sector j will be motivated to produce the variety whose productivity draw is z_n^j as long as its price matches or exceeds $x_n^j \Big/ \left(z_n^j \left[T_n^j\right]^{\gamma_n^j}\right)$. Assuming a competitive market for intermediate goods, firms that produce a given variety in (n, j) will price it according to its corresponding unit cost.

2.2.2 Final Goods

Final goods in region n and sector j are produced by combining intermediate goods in sector j. Denote the quantity of final goods in (n, j) by Q_n^j, and denote by $\tilde{q}_n^j(z^j)$ the quantity demanded of an intermediate good of a given variety such that, for that variety, the particular vector of productivity draws received by the different n regions is $z^j = (z_1^j, z_2^j, ...z_N^j)$. The production of final goods is given by

$$Q_n^j = \left[\int \tilde{q}_n^j(z^j)^{1-1/\eta_n^j} \phi^j\left(z^j\right) dz^j\right]^{\eta_n^j/\left(\eta_n^j-1\right)}, \tag{4}$$

where $\phi^j(z^j) = \exp\left\{-\sum_{n=1}^{N}\left(z_n^j\right)^{-\theta^j}\right\}$ denotes the joint density function for the vector z^j, with marginal densities given by $\phi_n^j(z_n^j) = \exp\left\{-\left(z_n^j\right)^{-\theta^j}\right\}$, and the integral is over $\mathbb{R}_+^N$. For non-tradeable sectors, the only relevant density is $\phi_n^j\left(z_n^j\right)$ since final good producers use only locally produced goods.

The demand function from the solution to the final food producer is given by

$$\tilde{q}_n^j(z^j) = \left[\frac{p_n^j(z^j)}{P_n^j}\right]^{-\eta_n^j} Q_n^j,$$

where P_n^j is a price index for sector j in region n,

$$P_n^j = \left[\int p_n^j(z^j)^{1-\eta_n^j} \phi^j\left(z^j\right) dz^j\right]^{1/\left(1-\eta_n^j\right)}.$$

There is free entry in the production of final goods with competition implying zero profits.

2.3 Prices and Regional Trade

Final goods are non-tradable. Intermediate goods in tradable sectors are costly to trade. One unit of any intermediate good in sector j shipped from region i to region n requires producing $\kappa_{ni}^j \geq 1$ units in i, with $\kappa_{nn}^j = 1$ and, for intermediate goods in non-tradable sectors, $\kappa_{ni}^j = \infty$. Thus, the price paid for a particular variety whose vector of productivity draws is z^j, $p_n^j(z^j)$, is given by the minimum of the unit costs across

locations, adjusted by the transport costs κ_{ni}^j. That is,

$$p_n^j\left(z^j\right) = \min_i \left\{ \frac{\kappa_{ni}^j x_i^j}{z_i^j [T_i^j]^{\gamma_i^j}} \right\}. \tag{5}$$

Given our assumptions governing the distribution of idiosyncratic productivities, z_i^j, we follow Eaton and Kortum (2002) to solve for the distribution of prices. Having solved for the distribution of prices, when sector j is tradeable, the price of final good j in region n is given by

$$P_n^j = \Gamma\left(\xi_n^j\right)^{1-\eta_n^j} \left[\sum\nolimits_{i=1}^N \left[x_i^j \kappa_{ni}^j\right]^{-\theta^j} \left[T_i^j\right]^{\theta^j \gamma_i^j} \right]^{-1/\theta^j}, \tag{6}$$

where $\Gamma\left(\xi_n^j\right)$ is a Gamma function evaluated at $\xi_n^j = 1 + \left(1 - \eta_n^j\right)/\theta^j$. When j denotes a non-tradeable sector, the price index is instead given by

$$P_n^j = \Gamma\left(\xi_n^j\right)^{1-\eta_n^j} x_n^j \left[T_n^j\right]^{-\gamma_n^j}. \tag{7}$$

Let π_{ni}^j denote the share of region n's total expenditures on sector j's intermediate goods purchased from region i. Following Eaton and Kortum (2002), and Alvarez and Lucas (2007), using the properties of the Frechet distribution, we can solve for the expenditure shares π_{ni}^j, given by

$$\pi_{ni}^j = \frac{\left[x_i^j \kappa_{ni}^j\right]^{-\theta^j} T_i^{j\ \theta^j \gamma_i^j}}{\sum\limits_{m=1}^N \left[x_m^j \kappa_{nm}^j\right]^{-\theta^j} T_m^{j\ \theta^j \gamma_m^j}}. \tag{8}$$

In non-tradable sectors, $\kappa_{ni}^j = \infty$ for all $i \neq n$ so that $\pi_{nn}^j = 1$.

2.4 Labor Mobility and Market Clearing

Regional labor market clearing requires that

$$\sum\nolimits_{j=1}^J L_n^j = \sum\nolimits_{j=1}^J \int_0^\infty l_n^j(z) \phi_n^j(z)\, dz = L_n, \text{ for all } n \in \{1, ..., N\}, \tag{9}$$

where L_n^j denote the number of workers in (n, j), and national labor market clearing is given by

$$\sum\nolimits_{n=1}^N L_n = L.$$

In a regional equilibrium, land and structures must satisfy

$$\sum\nolimits_{j=1}^J H_n^j = \sum\nolimits_{j=1}^J \int_0^\infty h_n^j(z) \phi_n^j(z)\, dz = H_n, \text{ for all } n \in \{1, ..., N\}, \tag{10}$$

where H_n^j denotes land and structure use in (n, j).

Profit maximization by intermediate goods producers, together with these equilibrium conditions, implies

that

$$r_n H_n = \frac{\beta_n}{1-\beta_n} w_n L_n, \text{ for all } n \in \{1, ..., N\}.$$

Then, defining $\omega_n \equiv [r_n/\beta_n]^{\beta_n} [w_n/(1-\beta_n)]^{(1-\beta_n)}$, free mobility gives us

$$L_n = H_n \left[\frac{\omega_n}{P_n U + u_n} \right]^{\frac{1}{\beta_n}},$$

where $u_n \equiv \Upsilon_n / L_n = \iota_n r_n H_n / L_n - \chi$ denotes the trade surplus per capita in n. Combining these conditions with the labor market clearing condition, yields an expression for labor input in region n,

$$L_n = \frac{H_n \left[\frac{\omega_n}{P_n U + u_n} \right]^{1/\beta_n}}{\sum_{i=1}^{N} H_i \left[\frac{\omega_i}{P_i U + u_i} \right]^{1/\beta_i}} L. \tag{11}$$

Equilibrium condition (11) states that the employment share in region n is increasing in its endowment of land and structures H_n, and in factor prices as captured by ω_n. Conversely, employment in region n is decreasing in the size of trade surplus in that region u_n, as larger transfers to the global portfolio reduces per-capita income available in region n.

It remains to describe market clearing in final and intermediate goods markets. Regional market clearing in final goods is given by

$$L_n c_n^j + \sum_{k=1}^{J} M_n^{kj} = L_n c_n^j + \sum_{k=1}^{J} \int_0^\infty M_n^{kj}(z) \phi_n^k(z)\, dz = Q_n^j, \tag{12}$$

for all $j \in \{1, ..., J\}$ and $n \in \{1, ..., N\}$, where M_n^{kj} represents the use of materials of sector j in sector k at n.

Let X_n^j denote total expenditures on final good j in region n (or total revenue). Then, regional market clearing in final goods implies that

$$X_n^j = \sum_{k=1}^{J} \gamma_n^{kj} \sum_{i=1}^{N} \pi_{in}^k X_i^k + \alpha^j I_n L_n, \tag{13}$$

In equilibrium, in any region n, total expenditures on intermediates purchased from other regions must equal total revenue from intermediates sold to other regions, formally,

$$\sum_{j=1}^{J} \sum_{i=1}^{N} \pi_{ni}^j X_n^j + \Upsilon_n = \sum_{j=1}^{J} \sum_{i=1}^{N} \pi_{in}^j X_i^j. \tag{14}$$

Trade is, in general, not balanced within each region since a particular region can be a net recipient of national returns on land and structures while another might be a net contributor. As such, our model, through its ownership structure, accounts for trade imbalances and how these imbalances are affected by changes in fundamental productivity. In Section 4 we explain how to use information on regional trade imbalances to estimate the parameters that determine the ownership structure, $\{\iota_n\}_{n=1}^N$.

Definition: *Given factor supplies, L and $\{H_n\}_{n=1}^N$, a competitive equilibrium for this economy is a utility level U, a set of factor prices in each region, $\{r_n, w_n\}_{n=1}^N$, a set of labor allocations, structure allocations, final good expenditures, consumption of final goods per person, and final goods prices, $\{L_n^j, H_n^j, X_n^j, c_n^j, P_n^j\}_{n=1,j=1}^{N,J}$, pairwise sectoral material use in every region, $\{M_n^{jk}\}_{n=1,j=1,k=1}^{N,J,J}$, regional transfers $\{\Upsilon_n\}_{n=1}^N$, and pairwise*

regional intermediate expenditure shares in every sector, $\{\pi_{ni}^{j}\}_{n=1,i=1,j=1}^{N,N,J}$, such that the optimization conditions for consumers and intermediate and final goods producers hold, all markets clear - equations (9), (10), (13), (8) hold -, aggregate trade is balanced - (14) holds- , and utility is equalized across regions, - (11) holds.

3. AGGREGATION AND CHANGES IN MEASURED TFP, GDP, AND WELFARE

Given the model we have just laid out, this section describes how to arrive at measures of total factor productivity, GDP, and welfare, that are disaggregated across both regions and sectors. These calculations of measures at the level of sector in a region, using available industry and regional trade data for the U.S., underlie Figures 4 through 6 and their discussion in Section 1.1, as well as all calculations in the rest of the paper.

3.1 Measured TFP

Measured sectoral total factor productivity in a region-sector pair (n, j) is commonly calculated as

$$\ln A_n^j = \ln \frac{w_n L_n^j + r_n H_n^j + \sum_{k=1}^{J} P_n^k M_n^{jk}}{P_n^j} - (1-\beta_n)\,\gamma_n^j \ln L_n^j - \beta_n \gamma_n^j \ln H_n^j - \sum\nolimits_{k=1}^{J} \gamma_n^{jk} \ln M_n^{jk}. \tag{15}$$

The first term is gross output revenue over price –a measure of gross production in (n, j) which we denote by Y_n^j/P_n^j, and which is equal to Q_n^j in the case of non-tradables–, while the last three terms denote the log of the aggregate input bundle.[17] This last equation assumes that we use gross output and final good prices to calculate region-sector TFP. Observe that the equilibrium factor demands of the intermediate good producers imply that

$$Y_n^j = w_n L_n^j + r_n H_n^j + \sum\nolimits_{k=1}^{J} P_n^k M_n^{jk} = \frac{w_n L_n^j}{\gamma_n^j\,(1-\beta_n)}. \tag{16}$$

Therefore, we may calculate changes in measured TFP, $\hat{A}_n^j$, following a change in fundamental productivity, $\widehat{T}_n^j$, using the ratio of the change in the cost of the input bundle to the change in the price of final goods.[18] That is,

$$\ln \hat{A}_n^j = \ln \frac{\widehat{x}_n^j}{\widehat{P}_n^j} = \ln \frac{[\hat{T}_n^j]^{\gamma_n^j}}{[\hat{\pi}_{nn}^j]^{1/\theta^j}}, \tag{17}$$

where the second equality follows from (8).

Equation (17) is central to understanding the sources of changes in *measured* productivity in an individual sector within a region following a change in *fundamental* productivity, $\hat{T}_n^j$.[19]

[17] One can prove that total gross output in (n, j) uses this aggregate input bundle. To do so, we aggregate the equilibrium factor demands of the intermediate good producers. After that, it is straightforward to derive that factor usage for an intermediate is just the revenue share of that intermediate in gross revenue, Y_n^j. Substituting in Equation (2), and using the fact that prices of produced intermediates are equal to unit costs, leads to

$$\frac{Y_n^j}{P_n^j} = \frac{x_n^j}{P_n^j}\left[\left(H_n^j\right)^{\beta_n}\left(L_n^j\right)^{(1-\beta_n)}\right]^{\gamma_n^j} \prod\nolimits_{k=1}^{J}\left(M_n^{jk}\right)^{\gamma_n^{jk}},$$

where $A_n^j = x_n^j/P_n^j$ measures region and sector specific TFP.

[18] The 'hat' notation denotes A'/A, where A' is the new level of total factor productivity.

[19] Note from (17) that the key distinction between measured and fundamental TFP is the selection effect. Empirically, the U.S. Bureau of Labor Statistics (BLS) is the statistical agency that measures TFP changes. In order to control for changes

Consider first an economy with infinite trading costs $\kappa_{ni}^j = \infty$ for all j, so that trade is non-operative and $\pi_{nn}^j = 1$ in every region. Furthermore, let us abstract from material input use so that the share of value added in gross output is equal to one, $\gamma_n^j = 1$. In such an economy, Equation (17) implies that changes in measured productivity $\hat{A}_n^j$ are identical to changes in fundamental productivity, $\hat{T}_n^j$. Any fundamental productivity change at the level of a sector within a region translates into an identical change in measured productivity in that sector and region, and has otherwise no effect on the productivity of any other sector or region.

This exact relationship between fundamental and measured productivity, $\ln \hat{A}_n^j = \ln \hat{T}_n^j$, no longer holds once either trade or sectoral linkages are operative. Consider first adding sectoral linkages, so that $\gamma_n^j < 1$, but still abstracting from trade. In that case, Equation (17) indicates that the effect of a change, $\hat{T}_n^j$, improves measured productivity less than proportionally. The reason is that the change affects the productivity of value added in that region and sector but not the productivity of sectors and regions in which materials are produced. Therefore, in the presence of input output linkages, the effect of a fundamental productivity change $\hat{T}_n^j$ on measured productivity in (n, j) falls with $1 - \gamma_n^j = \sum_{k=1}^J \gamma_n^{jk}$.

This last result follows from our assumption that productivity changes scale value added and not gross output (as in Acemoglu et al. 2012). If productivity instead affected all of gross output, a sector that just processed materials, without adding any value by way of labor or capital, would see an increase in output at no cost. That alternative modelling implies that aggregate fundamental productivity changes have abnormally large effects on real GDP while, with our technological assumption, aggregate fundamental changes have proportional effects on real GDP. This distinction matters greatly in quantitative exercises.

Evidently, with trade still shut down, a region and sector specific change in this economy has no effect on the measured productivity of any other region or sector. In contrast, with trade, productivity changes are propagated across sectors and regions. The main effect of regional trade on productivity arises by way of a selection effect. Thus, let κ_{ni}^j be finite for tradable sectors, and consider first the region-sector (n, j) that experiences a change or increase in fundamental productivity, $\hat{T}_n^j$. Equation (17) implies that the effect of trade is ultimately summarized through the change in the region's share of its own intermediate goods, $\hat{\pi}_{nn}^j$. Since an increase in fundamental productivity in (n, j) raises its region and sector comparative advantage, it generally also leads to an increase in π_{nn}^j so that $\hat{\pi}_{nn}^j > 1$. Similarly, it reduces π_{ii}^k, for $i \neq n$ and all k, since other regions and sectors now buy more sector-j intermediates from region n. Hence, since $\theta^j > 0$, trade reduces the effect of a fundamental productivity increase to (n, j) on measured productivity in that region-sector while, at the same time, raising measured productivity in other regions and sectors.

Intuitively, the selection effect underlying the change in expenditure shares works as follows. As everyone purchases more goods from the region-sector pair (n, j) that experienced a fundamental productivity increase, that region-sector pair now produces a greater variety of intermediate goods. However, the new varieties of intermediate goods, since they were not being initially produced, are associated with idiosyncratic productivities that are relatively worse than those of varieties produced before the change. This negative selection effect in (n, j) partially offsets the positive consequences of the fundamental productivity change, relative to an economy with no trade, in that region-sector pair. In other region-sector pairs, (i, j) for $i \neq n$,

in the production structure of the economy (due to selection effects), the BLS periodically (every five years according to Page 10, Chapter 14, Handbook of Methods) changes the weights in their producer prices indexes (PPI), which are used for the construction of Multifactor Productivity by the Bureau of Economic Analysis (BEA) and the BLS. Given this, in periods between changes in weights, one can directly infer changes in fundamental TFP from changes in the measured TFP calculated by the BEA and BLS as $\hat{A}_n^j = (\hat{T}_n^j)^{\gamma_n^j}$, as we do later for the case of Computers and Electronics in California. For further discussion on the implications of trade models for the computation of TFP and GDP as measured by statistical agencies see Burstein and Cravino (2015).

the opposite effect takes place. As the latter regions do not directly experience the fundamental productivity change, their own trade share of intermediates decreases. As a result, the varieties of intermediate goods that continue being produced in those regions have relatively higher idiosyncratic productivities, thereby yielding higher measured productivity in those locations. All of these trade-related effects are present whether material inputs are considered or are absent from the analysis.

Measured TFP at the level of a sector in a region is calculated based on gross output in equation (15), so we use gross output revenue shares to aggregate these TFP measures into regional, sectoral, or national measures. Our aggregate TFP measures are described in more detail in Appendix A.8.

3.2 GDP

Real GDP is calculated by taking the difference between real gross output and expenditures on materials. Given the equilibrium factor demands of the intermediate good producers, as well as factor market equilibrium conditions, changes in real GDP may be written as

$$\ln \widehat{GDP}_n^j = \ln \hat{w}_n + \ln \hat{L}_n^j - \ln \hat{P}_n^j$$

This expression simplifies further since, from (8), $\hat{P}_n^j = [\hat{\pi}_{nn}^j]^{\frac{1}{\theta^j}} \hat{x}_n^j [\hat{T}_n^j]^{-\gamma_i^j}$, so that GDP changes in a region-sector pair (n, j), resulting from changes in fundamental TFP, $\hat{T}_n^j$, are given by

$$\ln \widehat{GDP}_n^j = \ln \hat{A}_n^j + \ln \hat{L}_n^j + \ln \left(\frac{\hat{w}_n}{\hat{x}_n^j} \right), \tag{18}$$

where we used Equation (17). Given that real GDP is a value added measure, we use value added shares in constant prices to aggregate changes in GDP.[20]

Equation (18) represents a decomposition of the effects of a change in fundamental productivity on GDP. The first term reflects the effect of the change on measured productivity discussed in Section 3.1. This effect is such that measured TFP and output move proportionally. In other words, the selection effect associated with intermediates and input-output linkages acts identically on measured TFP and real GDP. In addition to these effects, GDP is also influenced by two other forces captured by the second and third terms in Equation (18).

The second term in Equation (18) describes the effect of labor migration across regions and sectors on GDP. A positive productivity change that attracts population to a given region-sector pair (n, j) will increase GDP proportionally to the amount of immigration, $\ln \hat{L}_n^j$. The reason is that all factors in (n, j) change in the same proportions and the production function of intermediates in Equation (2) is constant-returns-to-scale. The effect of migration will be positive when the change in fundamental TFP is positive.

The third term in Equation (18) corresponds to the change in factor prices associated with the change in fundamental TFP. Consider first a case without materials. In that case, $\ln \left(\hat{w}_n / \hat{x}_n^j \right) = \beta_n \ln \left(\hat{w}_n / \hat{r}_n \right) = \beta_n \ln 1/\hat{L}_n$. Since land and structures are fixed, and therefore do not respond to changes in T_n^j, while labor is mobile across locations, a positive productivity change that attracts people to the region will increase land and structure prices more than wages. This mechanism leads to a reduction in real GDP, relative to the proportional increase associated with the first two terms. The presence of decreasing returns resulting from a regionally fixed factor implies that shifting population to a location strains local resources, such as local

[20] In Appendix A.8 we describe the aggregate GDP measures at the regional, sectoral, and national levels.

infrastructure, in a way that offsets the positive GDP response stemming from the inflow of workers. In regions that do not experience the productivity increase, the opposite is true so that the second and third terms in (18) will be negative and positive respectively. These forces are also present when we consider material inputs although, in that case, the relevant ratio is that of changes in wages to changes in the cost of the input bundle, x_n^j. The input bundle includes the rental rate, but it also includes the price of all materials. An overall assessment of the effects of fundamental productivity changes then requires a quantitative evaluation.

Observe that when considering the aggregate economy-wide effects of a positive $\hat{T}_n^j$, the end result for GDP may be larger or smaller than the original change. The overall impact of the last two terms in Equation (18) will depend on whether the direct effect of migration dominates the strain on local resources in the region experiencing the change, n, as well as the intensiveness with which this fixed factor is used in the regions workers leave behind, $i \neq n$. Thus, the size and sign of these effects depend on the overall distribution of H_n and population L_n in the economy and, therefore, on whether the productivity change increases the dispersion of the wage-cost bundle ratio, $\hat{w}_n/\widehat{x}_n$, across regions. If a productivity change leads to migration towards regions that lack abundant land and structures, the aggregation of the last two terms in Equation (18) may be negative or very small. In contrast, if a change moves people into regions with an abundance of local fixed factors, the impact of these last two terms will be positive. Evidently, whatever the case, one must still add the direct effect of the fundamental productivity change on measured productivity. These different mechanisms underscore the importance of geography, and that of the sectoral composition of technology changes, in order to assess the magnitude of such changes. In very extreme cases (only Hawaii in our numerical exercises), these mechanisms may even lead to negative aggregate GDP effects of productivity increases. However, even though the equilibrium allocation is not Pareto efficient, in practice positive technological changes always lead to welfare gains.

Finally, it is worth noting that in the case of aggregate productivity changes, the distribution of population across locations is unchanged since people do not seek to move when all locations are similarly affected. Therefore, measured productivity and GDP unambiguously increase proportionally in that case.

3.3 Welfare

We end this section with a brief discussion of the welfare effects that result from changes in fundamental productivity. Using (1), and the equilibrium factor demands of the intermediate good producers, it follows that the change in welfare is given by $\hat{U} = \hat{I}_n/\hat{P}_n$. Then, using the definition of P_n and equations (8) and (17), we have that

$$\ln \hat{U} = \sum\nolimits_{j=1}^{J} \alpha^j \left(\ln \hat{A}_n^j + \ln \left(\varpi_n \frac{\hat{w}_n}{\hat{x}_n^j} + (1 - \varpi_n) \frac{\hat{\chi}}{\hat{x}_n^j} \right) \right), \tag{19}$$

where $\varpi_n = \frac{(1-\beta_n \iota_n) w_n}{(1-\beta_n \iota_n) w_n + (1-\beta_n)\chi}$. Note that if $\iota_n = 0$ for all n, then $\chi = 0$ and $\varpi_n = 1$. In that case $\ln \hat{U} = \sum_{j=1}^{J} \alpha^j \left(\ln \hat{A}_n^j + \ln \frac{\hat{w}_n}{\hat{x}_n^j} \right)$.

A change in fundamental productivity, $\hat{T}_n^j$, affects welfare through three main channels. First, the change affects welfare through changes in measured productivity, $\ln \hat{A}_n^j$, in all sectors (which in turn are influenced by the selection effect in intermediate goods production described earlier), weighted by consumption shares, α^j. Second, the productivity change affects welfare through changes in the cost of labor relative to the input bundle, $\ln \left(\hat{w}_n / \widehat{x}_n^j \right)$. As in the case of GDP, when we abstract from materials, the second term is equivalent to the change in the price of labor relative to that of land and structures or, alternatively, the inverse of the

change in population. Therefore, when a region-sector pair (n, j) experiences an increase in fundamental productivity, it benefits from the additional measured productivity but loses from the inflow of population. In other regions that did not experience the productivity increase, population falls while measured productivity tends to increase (through a selection effect where remaining varieties in those regions are more productive), so that both effects on welfare are positive. These mechanisms are more complex once sectoral linkages are taken into account by way of material inputs, and their analysis then requires us to compute and calibrate the model. As Equation (19) indicates, welfare also simply reflects a weighted average across sectors of real GDP per capita. Third, welfare is affected by the change in the returns to the national portfolio, which constitutes part of the real income received by individuals.

The international trade literature has studied the welfare implications of a similar class of models in detail, as discussed in Arkolakis et al. (2012). Relative to these models, the study of the domestic economy compels us to include multiple sectors, input-output linkages, and two factors, one of which is mobile across sectors and the other across locations and sectors. Finally, our model also endogenizes trade surpluses and deficits. If we were to close all of these margins, it is straightforward to show that the implied change in welfare simply reduces to the change in measured productivity in the resulting one-sector economy, reproducing the formula highlighted by Arkolakis et. al. (2012).

4. CALCULATING COUNTERFACTUALS AND CALIBRATION

From the discussion in the last section, it should be clear that the ultimate outcome of a given change in fundamentals on the U.S. economy will depend on various aspects of its particular sectoral and regional composition. These aspects include the distribution of population across regions, that of land and structures, the nature of transport costs, material shares, etc. Therefore, to assess the magnitude of the responses of measured TFP, GDP and welfare to fundamental technology changes, one needs to compute a quantitatively meaningful variant of the model. This requires addressing four practical issues.

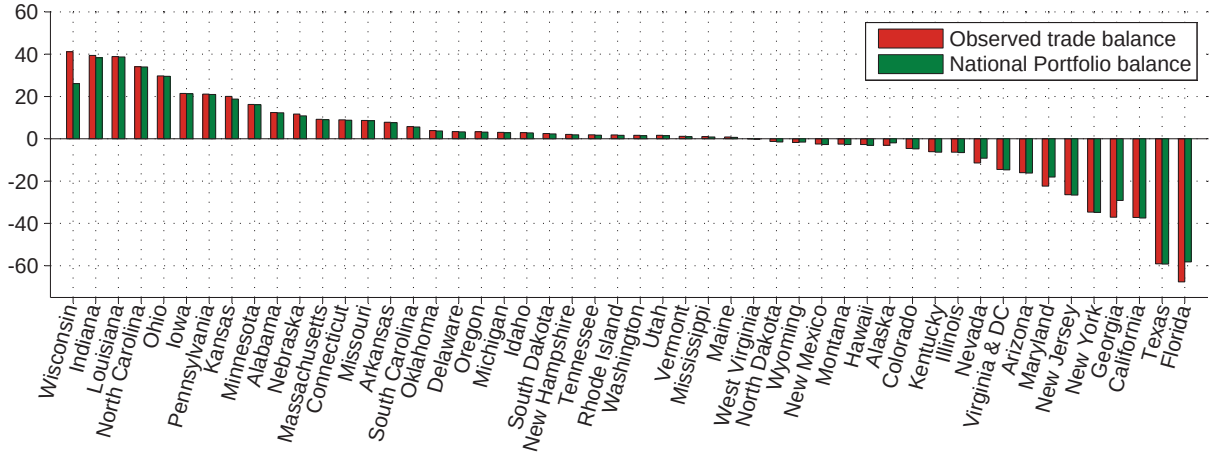
First, the U.S. economy exhibits aggregate trade deficits and surpluses between states. The model presented in Section 2 allows for the possibility of sectoral trade imbalances across states as well as aggregate trade imbalances due to inter-regional transfers of the returns from land and structures, (see equation 14). By incorporating variation in regional contributions to the national portfolio through the parameters ι_n, our model is capable of matching quite well the observed aggregate trade imbalances in the U.S. economy.[21] We estimate the regional contributions to the national portfolio, ι_n, by minimizing the square differences between observed regional trade imbalances and those that emerge in the model through interregional transfers implied by the national portfolio of fixed assets. Figure 7 presents the resulting ι_n's as well as the observed and predicted trade imbalances. Figure 7a shows the match between the observed and predicted regional trade imbalances. The match is not perfect since the constraint $\iota_n \in [0, 1]$ for all n occasionally binds both above and below for some states, as shown in Figure 7b. States with large surpluses like Wisconsin contribute all of the returns to their land and structures to the national portfolio, while states with large deficits, like Florida, contribute nothing. Intuitively, Floridians own assets in the rest of the U.S. and live in part from the returns to these assets. In what follows, we set the unexplained component of trade imbalances to zero, as described in Appendix A.1., and we use the resulting economy as the baseline economy from which we

[21] Unless one writes a dynamic model in which imbalances are the result of fundamental sources of fluctuations, one cannot explain either the level, or the potential changes, in the value of ι_n. Explaining the observed ownership structure is certainly an interesting direction for future research, but one that is currently beyond reach in a rich quantitative model comparable to the one studied in this paper.

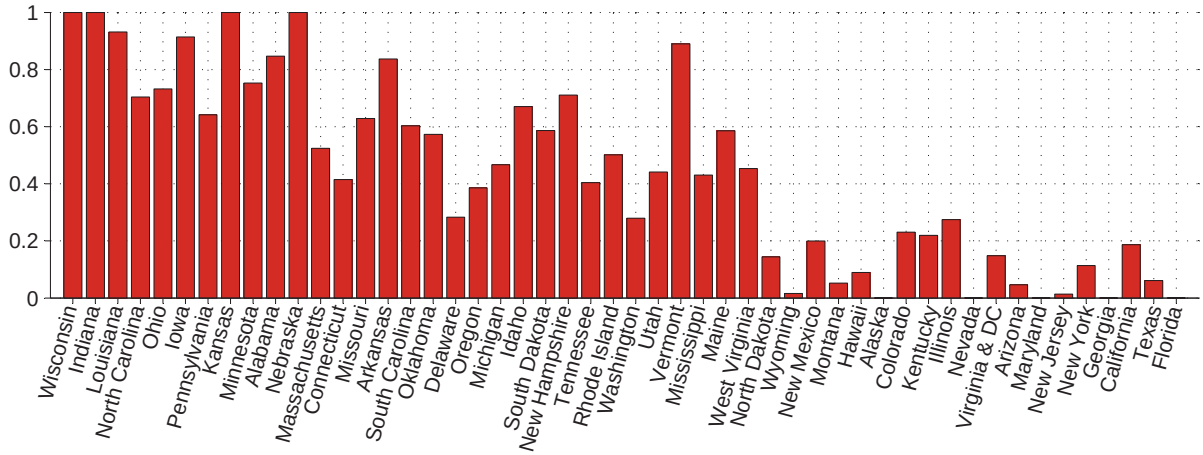
calculate the elasticities to fundamental regional and sectoral changes.[22]

FIG. 7. Regional trade inbalances and contributions to the National Portfolio

a: Trade Balance: Model and data (2007 U.S. dollars, billions)



b: Share of local rents on land and structures contributed to the National Portfolio



The second issue relates to our model incorporating regional but no international trade. Fortunately, the trade data across U.S. states that we use to calibrate the model, which is described in detail below, gives us expenditures in domestically produced goods across states. Even then, small adjustments are needed but, overall, we are able to use these data to assess the behavior of the domestic economy without considering international economic links.[23] Thus, we study the domestic economy subject to the small data adjustments described below.

The third issue of practical relevance is that solving for the equilibrium requires identifying technology levels in each region-sector pair (n, j), bilateral trade costs between regions for different sectors (n, i, j), and the elasticity of substitution across varieties, all of which are not directly observable from the data.

[22] Our approach differs from the one in Dekle, Eaton and Kortum (2007) in that we focus on trade across regions rather than countries and, more importantly, allow for endogenous transfers across regions that match observed trade imbalances.

[23] In principle, one might potentially think of the 'rest of the world' as another region in the model but, to the best of our knowledge, information on international trade by states is not systematically recorded.

Following the method first proposed by Dekle, Eaton and Kortum (2008), and adapted to an international context with multiple sectors and input-output linkages by Caliendo and Parro (2015), we bypass this third issue by computing the model in changes. In particular, let x be an equilibrium outcome given fundamental productivity T, and x' be a new equilibrium outcome given a new fundamental productivity T'. Let us denote by $\hat{x} = x'/x$ the relative change of x given a change in fundamental productivity from T to T' that we denote by $\hat{T} = T'/T$. Rather than solving the model in levels, we will solve for changes in equilibrium allocations given changes in productivities $\hat{T}$. In Appendix A.2, we show that this method works well in our setup and present the equilibrium conditions of the model in relative changes. In particular, given a set of parameters $\{\theta^j, \alpha^j, \beta_n, \iota_n, \gamma_n^j, \gamma_n^{jk}\}_{n=1,j=1,k=1}^{N,J,J}$, data for $\{I_n, L_n, \Upsilon_n, \pi_{ni}^j\}_{n=1,i=1,j=1}^{N,N,J}$, and changes in exogenous variables $\{\hat{T}_n^j, \hat{\kappa}_{ni}^j\}_{n=1,i=1,j=1}^{N,N,J}$, the system of $2N + 3JN + JN^2$ equations yields the values of $\{\hat{w}_n, \hat{L}_n, \hat{x}_n^j, \hat{P}_n^j, \hat{X}_n^j, \hat{\pi}_{ni}^j\}_{n=1,i=1,j=1}^{N,N,J}$, where $\hat{X}_n^j$ and $\hat{\pi}_{ni}^j$ denote expenditures and trade shares following fundamental changes $\{\hat{T}_n^j, \hat{\kappa}_{ni}^j\}_{n=1,i=1,j=1}^{N,N,J}$. Note that, although transport cost levels (κ_{ni}^j) are essential to determine the impact of, say, productivity changes in our framework, we do not need direct information on transport costs since all the relevant information is embedded in the observed trade flows, π_{ni}^j.

We use all 50 U.S. states and 26 sectors, where 15 sectors produce tradable manufactured goods. Ten sectors produce services and we add construction for a total of 11 non-tradeable sectors. The next section briefly describes the data sources and Appendix A.4 provides greater details. Assessing the quantitative effects on the U.S. economy of fundamental changes at the level of a sector within a region then requires solving a system of 69,000 equations and unknowns (endogenous variables to be determined in equilibrium). This system can be solved in blocks recursively using well established numerical methods. The exact algorithm is described in Appendix A.3. Having carried out these calculations, it is then straightforward to obtain any other variable of interest such as $\hat{r}_n$, $\hat{\pi}_{nn}^j$, $\hat{A}_n^j$, $\widehat{GDP}_n^j$ and $\hat{U}$, among others.

Finally, the fourth issue relates to our assumption that labor can move freely across regions. The potential concern is that, in practice, there are frictions to labor mobility across regions in the U.S. Hence, our model could systematically generate too much labor mobility as a result of fundamental productivity changes. In order to study the extent to which the omission of mobility frictions can affect our results, we perform a set of exercises where we introduce the observed changes in fundamental TFP for all regions and sectors from 2002 to 2007 into the model and calculate the implied changes in employment shares.[24] We find that the model generates changes in employment that are of the same order of magnitude as in the data. For instance, the mean annualized percentage change in employment shares implied by the model is 0.257 while the observed change was 0.213. Of course, we do not expect the results of this exercise to match the observed changes in employment given that several factors, other than productivity changes, could have impacted the U.S. economy during this period. Still, the message from this exercise is that, although migration frictions might hinder mobility in the short run, over a five-year period the changes in employment generated by observed productivity changes in our model are similar to those observed in the data.

4.1. Taking the model to the data

As explained in the previous section, in order to generate a calibrated model of the U.S. economy that gives a quantitative assessment of the effects of disaggregated changes in fundamental productivity, we need to obtain values for all parameters, $\{\theta^j, \alpha^j, \beta_n, \iota_n, \gamma_n^j, \gamma_n^{jk}\}_{n=1,j=1,k=1}^{N,J,J}$ and variables $\{I_n, L_n, \Upsilon_n, \pi_{ni}^j\}_{n=1,i=1,j=1}^{N,N,J}$.

[24] To compute changes in observed fundamental TFP we use equation (17). Note that the change in fundamental TFP is the same as the change in measured TFP, scaled by the share of value added in gross output, if the selection channel is not active. This is the case when using price indexes with constant weights as reported from 2002 to 2007 (see Footnote 19).

We now briefly describe how we obtain the parameters. Appendix A.4 describes in greater detail the data underlying our calculations and presents a detailed account of the calibration strategy.

Our main data sources are the Bureau of Economic Analysis (BEA) and the Commodity Flow Survey (CFS). Using data from the CFS, we obtain the bilateral trade flows across sectors, and regions in the U.S, $\{X_{ni}^j\}_{n=1,i=1,j=1}^{N,N,J}$ for a total of 15 manufacturing tradable sectors. Using trade flows, we can compute the bilateral trade shares as $\pi_{ni}^j = X_{ni}^j / \sum_{i=1}^{N} X_{ni}^j$, and the regional trade surpluses $\{\Upsilon_n\}_{n=1}^N$.

From the BEA we obtain data on total employment across U.S. states, $\{L_n\}_{n=1}^N$, data on value added and gross production across sectors and regions which we denote as $\{VA_n^j, Y_n^j\}_{n=1,j=1}^{N,J}$, U.S. input-output linkages, and data on the compensation of employees. Using these data, we compute the shares of value added in gross output $\{\gamma_n^j\}_{n=1,j=1}^{N,J}$. Using these shares and the information contained in the U.S. input-output matrix, we compute the input-output coefficients γ_n^{jk} as the share of intermediate consumption of sector j in sector k over the total intermediate consumption of sector j times the share of materials in gross output in sector j, $1 - \gamma_n^j$. Final consumption shares, α^j, are calculated by taking aggregate sectoral expenditure, subtracting the intermediate goods expenditure and dividing by total final absorption.

In our model, we include capital equipment as materials, and we include structures in value added. Using the data on the compensation of employees and value added, we can obtain the non-labor shares in value added which includes payments to capital equipment and to structures and land. We then subtract the share of capital equipment in value added using the estimates for the U.S. from Greenwood, Hercowitz, and Krusell (1997) and renormalize so that the new shares add to one. As a result of this adjustment, our quantitative exercise uses shares for labor as well as for land and structures at the regional level that are consistent with aggregate value added shares in the U.S. (see Appendix A.4. for details).

Per capita income at each region, $\{I_n\}_{n=1,i=1,j=1}^{N,N,J}$ is directly obtained by using information on value added and regional trade surplus, namely $I_n = VA_n/L_n - \Upsilon_n/L_n$. Finally we need to solve for $\{\iota_n\}_{n=1}^N$, as we explained before in this section, by minimizing the distance between the trade surplus in the data (Υ_n^{Data}) and the regional national portfolio balances consistent with our model (Υ_n^{Model}). We do so by calculating $\Upsilon_n^{Model} = \iota_n r_n H_n - \chi L_n$ where $\chi = \sum_i \iota_i r_i H_i / \sum_i L_i$. The payment to structures and land is measured as $r_n H_n = \beta_n VA_n$. Then, using this information and data on L_n we can obtain χ as a function of a vector of $\{\iota_n\}_{N\times 1}$. Lastly, we solve for $\{\iota_n\}_{N\times 1}$ by minimizing the sum square of $\{S_n\}_{N\times 1} \equiv \{\Upsilon_n^{Model} - \Upsilon_n^{Data}\}_{N\times 1}$.

Finally, we need values for the dispersion of productivities (or trade elasticities), θ^j. We obtain these parameters by using the estimates from Caliendo and Parro (2015), a multi-sector Ricardian model consistent with our model, by mapping their sectoral elasticities into our sectors. The values of θ^j are presented in Table A4.1.

5. THE IMPACT OF FUNDAMENTAL PRODUCTIVITY CHANGES

Having calibrated the model against available industry and trade data, we study the effects of disaggregated productivity changes. Throughout the analysis, the calculations of all the elasticities are based on 10 percent changes in fundamental productivity. So we let $\hat{T}_n^j = 1.1$ for a set of j's and n's depending on the particular counterfactual exercise and let $\hat{\kappa}_{ni}^j = 1$, for all j, n, i. The average annual growth in fundamental TFP across sectors and regions was 10.9% over the period 2002-2007, and the median over the period 2002-2007 and 2007-2012 was 8.4%. These numbers motivate our choice of 10% as the baseline productivity changes to calculate elasticities, although the choice is not particularly important given that for these magnitudes non-linearities are quite small. We begin by analyzing changes to all sectors in one region, which we refer

to as regional changes. We then study changes to all regions in one sector, which we refer to as sectoral changes. Finally, we present examples of changes specific to a sector within a region.

To facilitate comparisons across states and sectors we present our results in terms of elasticities. Moreover these elasticities can be used to simply calculate general equilibrium counterfactuals of the kind that are carried out in Section 6. To calculate aggregate elasticities of a given regional or sectoral productivity change we divide the effects by the share of the region or industry where the change was originated, and multiply by the size of the fundamental productivity change (which in our exercises is always 10%). So the interpretation of an aggregate elasticity is the effect of a percentage change with constant national magnitude. Specifically, denote the percentage change of a variable as $dx = (x' - x)/x$. Then the normalized aggregate TFP, GDP, and Welfare elasticities to a regional productivity change are given by,

$$TFP\ elast. = \frac{dA}{(Y_n/Y)dT_n}; \quad GDP\ elast. = \frac{dGDP}{(w_n L_n/wL)dT_n}; \quad Welfare\ elast. = \frac{dU}{(L_n/L)dT_n}$$

The purpose of this normalization is to compare across regions and sectors the degree of propagation of disaggregated fundamental productivity changes. Clearly, a shock might have larger effects simply because it affects a larger region or sector. This effect is straightforward comparison of elasticities across sectors and regions, hence when we calculate aggregate elasticities we normalize by the share of the impacted region or sector. In Appendix A.9 we also compute the aggregate TFP and GDP elasticities of local shocks taking into account differences in region and sector sizes. Naturally, in Section 5.1.1 and 5.2.1 when we calculate regional or sectoral elasticities, rather than aggregate ones, we do not normalize by regional or sectoral shares.

We compute counterfactual exercises in which i) we eliminate regional trade and sectoral linkages by setting $\kappa_{ni}^j = \infty$ for all j, n, i, and $\gamma_n^{jk} = 0$, and $\gamma_n^j = 1$, for all j, k, n, which we label NRNS; ii) we eliminate sectoral linkages but allow interregional trade so we set $\gamma_n^{jk} = 0$, and $\gamma_n^j = 1$, for all j, k, n, labeled RNS; iii) we allow for sectoral linkages but eliminate interregional trade, $\kappa_{ni}^j = \infty$ for all j, n, i, labeled NRS; iv) we allow for regional trade and sectoral linkages, so all parameters are as in the calibration described above, labeled RS. The latter case is the one relevant for assessing the consequences of fundamental changes in technology on the U.S. economy. The other cases help us to assess the role of individual economic channels. To study alternative scenarios under these variants of our model, we first compute allocations in the particular case of interest (say, without sectoral trade). We then introduce a fundamental change in that counterfactual economy to calculate the effect of the productivity change in that scenario.

5.1 Regional Productivity Changes

5.1.1 Aggregate Effects of Regional Productivity Changes.—

As a starting point for our findings, consider Figure 8. The figure shows the aggregate elasticities of measured TFP and GDP to an increase in productivity in each of the 50 U.S. states in the three alternative models (NRNS, RNS, RS). For example, when all channels are included (RS), the elasticity of aggregate TFP to a fundamental productivity increase in all sectors in Texas is 0.4 and the elasticity of aggregate GDP is 1.1.

Let us focus first on measured TFP in the top-left-hand map of the figure, Panel 8a. In the NRNS case, with no materials or trade, Equation (17) tells us that changes in measured TFP are simply the direct consequence of the change in fundamental productivity. The impact on aggregate TFP, therefore, amounts to the share of that region times the magnitude of the change, and so the elasticity of aggregate TFP to

a regional change in TFP is equal to one. Note that, in the NRNS case, the aggregate TFP elasticity is the same as in a one region economy with multiple sectors and a constant returns to scale technology. Thus, we can interpret the impact on these elasticities when we compute economies with regional trade and input-output linkages as the aggregate TFP effects of regional and sectoral trade.[25]

As we move down to Figure 8c, we see the effect on measured TFP in the presence of regional trade only (RNS). As discussed earlier, trade leads to a negative selection effect in the states that experience the change, whereby newly produced varieties in that state have relatively lower idiosyncratic productivities, and to a positive selection effect in other states. The overall effect on the aggregate elasticity of measured TFP stemming from selection may thus have either sign, but it will tend to be more negative the larger the state experiencing the fundamental productivity increase. This selection effect implies that the impact on aggregate measured TFP in the case of, say, California, is dampened from 1 in the NRNS case to 0.9938 in the RNS case. Similarly, the aggregate elasticity of a fundamental regional change in Texas is also dampened from 1 to 0.9928. In contrast, the selection effect tends to amplify the elasticity in aggregate measured TFP arising from fundamental changes in many small states. For example, Nebraska's aggregate measured TFP elasticity increases to 1.037 in the RNS case.

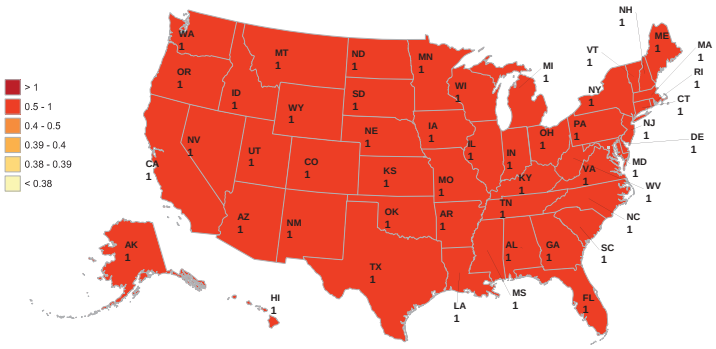
Including input-output linkages reduces the elasticity of aggregate TFP significantly in all states. Recall from Equation (17) that fundamental TFP changes affect value added and not gross production directly. Hence, their effect on measured productivity are attenuated by the share of value added. The end result is that the effect of fundamental changes on measured TFP declines substantially relative to the models without input-output linkages. As we discuss below, this effect is not present in the case of real GDP. Indeed, input-output linkages imply that more of the gains from fundamental changes in productivity ensue from lower material prices, rather than direct increases in measured productivity.

Let us now turn to the second column in Figure 8. Since a productivity change in all regions and sectors has no implications on migration or trade flows, the aggregate elasticity of GDP to such a change is always equal to one in our model. This is not the case for regional changes. In the NRNS case in the top right-hand panel, 8b, the effect on aggregate GDP derives from the changes in measured TFP just discussed combined with the impact of migration. Thus, the outcome for aggregate GDP now depends on the whole distribution of land and structures across states. In some cases there is a large positive effect from migration on aggregate real GDP, as in the case of productivity changes in Illinois or New York. These are states that are relatively abundant in land and structures (see Figure 6) so that the economy benefits from immigration even at the cost of emptying other regions. The opposite is true of Wisconsin, where migration turns an elasticity of aggregate measured TFP of one (top left-hand map, 8a) into a negative elasticity of aggregate real GDP of -0.4 (top right-hand map, 8b). From Figure 8d, adding trade (RNS) generally implies smaller differences between aggregate measured TFP effects and real GDP effects. Trade allows residents in all locations to benefit from the high productivity of particular regions without them having to move. Put another way, trade substitutes for migration. This substitution is more concentrated towards nearby states when input-output linkages are added (RS). Specifically, trade makes firms benefit from a change in fundamental productivity in nearby states through cheaper materials as well. As alluded to earlier, more of the benefits from a given regional fundamental productivity increase are transmitted through the price of material inputs in the RS case so that the importance of regional trade increases. Ultimately, the difference between changes in measured TFP and changes in output are generally larger in the absence of one of these two channels.

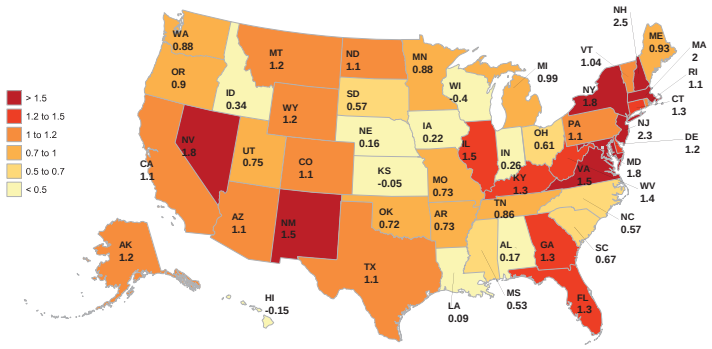
[25] Of course, since an equal size productivity change in all regions and sectors has no implications on migration or trade flows, the aggregate elasticities of TFP and GDP to such a change is always equal to one in our model and in a one-region economy.

Fig. 8. Aggregate effects of regional fundamental productivity changes

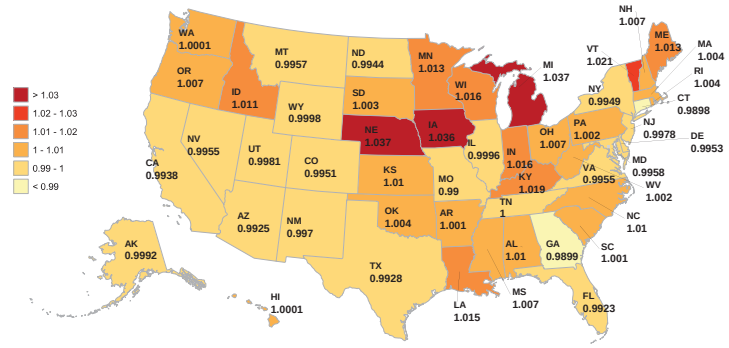
a: Elasticity of aggregate TFP (model NRNS)



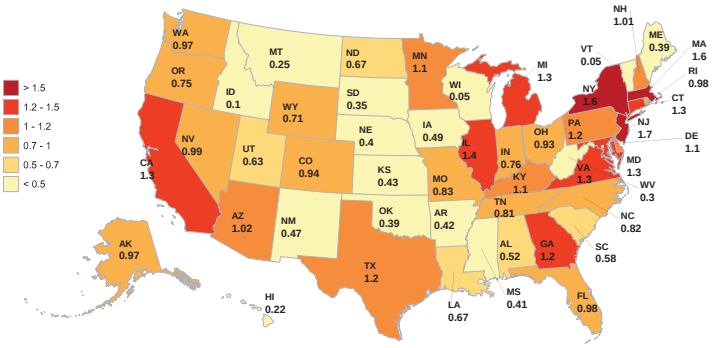
b: Elasticity of aggregate GDP (model NRNS)



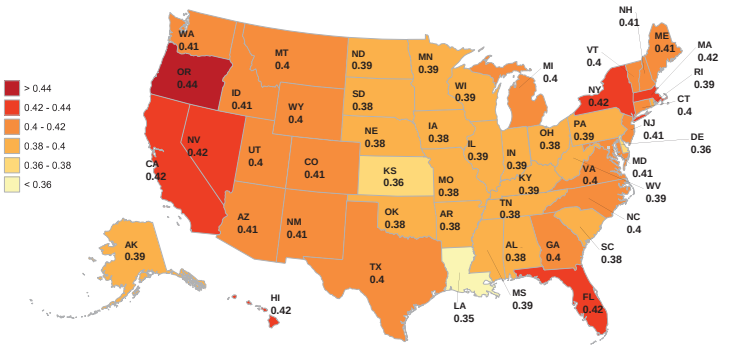
c: Elasticity of aggregate TFP (model RNS)



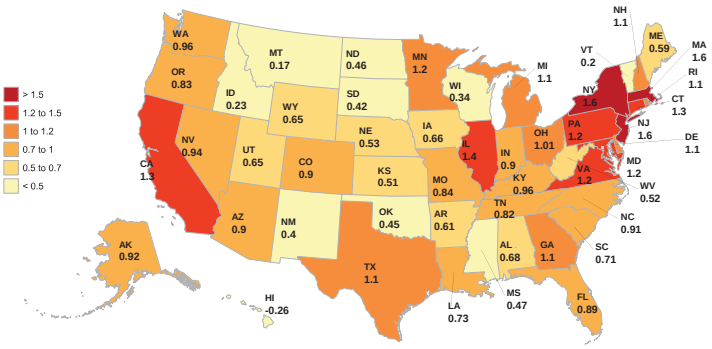
d: Elasticity of aggregate GDP (model RNS)



e: Elasticity of aggregate TFP (model RS)



f: Elasticity of aggregate GDP (model RS)



When both input-output and trade linkages are present (RS), which captures the actual effect of regional fundamental productivity changes, we find that the aggregate elasticity of GDP to regional productivity changes substantially in many regions. This is clear for Florida. In terms of land and structures, Florida is small with relatively low wage to rental ratios.[26] As a result of increased immigration the state's output

[26] Even though some of these states are large in terms of area, they have low levels of infrastructure and other structures, as we saw in Figure 6.

increases less than it would in fixed-factor-abundant regions. Input-output linkages tend to reduce even more the elasticity in fixed-factor scarce states by inducing a larger inflow of workers. This leads to an elasticity of only 0.89 in Florida. In contrast, for California, with its abundant land and structures, we estimate an elasticity of 1.3. The difference is large in magnitude. A productivity change of the same national magnitude in California increases national output 46% more than in Florida. Figure 8f shows that the range of elasticities is even larger than that. It goes from -0.26 in Hawaii and 0.17 in Montana to 1.6 in New Jersey, New York, and Massachusetts. These large range illustrates how the geography of productivity changes is essential to understanding their aggregate consequences.

We also evaluated how the elasticities from our model change if we restrict labor not to move across regions. When there is no mobility and no interregional trade, both the aggregate TFP and GDP elasticities to regional fundamental productivity changes are equal to one. Adding trade makes the selection channel operative in both cases, and we find that the TFP elasticities are similar in both models. However, GDP elasticities are considerably different, and in our view much more pertinent when we add migration.[27]

Fig. 9. Welfare elasticity of regional productivity changes

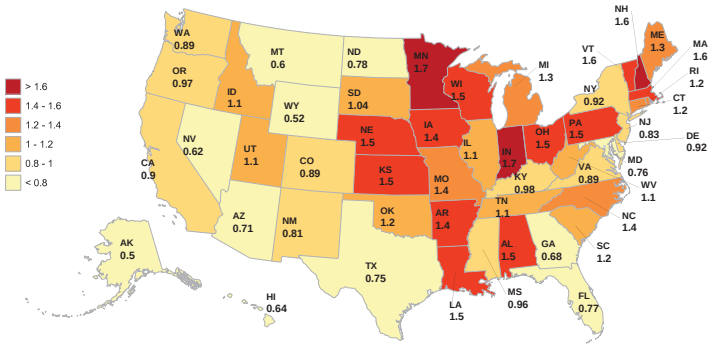


Figure 9 presents the welfare elasticity to regional fundamental productivity changes.[28] Recall that because of free migration, welfare is identical across regions. Welfare elasticities are always positive but their range is again quite large. Welfare elasticities are in general large for centrally located states in the Midwest and the South. They range from 1.7 in Minnesota and Indiana to 0.6 in western states like Montana and 0.62 in Nevada. This is natural as the consumption price index tends to be lower in central states due to lower average transportation costs to the rest of the country. Adjustments through the ownership structure matter also when comparing aggregate GDP and welfare elasticities. In states where the contribution to the national portfolio is zero, $\iota_n = 0$, like Florida, the welfare elasticity tends to be smaller than that of GDP. The reverse is true in states like Wisconsin, where $\iota_n = 1$. In the latter states, agents benefit –through their ownership of the national portfolio– from the increase in the price of local factors that result from the fundamental productivity change without having to move to the state. This mitigates the congestion caused by local decreasing returns to labor in these states leading to larger welfare gains.

[27] In Section 4 we feed into the model the observed change in fundamental TFP by regions and sectors to show that the model implied changes in employment shares are consistent with the patterns observed in the data. We also introduced these changes into a model with no migration and compare the implied regional GDP effects with the data. We find that the correlation is 26.3% while the correlation between the regional GDP effects implied from the model with mobility and the data is 56.5%.

[28] To calculate welfare elasticities we use the share of employment in the state.

5.1.2 Regional Propagation of Local Productivity Changes.—

Thus far, we have emphasized the aggregate effect of regional changes. The model, evidently, also tells us how productivity changes in particular states propagate to other states. As an example, Figure 10 panels a, c, and e present the regional elasticity of measured TFP, GDP, and employment from an increase in fundamental TFP in California.[29] The top panel focuses first on the response of measured TFP. California presents an own elasticity of measured TFP of 0.4. The fact that the elasticity is lower than one reflects, first, the negative selection mechanism and, second, the fact that fundamental productivity scales value added. The elasticity of measured productivity in other states is mostly positive because the selection effect in those states means that varieties that continue to be produced there have relatively higher idiosyncratic productivities. Regions close to California, such as Nevada, benefit the most, with the effect decreasing as we move east due to higher transport costs. That is, distance matters, although its implications are not uniform. As a result of sectoral linkages, industries in states that supply material inputs to California benefit to a greater degree from their positive selection effect. Other states that compete with California, such as Texas and Louisiana in Petroleum and Coal, gain little or even lose in terms of measured TFP.

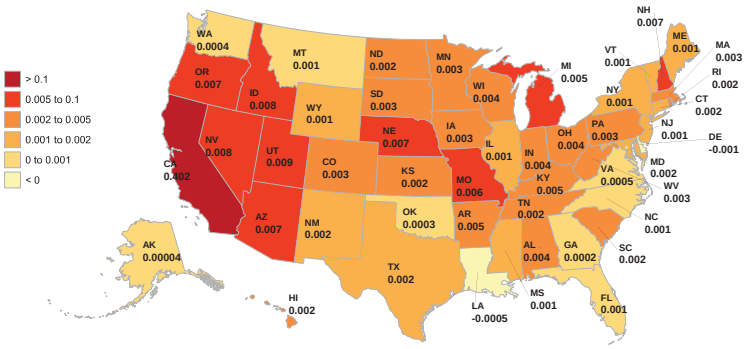
Figure 10 panel c depicts the regional elasticity of GDP of a fundamental productivity increase in California. California's own GDP elasticity with respect to a fundamental productivity increase is 2.8 and, in part, derives from the influx of population to the state, (Figure 10 panel e shows that the employment elasticity is equal to 2.7). All other states lose in terms of GDP and employment, and lose to a greater extent if they are farther away from California. This effect is particularly large since California has a relatively high wage to unit cost ratio. Therefore, the influx of population adds more to California than it subtracts from other states. Furthermore, the relatively small contribution of California to the national portfolio of land and structures results in a high regional elasticity of employment. Some large Midwestern states, like Illinois, and Northeastern states, like New York, lose substantial from the decrease in population caused by the migration to California. The reason is partly that the relatively high stock of land and structures in these states makes the population losses particularly costly there. Other states like Wisconsin or Minnesota are affected by the decline in the returns to the national portfolio of land and structures without benefiting disproportionately from the increase in their local returns given their high ι_n.

As a last example of the effects of regional changes, we briefly discuss the case of Florida. Florida is interesting in that a an increase in its fundamental TFP generates a relatively small aggregate elasticity of real GDP. Figure 10 panels b, d, and f present a set of figures analogous to those in Figure 10 panels a, c, and e but for Florida's case. Most of the effects that we underscore for California are evident for Florida as well. However, the region-specific productivity change induces more pronounced immigration. Florida's employment elasticity is equal to 3.3 which is very large even compared to California (2.7). This shift in population puts a strain on local fixed factors and infrastructure that are significant to the extent that Florida's real GDP increases only slightly more than its population. This strain on Florida's fixed resources is magnified by the fact that the state is relatively isolated and, in particular, sells relatively few materials to other states. Furthermore, because Florida contributes nothing to the national portfolio of land and structures, agents in other regions do not share the gains from the fundamental productivity change, which exacerbates migration flows into the state. The end result is that the loss in output in other regions balances to a larger extent Florida's increase in GDP, thus leading to a smaller overall aggregate elasticity of GDP.

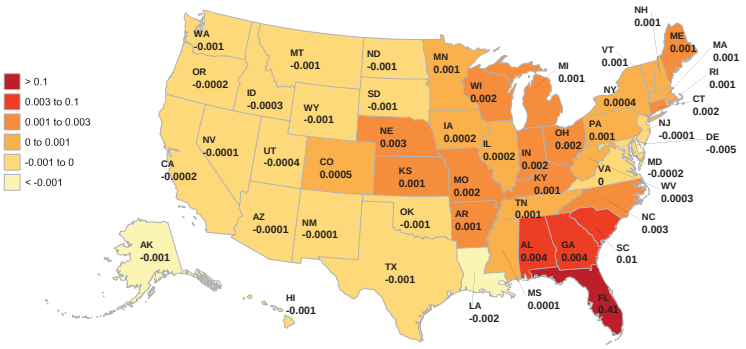
[29] To calculate this elasticity, we multiply the effect of the regional fundamental productivity increase only by the size of the fundamental productivity change.

Fig. 10. Regional elasticities to a fundamental productivity change in California and Florida

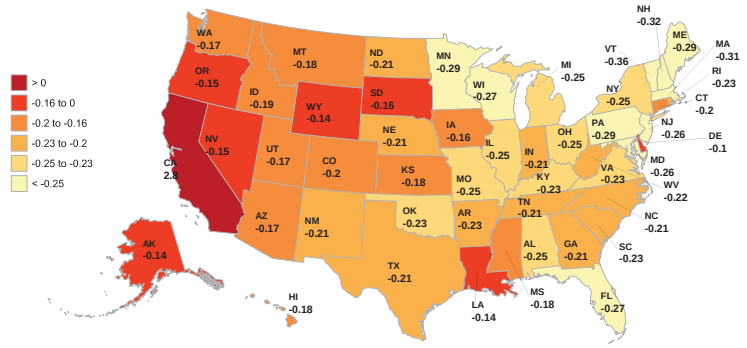
a: Regional TFP elasticity to California change



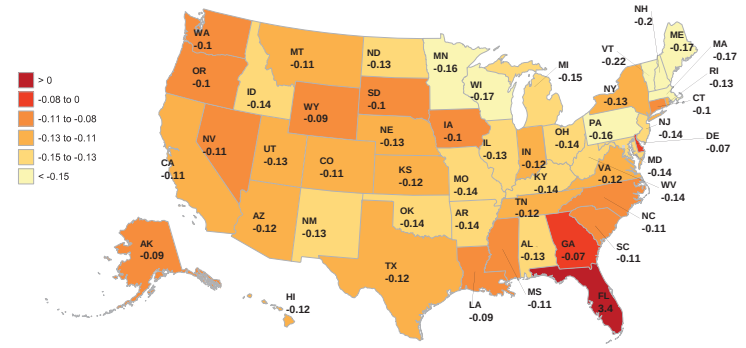
b: Regional TFP elasticity to Florida change



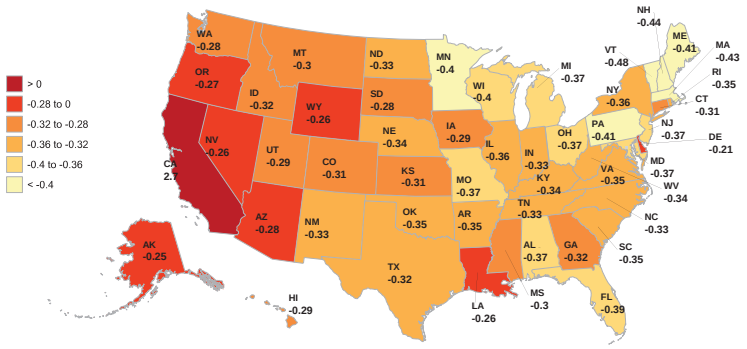
c: Regional GDP elasticity to California change



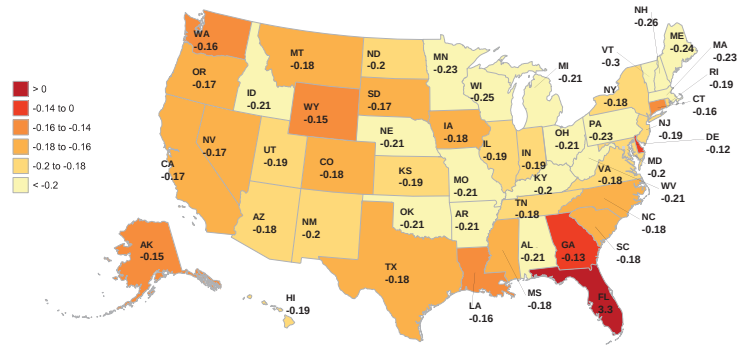
d: Regional GDP elasticity to Florida change



e: Regional Employment elasticity to California change



f: Regional Employment elasticity to Florida change

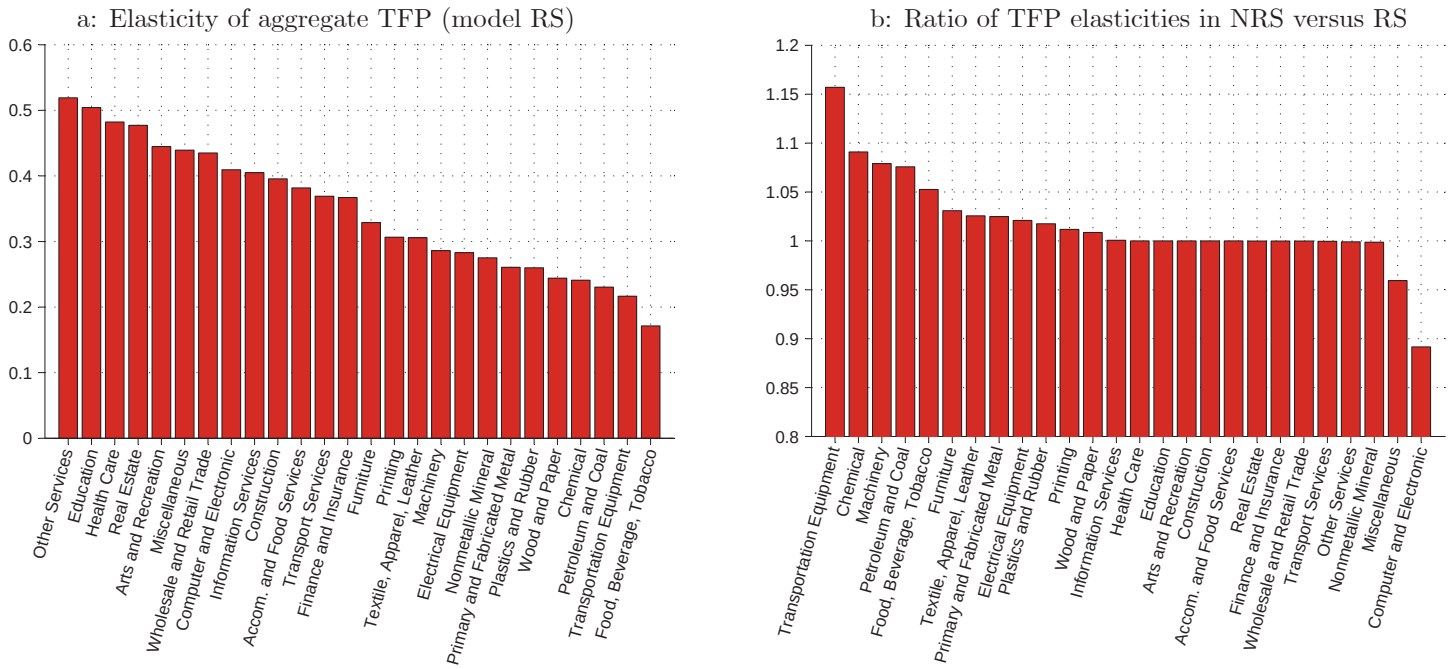


5.2 Sectoral Productivity Changes

In contrast to regional changes, studying the effects of sectoral changes has a long tradition in the macroeconomics literature (see Long and Plosser, 1983, Horvath, 1998, Dupor, 1999, Foerster et al. 2011, and Acemoglu, et al. 2012, among many others). Despite this long tradition, little is known about how the geography of economic activity impinges on the effects of sectoral productivity changes. Our framework

highlights two main channels through which geography affects the aggregate impact of sectoral changes. First, regional trade is costly so that, given a set of input-output linkages, sectoral productivity changes will produce different economic outcomes depending on how geographically concentrated these changes are. Second, land and structures, including infrastructure, are locally fixed factors. Therefore, changes that affect sectors concentrated in regions that have an abundance of these factors will tend to have larger effects.

FIG. 11. Aggregate measured TFP elasticities to a sectoral fundamental productivity change



5.2.1. Aggregate Effects of Sectoral Productivity Changes.—

Figure 11 presents aggregate responses of measured productivity to changes in fundamental productivity in each sector. In this case, a fundamental change in a given sector is identical across all regions in which the sector is represented. We present aggregate elasticities for the case in which all channels are operative (RS), as well as the ratio of the elasticity in the cases without and with regional trade, NRS and RS. The latter case is the one absent in standard multisector macroeconomic models.[30] Absent sectoral linkages, a given sectoral fundamental TFP change does not affect the distribution of employment across regions. Therefore, in both the NRNS and RNS cases, the aggregate TFP elasticity with respect to changes in sectoral fundamental productivity is equal to one for all sectors.

Figure 11a shows that, compared to an economy with only land, structures, and labor, adding material inputs reduces significantly the aggregate TFP elasticity with respect to a given sectoral productivity change. Input-output linkages also skew the distribution of aggregate sectoral effects. These differences arise because material inputs serve as an insurance mechanism against changes that are idiosyncratic to a particular sector. That is, with input-output linkages, output in any sector depends on the productivity in other sectors. Trade

[30] Under the maintained assumptions that the share of land and structures in value added is constant across sectors (β_n), and that the share of consumption across sectors is identical across regions (α^j), trade matters for the aggregate effects of sectoral fundamental TFP changes only in the presence of sectoral linkages.

influences this mechanism because intermediate inputs cannot be imported costlessly from other locations. For example, as Figure 11b shows, eliminating trade leads to an elasticity of aggregate TFP that is about 15% larger in the Transportation Equipment industry, but about 10% smaller in the Computer and Electronics industry.

When we focus on the elasticity of aggregate GDP, it is even clearer that in sectors that are very concentrated geographically, this influence of regional trade is smaller than in sectors that are more dispersed across regions. The Petroleum and Coal industry, for instance, is concentrated across less than a handful of states. Hence failure to account for regional trade understates the aggregate elasticity of GDP in that sector by about 10% (see 12b). In contrast in the relatively dispersed Transportation Equipment industry disregarding regional trade overstates the elasticity by 19%. Trade has a negligible effect on the aggregate elasticities of changes to non-tradable sectors.

Fig. 12. Aggregate GDP elasticities to a sectoral fundamental productivity change

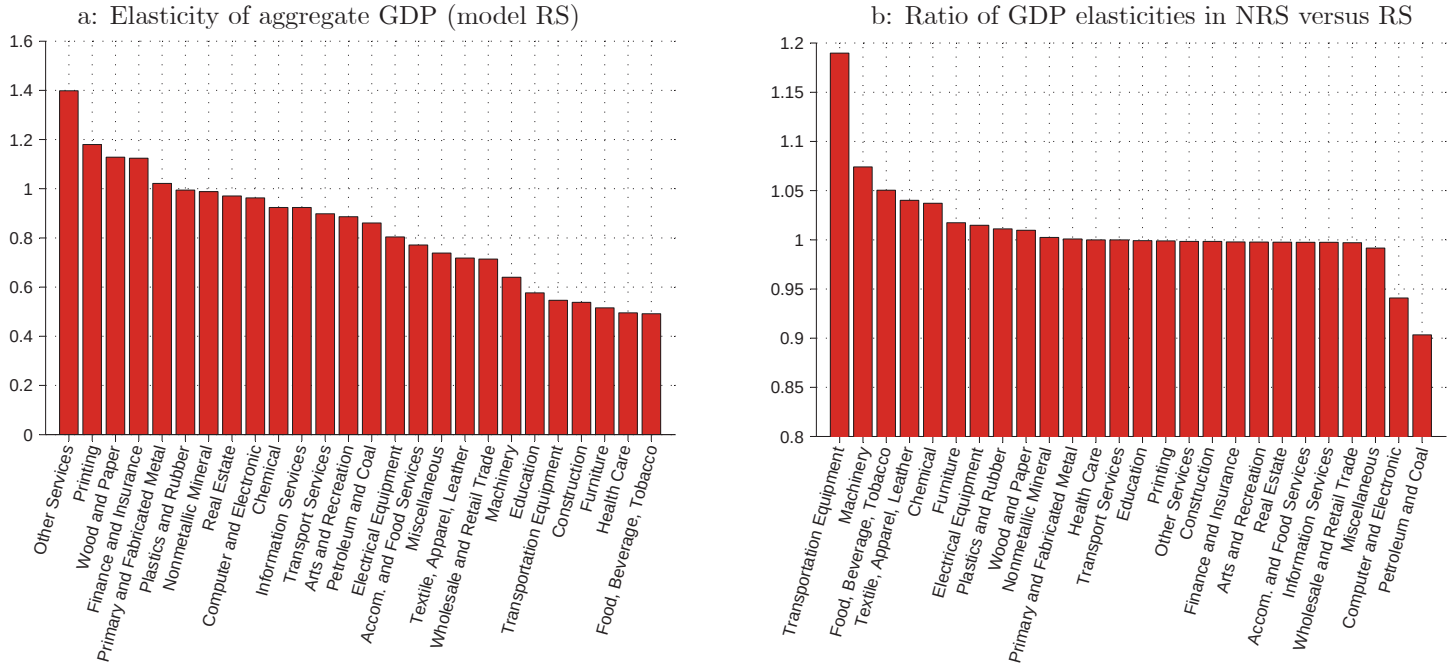
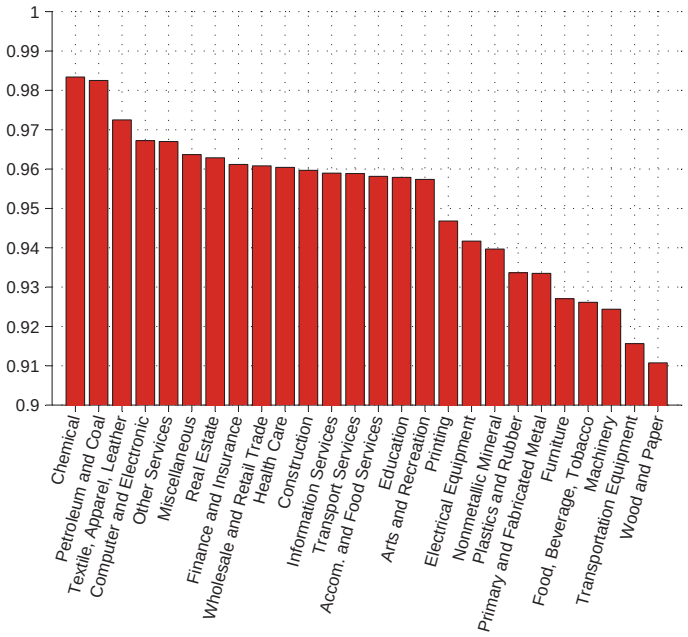


Figure 13 illustrates the welfare implications of sectoral changes in productivity. As with regional productivity changes, these exhibit a fairly large range. A fundamental productivity change in the Wood and Paper industry –the most dispersed industry in the U.S.– has an effect on welfare that is about 10% lower than in the much more concentrates Petroleum and Coal and Chemical industries (see Figure 3b). The sectoral distribution of welfare elasticity is also less skewed than that of GDP since measured TFP in general responds less than employment to changes in fundamental productivity (see Equation (19)).

5.2.2. Regional Propagation of Sectoral Productivity Changes.—

Because they lack a geographic dimension, disaggregated structural models that have been used to study the effects of sectoral productivity changes have been silent on the consequences of these changes across regions. While improvements or worsening conditions in a given sector have aggregate consequences, it is also the case that these effects have a geographic distribution that is typically not uniform across states.

Fig. 13. Welfare elasticities to sectoral fundamental productivity changes



Thus, we now turn our attention to the regional implications of sectoral fundamental TFP changes.

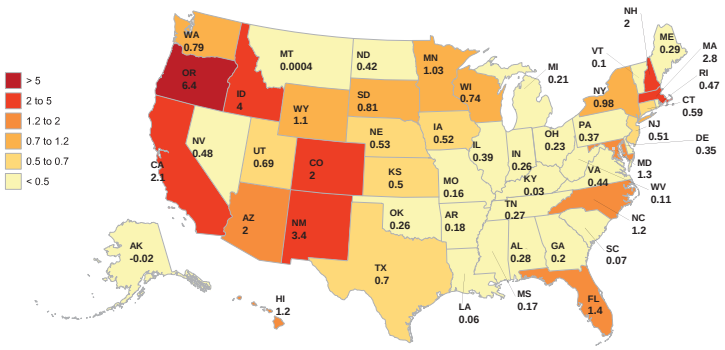
Figure 14 panels a, c, and e show regional elasticities of measured TFP, GDP and employment to a fundamental TFP change in the Computer and Electronics industry. The share of the industry in total value added is slightly less than 2 percent. Evidently, states whose production is concentrated in that industry experience a more pronounced increase in measured TFP. However, as seen earlier, the direct effect of the productivity increase is mitigated somewhat by the negative selection effect in those industries. In states that do not produce in the industry, measured TFP is still affected through the selection effect, since unit costs change as a result of changes in the price of materials. As Figure 14 panels a, c, and e make clear, the productivity change in Computer and Electronics affects mostly western states where this industry has traditionally been heavily represented.

Perhaps remarkably, the productivity increase in Computer and Electronics has very small or negative consequences for GDP and population in some states that are near those where the industry is concentrated. Consider, for instance, the cases of California and Massachusetts, two states that are active in Computers and Electronics. As the result of the productivity change, their populations grow. However, neighboring states such as Nevada, Connecticut, Rhode Island, and Vermont lose population and thus experience a decline, or a negligible increase, in GDP. These neighboring states, in fact, are the only states that experience a decline in real GDP in this case (apart from Tennessee which is affected by the growth of the sector in North Carolina). All of the effects we have described are influenced in turn by the size of the stocks of land and structures in those states. In that sense, the geographic distribution of economic activity determines the impact of sectoral fundamental productivity changes. Specifically, the aggregate impact of these changes is mitigated by these patterns, with an elasticity of aggregate GDP to fundamental productivity changes in the computer industry which is slightly lower than one.

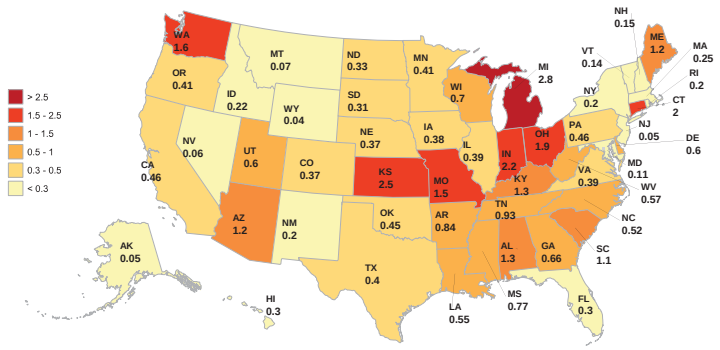
Other industries, such as Transportation Equipment, are less concentrated geographically and yield lower elasticities of changes in aggregate GDP with respect to changes in fundamental sectoral TFP. In the case

Fig. 14. Regional elasticities to a sectoral change in fundamental productivity (hundreds)

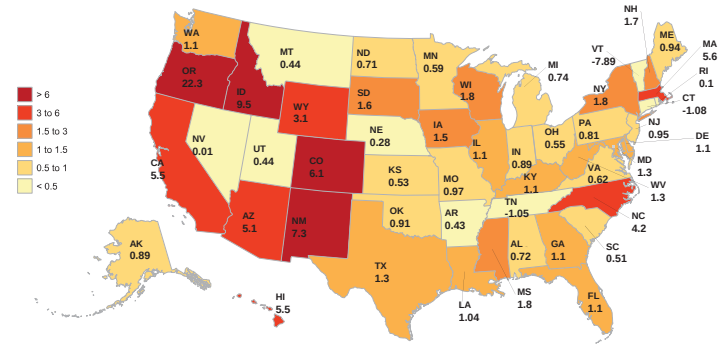
a: TFP elasticity to Computer and Elect. change



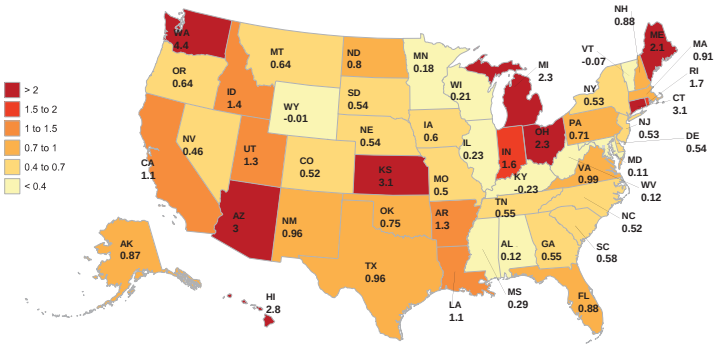
b: TFP elasticity to Transportation Equip. change



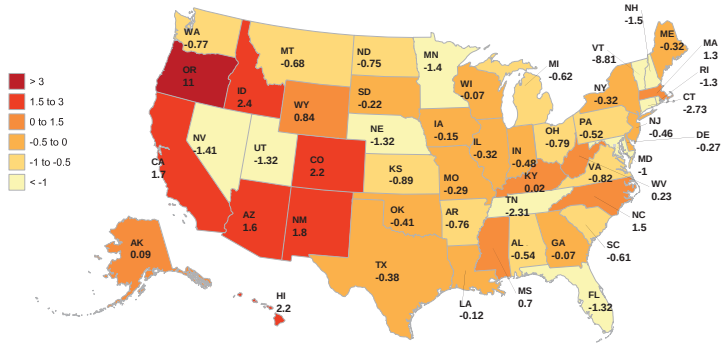
c: GDP elasticity to Computer and Elect. change



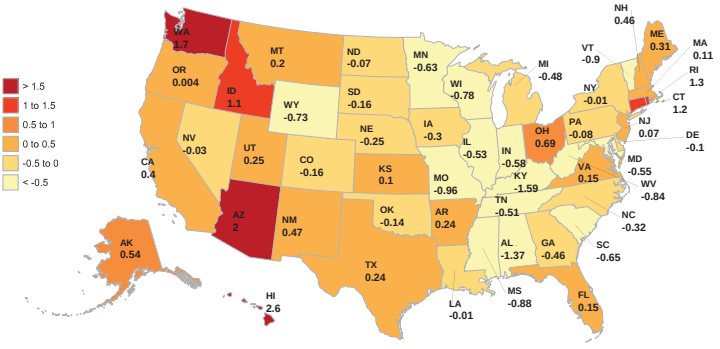
d: GDP elasticity to Transportation Equip. change



e: Employment elasticity to Comp. and Elect. change



f: Employment elasticity to Transp. Equip. change



of Transportation Equipment, this elasticity is 0.55 (it is 0.54 in construction which is even more dispersed geographically, see Figure 3). The transportation industry is interesting in that although relatively small, with a value added share of just 1.84 percent, it is also more centrally located in space with Michigan and other Midwestern states being historically important producers in that sector. The implications of a productivity increase in the Transportation Equipment sector for other states is presented in Figure 14 panels b, d, and f. Changes in measured TFP are clearly more dispersed across sectors and regions than for Computer

and Electronics, although the largest increases in measured TFP are located in states involved in automobile production such as Michigan. In contrast to the case of Computer and Electronics, all regions see an increase in state GDP (except Vermont, Kentucky, and Wyoming which decline slightly) and much smaller population movements take place. In fact, Midwestern states, including Michigan, Illinois, and Indiana, tend to lose population while western and eastern states gain workers. To understand why, note that transportation equipment is an important material input into a wide range of industries. Therefore, increases in productivity in that sector benefit many other sectors as well. Although, in this case, a fundamental productivity increase does not induce much migration, aggregate gains from the change are lower than in other sectors, since the change strains resources in some of already relatively congested regions. The result is a lower elasticity of real GDP to productivity gains in the Transportation sector compared to the Computer and Electronics industry, specifically 0.55. The elasticity of welfare to the productivity change is equal to 0.92, also smaller than the 0.97 for the Computer and Electronics sector.

6. APPLICATIONS

The model we have laid out allows us to calculate the regional, sectoral, and aggregate elasticities of TFP, GDP, and employment with respect to a productivity change in any sector in any region. In this section we trace out the effects of four specific changes in the U.S. economy that are of interest given their large magnitude, prominence, or rarity. We select four applications that exemplify different types of shocks.

6.1 The Productivity Boom in Computers and Electronics in California

The state of California is well known for its role as the home of prominent information and technology firms, Apple, Cisco Systems, Hewlett-Packard, Intel and many others, and generally as a center for computer innovation. In 2007, California alone accounted for 24% or essentially a quarter of all employment in the Computers and Electronics industry. For comparison, the states with the next two largest shares of employment in that sector were Texas and Massachusetts with 8% and 6% respectively, while most other states (37) had shares of employment in Computers and Electronics of less than 2%. Despite the dot-com bust of 2001 causing a loss of significant market capitalization for many firms in Computers and Electronics, California then saw over the next five years annual TFP changes in that sector on the order of 31% on average. Given the continually rising importance of Computers and Electronics as an input to other sectors, and the importance of California as a home to computer innovation, we now describe the way in which TFP changes in that sector and state propagated to all other sectors and states of the U.S. economy.

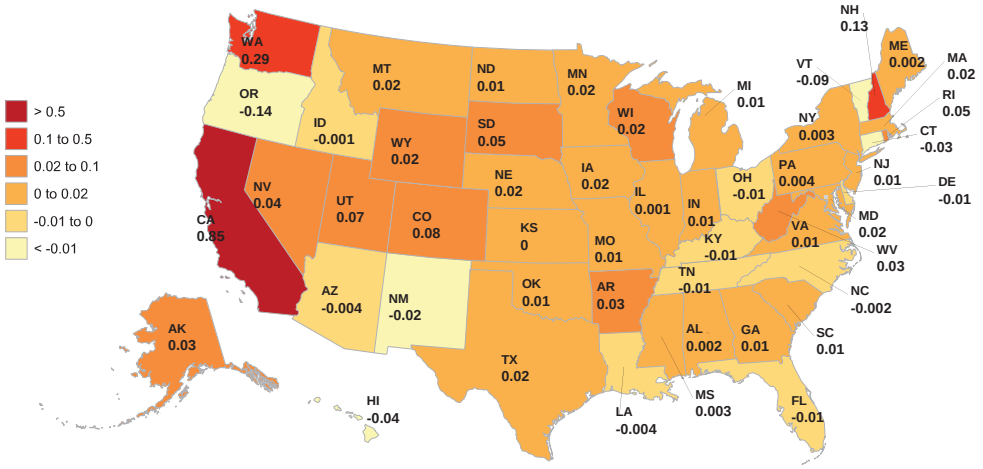
We find that the boom in the Computers and Electronics industry in California increased U.S. welfare by 0.2 percent per year.[31] Figure 15 shows the effects of observed changes in TFP in the Computers and Electronics industry specific to California, a sector that amounts to 5.5% of value added in that state, on measured regional TFP, GDP, and employment in other regions and states. The regional effect on measured TFP, GDP, or employment, can be computed by multiplying the size of the productivity change in California by the relevant elasticity in the region of interest.[32] Thus, a 31% fundamental TFP increase in Computers and

[31] To put this aggregate welfare effect into context, Caliendo and Parro (2015) find that aggregate U.S. welfare increased by 0.1 percent as a consequence of NAFTA's tariff reductions.

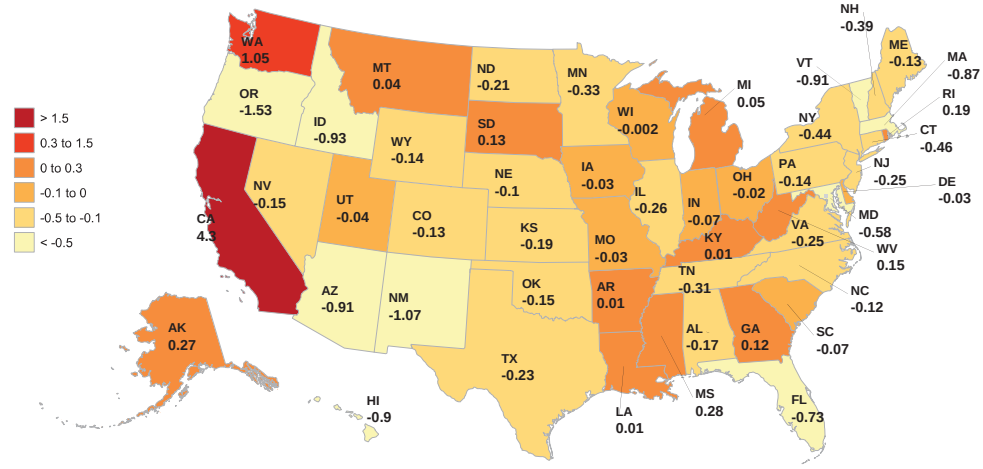
[32] In this section we compute all the results by feeding the annual observed change in fundamental TFP between 2002 and 2007 into the model. Alternatively, we could have computed these results by multiplying the fundamental TFP changes by the relevant regional or sectoral elasticities, as we have argued in the text. The difference between both calculations is related to the model's non-linearities. In this case, we find that the aggregate welfare gain is similar at 0.18 percent per year. Furthermore the

Fig. 15. Regional effects to a 31 percent fundamental productivity change in Comp. and Elec. in California

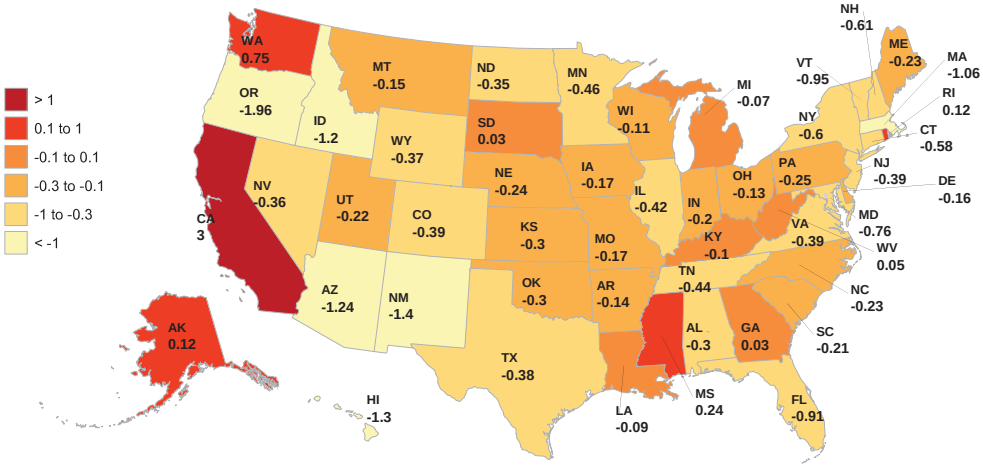
a: Regional TFP effects (percent)



b: Regional GDP effects (percent)



c: Regional Employment effects (percent)



Electronics in California, which corresponds to a 14.6% yearly increase in measured TFP, results in a 0.85% increase in overall measured TFP in that state per year. This finding reflects in part the weight of Computers and Electronics relative to other sectors in California, and in part the dampening effects associated with negative selection, whereby newer varieties have relatively lower idiosyncratic productivities. States in the West that compete with California, such as Arizona, Oregon, and Idaho, now experience losses in TFP on the order of -0.01%, -0.14% and -0.01% respectively. Recall from Section 5.2 that, when a productivity change to Computer and Electronics affects all regions, the latter states were those that experienced the largest gains in measured TFP. Other states benefited from the productivity increase in Computer and Electronics mainly through a positive selection effect that left remaining varieties with relatively higher productivities. When the TFP increase in Computer and Electronics is specific to California, states that are close by and compete with California now experience productivity losses.

Following the change to Computer and Electronics in California, population tends to relocate to California. In addition, since the productivity change is more localized in space, this relocation is larger than that observed for a change in Computers and Electronics that affected all regions. Population tends to migrate mainly from regions that compete directly with California. Therefore, a more localized change in a given industry results in a larger GDP increase in California and generally in larger declines in other states. Observe, in particular, that annual declines in regional GDP tend to be larger not only in neighboring states such as Oregon (-1.53%), Arizona (-0.91%), and New Mexico (-1.07%), but also in states farther out that compete directly with California in Computers and Electronics such as Massachusetts (-0.87%).

Aside from the effects related to Computers and Electronics, the productivity improvement in California in that industry also means that California now possesses a lower comparative advantage in other sectors. Other states, therefore, benefit through sectors not related to Computers and Electronics, especially where these other sectors are relatively large such as for Petroleum and Coal in the states of Washington and West Virginia. These other sectors also see a reduction in material costs. Ultimately, while employment in the computer industry falls in the states of Washington and West Virginia, other sectors such as Petroleum and Coal, Non-Metallic Minerals, and non-tradables, experience an increase in employment that more than offsets the decline in employment in computers. Thus, Washington, but also a state as far away from California as West Virginia with little production in Computers and Electronics, see their GDP rise by 1.05% and 0.15% respectively.

6.2 The Regional Productivity Boom in North Dakota

Since mid-2000s, the U.S. economy experienced a well-documented productivity slowdown.[33] According to our calculations average annual measured TFP growth slowed from 1 percent in 2002-2007 to 0.1 percent in 2007-2012 (see Figure 5 for the period 2002-2007 and Figure A5.1 for the period 2007-2012 in Appendix A.5).[34] This estimated measured TFP slowdown masks unequal TFP growth rates across states. For example, North Dakota's measured TFP growth accelerated during the period. This state experienced the highest measured TFP growth in the country. The annual measured TFP growth in North Dakota from 2007 to 2012 was 1.8 percent compared to 1.2 percent over 2002-2007; about 20 times higher than the average

differences between the two methods are negligible when we look at the implications for every state-region, with a correlation of 0.996, 0.996, and 0.995 and mean absolute deviation of 0.01%, 0.04% and 0.04% for the regional TFP, GDP and labor reallocation, respectively.

[33] See e.g. Byrne, Fernald, and Reinsdorf (2016), and Syverson (2016).

[34] These numbers represent the average growth rates across states rather than aggregate measured TFP growth.

TFP growth over this period. This is an example of a stark region-wide productivity change.

The solid performance of North Dakota's TFP growth is likely the result, at least in part, of the shale oil boom that started in 2007 that had a broad economic impact in the region.[35] In our model, we abstract from agriculture and mining, owing to their small employment shares, and so cannot strictly incorporate the increase in shale technology directly. However, the evidence suggests that the gains in measured productivity were broadly distributed across sectors. What was the impact of this rapid TFP growth on GDP and employment in North Dakota? How did this economic boom impact the rest of the U.S. states as well as the aggregate economy? To answer these questions, we feed into the model the estimated annual changes in fundamental TFP across all sectors in North Dakota, and then compute the effects on measured TFP, GDP and employment across all regions, as well as the aggregate welfare effects. Figure 16 shows the results.

The boom in North Dakota increased U.S. welfare by a mere 0.01 percent, a 20 times smaller impact compared to the boom in Computers and Electronics in California. Importantly, the size of the shock in productivity in that sector in California was only 8 times larger than the one in North Dakota. Furthermore, the Computers and Electronics sector has about the same employment size as North Dakota's economy. The reason the impact of North Dakota's boom on welfare is so much smaller than the technology boom in California is that North Dakota is much more isolated than California in terms of regional and sectoral trade. The productivity boom was a local event that did not spread out to the rest of the economy. Aggregate U.S. GDP is essentially unaffected, since the 0.03 percent increase contributed by North Dakota is balanced by a similar decline in the rest of the country. As Figure 16c shows employment moved to North Dakota, especially from neighboring states, to take advantage of the productivity boom.[36] Figure 16a shows that the boom in North Dakota increased measured TFP in the adjacent state of Montana due to a positive trade selection effect. Furthermore, one can observe an increase in production in Montana resulting from the better access to input materials from North Dakota which also attracted some population to that state.

In sum, the effects of the boom in North Dakota associated with the shale oil boom are quite isolated in that state. Only the state of Montana experienced significant effects, while the rest of the country lost employment and experienced small declines in production. A clear example of the importance of the location of a regional shock.[37]

6.3 Finance and Real Estate Contraction in New York

The U.S. financial crisis of 2007-2008 has naturally created a substantial body of work trying to understand its sources and consequences. However, this literature has focused on financial linkages and not on the real linkages emphasized here. In this application, we study the aggregate, regional and sectoral real effects of the associated measured TFP decline in the two industries at the center of that episode, namely, Finance

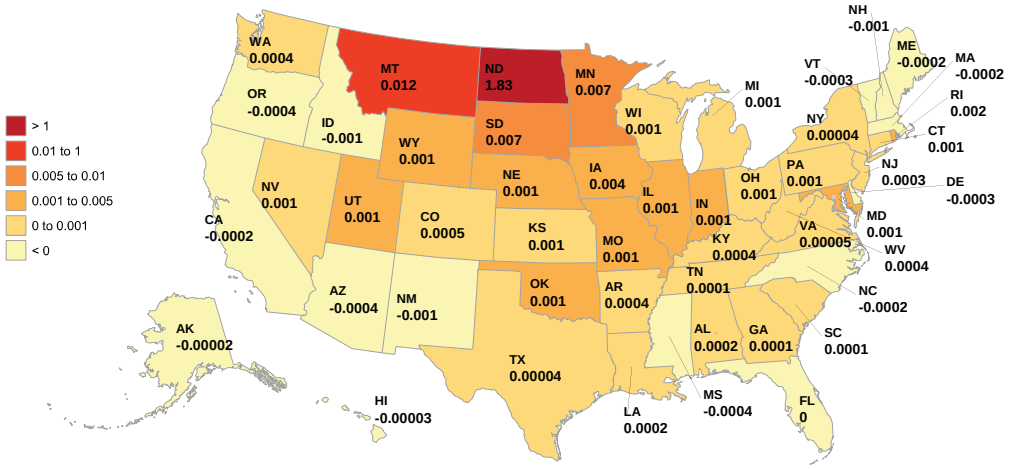
[35] The economic boom in North Dakota due to the shale gas exploration has been described in many articles and reports, for instance, see the New York Times article "North Dakota Went Boom" (Jan.31, 2013).

[36] The substantial increase in employment in North Dakota as a consequence of the shale oil boom is consisting with the finding in several reports. See, for instance, the Minneapolis Fed reports available at https://www.minneapolisfed.org/publications/special-studies/bakken/oil-production,

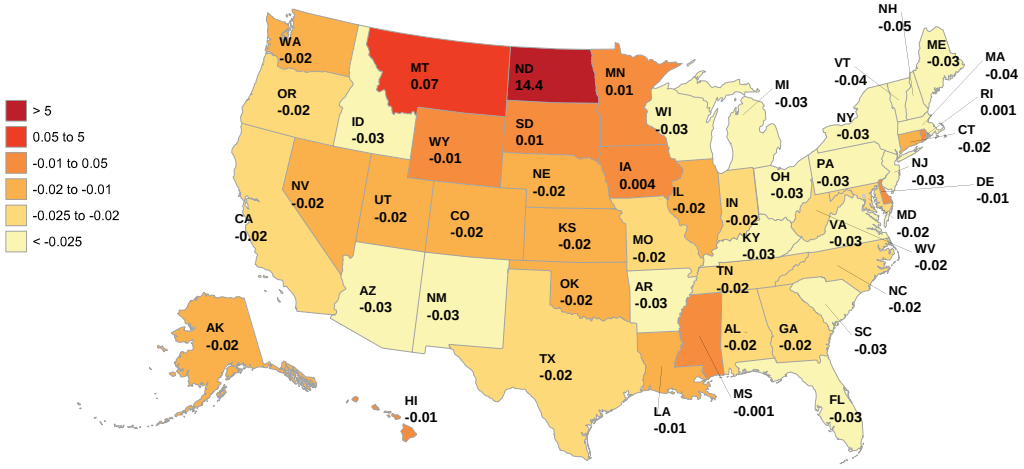
[37] The computations above use general equilibrium counterfactuals to measure the effect of the economic boom in North Dakota. We could also have simply multiplied the fundamental TFP change with the regional elasticities to such a shock in North Dakota in order to measure its aggregate and regional effects. This simpler calculation (once all the elasticities have been computed) yields very similar numbers. The corresponding aggregate effects are .03%, .04% and .08%, for TFP, GDP and welfare, respectively. For regional effects, the correlation between both calculations are all 0.999. The mean absolute deviation for the regional TFP, GDP, and employment are 0.01%, 0.07%, and 0.07%. Note that in this exercise we are applying a common regional elasticity to the fundamental TFP change in each sector in North Dakota. If we were to use the specific region-sector elasticities, the differences between both calculation would be even smaller.

Fig. 16. Regional effects of the productivity boom in North Dakota

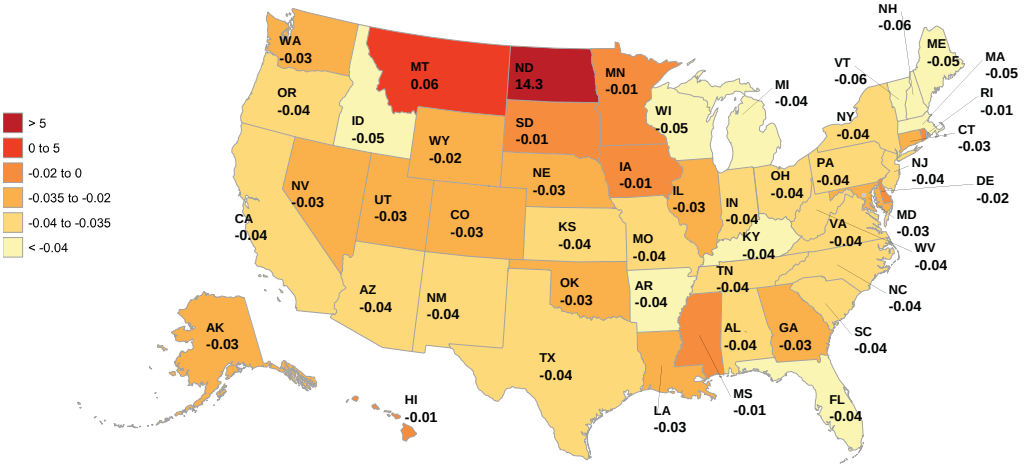
a: Regional TFP effects (percent)



b: Regional GDP effects (percent)



c: Regional Employment effects (percent)



and Insurance and Real Estate. These two industries are large in New York state, the home of Wall Street and of one of the most iconic skylines in the U.S and the world. In contrast to the previous applications, this crisis involves two service industries that we model as non-tradable. Furthermore, they concentrate in a state that is home to New York city, one of the most densely populated cities in the country, and the epicenter of the largest economic region in the U.S. We compute the changes in fundamental TFP in the Finance and Insurance and the Real Estate sectors over the period 2006-2008, that is, from the year before the crisis started to the year in which the crisis was triggered in New York with the collapse of Lehman Brothers. As a result, we feed into our model a computed decline in fundamental TFP in Finance and Insurance of 7.2 percent and in the Real Estate sector of 3.5 percent over 2006-2008.

The decline in fundamental TFP in these sectors in New York resulted in a decline in U.S. welfare of 0.06 percent and an aggregate U.S. GDP fall of 0.14 percent. Figures 17 shows the employment effects of this productivity decline. As seen in the figure, the productivity fall in Finance and Real Estate in New York had large employment relocation effects across U.S. states. Note that they are much larger than for the economic boom in North Dakota, even though the size of the change in fundamental TFP is of a similar order of magnitude, albeit localized in only two industries. The heterogeneity between these two states explains these results. North Dakota is an isolated state with little trade and infrastructure so the economic boom attracts fewer workers from other regions (although migration nevertheless has a significant impact on North Dakota given its small size). On the contrary, New York is a state with a large endowment of infrastructure and well-connected to the rest of the economy in terms of regional and sectoral trade; thus, a productivity drop has large effects that make population migrate to other states.[38]

Fig. 17. Regional effects of the Finance and Real Estate contraction in New York
Regional Employment effects (percent)

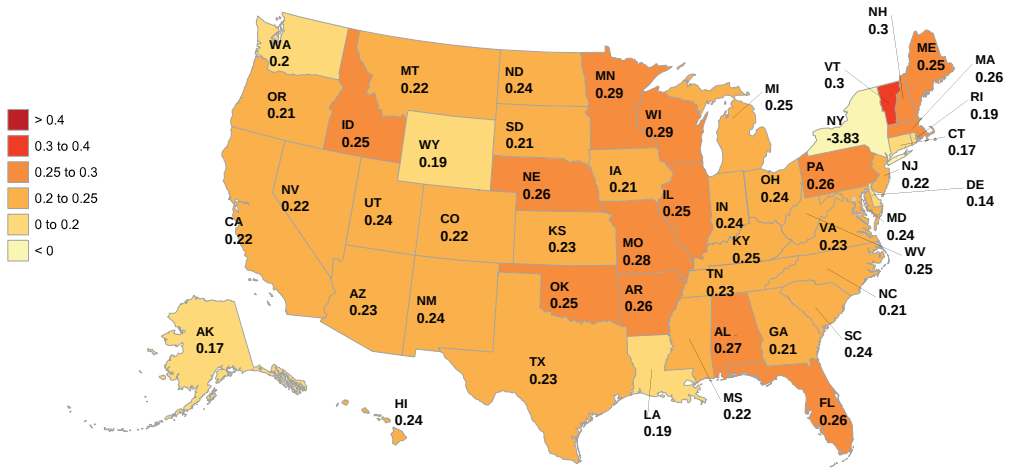


Figure 17 also shows that the workers that leave New York state as a result of the shock tend to flow much more uniformly across U.S. states than in the two previous applications. In particular, the change in employment shares across states ranges narrowly between 0.14 and 0.3 percent. Because Finance and Real Estate are non-tradable industries, all states must generate production in these industries to satisfy demand from their local residents and producers. As a result, economic activity in these two industries is

[38] If, as noted in the previous two applications, instead of calculating the general equilibrium elasticities we simply multiply the shock by the relevant elasticity we again obtain very similar results.

more evenly distributed and so all states are able to absorb the decline in the demand for labor in New York. Of course, population tends to migrate somewhat more to those states where Finance and Real Estate are more important such as Pennsylvania, Illinois, Minnesota, and California, but the differences are small.

These population mobility patterns are also reflected in the distribution of changes in GDP. Note that even though the direct effect of the shock affects two non-tradable industries, it also affects tradable industries in New York that use input materials from them. Through these indirect linkages, it impacts to a greater degree those states that trade more with New York.

6.4 The Impact of Hurricane Katrina

The three applications we have presented so far involve shocks to the productivity of particular sectors and regions. Clearly, we can also use our framework to study other types of changes. One of the novel elements of our framework is that it features a fixed factor that we measure as land and structures in the data. Thus, we can use our calibrated model to analyze changes in this factor that result from particular infrastructure investment projects or, inversely, from events that destroy part of this infrastructure as in the case of natural disasters. We do so in this application where we study the aggregate and regional effects of the infrastructure destruction inflicted by Hurricane Katrina.

On August 2005 Hurricane Katrina hit land where the Mississippi River enters the Gulf of Mexico as a category 4 hurricane and, hours later, it entered the continental mainland at the border of Louisiana and Mississippi as a category 3 hurricane. The damage inflicted by hurricane Katrina was extensive. Estimates of the cost of Katrina to the affected states are numerous, and fluctuate in the range of 100 to 200 billion dollars depending on whether economic impacts beyond direct costs are included in the calculations.[39] Damage to structures were estimated to be on the order of 75 to 90 billion dollars.[40]

To compute the impact of Katrina, we use the estimated structural damage of Burton and Hicks (2005) of \$75.3 million. We decompose it across the states of Alabama, Mississippi, and Louisiana according to the state shares of insured losses reported by the Insurance Information Institute. The result is a 34 percent decline in structures as a share of GDP in Mississippi, 25.2 percent in Louisiana, and 1.4 percent in Alabama. Since we are interested in the GDP and employment effects of Katrina, and given that the Hurricane did not strike Mississippi and Alabama's major population and industrial centers as it did in Louisiana, we will focus on the effects of the infrastructure destruction in Louisiana alone. Hence, we feed into the model the estimated structural damages in Louisiana, specifically $\hat{H}_{Louisiana} = 0.748$, and compute the regional aggregate employment and GDP effects. In Appendix A.2.1 we show the equilibrium conditions of the model in relative changes for counterfactuals that involve changes in H.

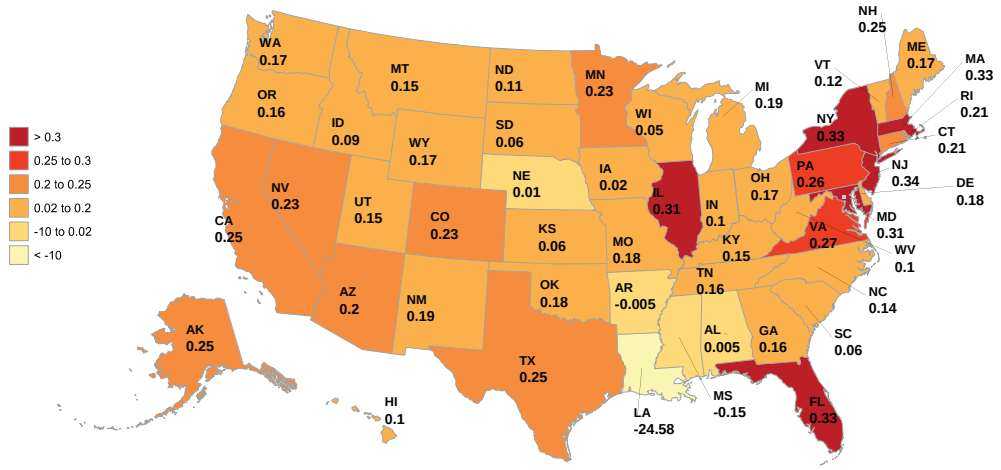
We find that Katrina reduced U.S. welfare by 0.24 percent, that is, the negative welfare impact of Katrina in the United States is of the same order of magnitude as the computed gains from the boom in Computers and Electronics in California. Aggregate U.S. GDP declines 0.12 percent, with Louisiana contributing with a 0.33 percent decline. That is, the economic impact on other states dampened about two-thirds of the direct

[39] Congleton (2006) put the total economic losses at over \$200 billion. The Federal Emergency Management Agency (2006) estimated total economic losses of \$125 billion and insured losses of \$35 billion. Meanwhile, the National Institute of Standards and Technology (2006) estimated economic losses from Hurricane Katrina and Hurricane Rita (that followed less than a month after Katrina) at about \$100 billion and insured losses at \$45-65 billion. Burton and Hicks (2005) estimated total damages of \$156 billion. Damages from Katrina estimated by National Oceanic and Atmospheric Administration are \$108 billion. Several private sector estimates also estimate losses in the range of \$100-200 billion.

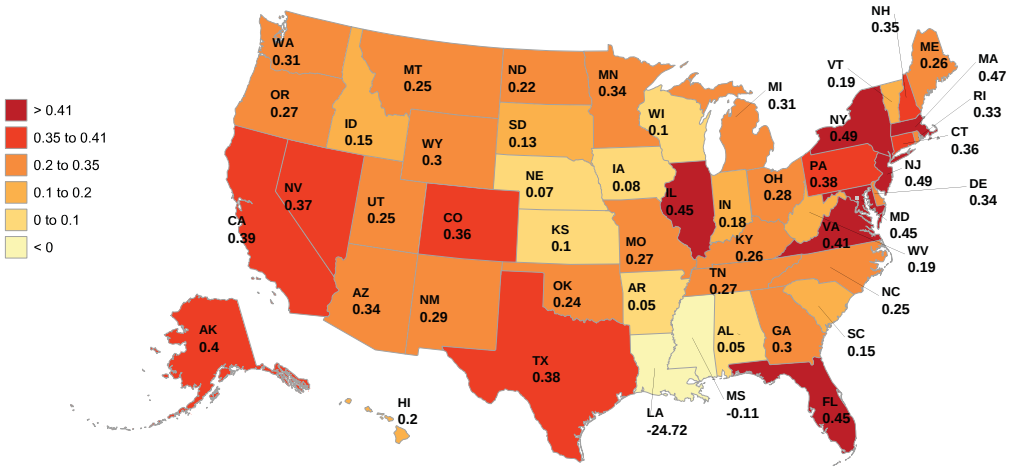
[40] See e.g. Burton and Hicks (2005) and the report "The Federal Response to Hurricane Katrina: Lessons Learned", elaborated by the White House in February 2006. Appendix A.6 provides more details on the facts about Hurricane Katrina and its estimated costs.

Fig. 18. Regional effects of the structural damage of Hurricane Katrina

a: Regional GDP effects (percent)



b: Regional Employment effects (percent)



impact of Louisiana on U.S. aggregate GDP. Figure 18 Panels a, b present the results. Panel b shows the employment effects in Louisiana and in the rest of the U.S. states. We find that 25 percent of employment in Louisiana, or about 490 thousand workers, moved to other states as a consequence of Katrina.[41] To put this change in employment in context, the BLS (2008) estimates that Katrina resulted in about 1.1 million emigrants (temporal or permanent) of which about 51 percent had employment status. That is, a total of 574 thousand workers moved out of Louisiana. Our model, therefore, captures virtually all of the movement in population, with the difference likely the result of other effects of the hurricane not related to structures.[42]

Figure 18 Panel b shows that, consistent with the pattern reported by the BLS, population relocated across all states, including far away regions. Still, we find that population tends to migrate more to states such as California, Texas, and some states in the east coast that compete with Louisiana in industries such

[41] For this calculation, we multiply the decline in employment share in Louisiana (0.25) by private non-farm employment (1.98 millions) in 2004 obtained from the BEA.

[42] For details, see the report "Hurricane Katrina evacuees: Who they are, Where they are, and How they are faring" prepared by the BLS in March 2008.

as Petroleum. Overall, we find that large states such as Virginia, California, New York and Texas received the biggest inflows of workers after Katrina. The fall in employment in Louisiana resulted in a GDP drop of a similar order of magnitude (Figure 18 Panel a). GDP increases in other states that benefited from migration, especially some states in the east coast and midwest that are abundant in structures. Finally, the impact of Katrina on measured TFP is generally small. Louisiana's measured TFP rose due to selection effects; in particular, structural damages increased the cost of producing goods in Louisiana so that it started importing a larger set of goods that previously were produced domestically with relative lower efficiency. The impact on measured TFP in other regions is small, reflecting the fact that Louisiana is relatively isolated in terms of regional and sectoral trade.

7. CONCLUDING REMARKS

Motivated by our finding that productivity changes that are specific to a region, or a region and sector, account for most of the changes in measured and fundamental productivity in the U.S., we study the effects of disaggregated productivity changes in a model that recognizes explicitly the role of geographical factors in determining allocations. This geographical element is manifested in several ways.

First, following a long tradition in macroeconomics, we take account of interactions between sectors, but we further recognize that these interactions take place over potentially large distances by way of costly regional trade. Thus, borrowing from the recent international trade literature, we incorporate multiple regions and transport costs in our analysis. Second, we consider the mobility and spatial distribution of different factors of production. Specifically, while labor tends to be mobile across regions, other factors, such as land and structures, are fixed locally and unevenly distributed across space. We calibrate the model to match data on pairwise trade flows across U.S. states by industry and other regional and industry data. Given this calibration, we are then able to provide a quantitative assessment of how different regions and sectors of the U.S. economy adjust to disaggregated productivity disturbances.

We find that disaggregated productivity changes can have dramatically different aggregate quantitative implications depending on the regions and sectors affected. Furthermore, particular disaggregated fundamental changes have very heterogenous effects across different regions and sectors. These effects arise in part because disaggregated productivity disturbances lead to endogenous changes in the pattern of trade. These changes in turn are governed by a selection effect that ultimately determines which regions produce what types of goods. Furthermore, labor is a mobile factor so that regions that become more productive tend to see an inflow of population. This inflow increases the burden on local fixed resources in those regions and, therefore, attenuates the direct effects of any productivity increases. In addition, the different estimated ownership structures of the fixed factor across states implies that changes in the returns to these factors are unequally distributed across regions, thereby exacerbating the role of geography in determining aggregate and regional elasticities. These implications of the model are the direct result of the observed trade imbalances across states.

Armed with our quantitative model of the U.S. economy we explore the role of specific disturbances in the U.S. economy. We study four different applications that study productivity changes in different industries and sectors, as well as changes in infrastructure. These applications are of interest in their own right, but also exemplified how the elasticities presented and studied in the paper can be used to study a wide variety of phenomena. Our hope is that they are used in the future to understand the impact of other events in the future. Importantly, the evaluations permitted by these elasticities fully include general equilibrium effects as

well as the dispersion of shocks through the trade and input-output network. So although extremely easy to use, these elasticities are the key element in producing full macroeconomic counterfactuals to disaggregated disturbances.

One missing aspect of our analysis is that land and infrastructures are fixed and so do not respond dynamically to shocks. Future work might further explore how local factors that can be gradually adjusted over time, such as private structures or infrastructure in the form of public capital, affect how regional and sectoral variables interact in responding to productivity disturbances. While the accumulation of local factors might attenuate somewhat the effects of migration, these effects depend on the stock of structures which moves slowly over time. The quantitative implications of this adjustment margin, therefore, are not immediate. The framework we develop might also be extended to assess the effects of different regional policies, such as state taxes or regulations (as in Fajgelbaum et al., 2016). Other extensions of this line or research could endogenize technology diffusion through migration, or study how regional and sectoral productivity shocks impact the employment and wages across different skill groups.[43] Finally, dynamic adjustments in trade imbalances would also be informative with respect to the behavior of regional trade deficits in the face of fundamental productivity disturbances, and how this behavior then relates to macroeconomic adjustments. For now, this paper suggests that the regional characteristics of an economy appear essential to the study of the macroeconomic implications of productivity changes.

[43] Recent estimates of how innovators respond to local market conditions from Akcigit, Baslandze, and Stancheva (2016) could be used as a guide to build on models where trade affects the distribution of technologies (see Alvarez, Buera and Lucas 2013, and Buera and Oberfield 2016).

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APPENDIX

A.1 Equilibrium Conditions with Exogenous Inter-regional Trade Deficit

Income of households in region n is given by $I_n = w_n + \chi + (1-\iota_n)\frac{r_n H_n}{L_n} - s_n$, where $s_n = S_n/L_n$ represents the part of observed per-capita trade surplus in region n unexplained by the model. Utility of an agent in region n is given by $U = \frac{I_n}{P_n}$. Using the equilibrium condition $r_n H_n = \frac{\beta_n}{1-\beta_n} w_n L_n$, and the definition of $\omega_n = (r_n/\beta_n)^{\beta_n} (w_n/(1-\beta_n))^{1-\beta_n}$, we can express wages as $\frac{w_n}{1-\beta_n} = \omega_n \left(\frac{H_n}{L_n}\right)^{\beta_n}$. Therefore, U may be expressed as

$$U = \left(\frac{H_n}{L_n}\right)^{\beta_n} \frac{\omega_n}{P_n} - \frac{u_n}{P_n} - \frac{s_n}{P_n},$$

where $u_n = \Upsilon_n/L_n = (\iota_n r_n H_n - \chi L_n)/L_n$. Solving for L_n and use the labor market clearing condition $\sum_{n=1}^{N} L_n = L$, to solve for U

$$U = \frac{1}{L}\sum_{n=1}^{N}\left(\frac{\omega_n}{P_n}(H_n)^{\beta_n} L_n^{1-\beta_n} - \frac{\Upsilon_n}{P_n} - \frac{S_n}{P_n}\right).$$

Finally we can use these conditions to obtain,

$$L_n = \frac{H_n \left[\frac{\omega_n}{P_n U + u_n + s_n}\right]^{1/\beta_n}}{\sum_{i=1}^{N} H_i \left[\frac{\omega_i}{P_i U + u_i + s_i}\right]^{1/\beta_i}} L.$$

The expenditure shares are given by

$$\pi_{ni}^j = \frac{\left[x_i^j \kappa_{ni}^j\right]^{-\theta^j} T_i^{j\ \theta^j \gamma_i^j}}{\sum\limits_{m=1}^{N}\left[x_m^j \kappa_{nm}^j\right]^{-\theta^j} T_m^{j\ \theta^j \gamma_m^j}}.$$

the input bundle and prices by

$$\begin{aligned} x_n^j &= B_n^j \left[r_n^{\beta_n} w_n^{1-\beta_n}\right]^{\gamma_n^j} \prod_{k=1}^{J} \left(P_n^k\right)^{\gamma_n^{jk}} \\ P_n^j &= \Gamma\left(\xi_n^j\right)^{1-\eta_n^j} \left[\sum_{i=1}^{N}\left[x_i^j \kappa_{ni}^j\right]^{-\theta^j} \left(T_i^j\right)^{\theta^j \gamma_i^j}\right]^{-1/\theta^j} \end{aligned}$$

Regional market clearing in final goods is given by

$$X_n^j = \sum_k \gamma_n^{kj} \sum_i \pi_{in}^k X_i^k + \alpha^j \left(\omega_n (H_n)^{\beta_n} (L_n)^{1-\beta_n} - \Upsilon_n - S_n\right)$$

Trade balance then is given by

$$\sum_{j=1}^{J} X_n^j + \Upsilon_n + S_n = \sum_{j=1}^{J}\sum_{i=1}^{N} \pi_{in}^j X_i^j.$$

Note that combining trade balance with goods market clearing we end up with the following equilibrium condition,

$$\omega_n (H_n)^{\beta_n} (L_n)^{1-\beta_n} = \sum_j \gamma_n^j \sum_{i=1}^{N} \pi_{in}^j X_i^j.$$

A.2 Equilibrium Conditions in Relative Changes

Input bundle (JN equations):

$$\widehat{x}_n^j = (\hat{\omega}_n)^{\gamma_n^j} \prod\nolimits_{k=1}^{J} (\widehat{P}_n^k)^{\gamma_n^{jk}}. \tag{A. 1}$$

Price index (JN equations):

$$\widehat{P}_n^j = \left(\sum\nolimits_{i=1}^{N} \pi_{ni}^j \left[\widehat{\kappa}_{ni}^j \widehat{x}_i^j \right]^{-\theta^j} \hat{T}_i^{j\ \theta^j \gamma_i^j} \right)^{-1/\theta^j}. \tag{A. 2}$$

Trade shares (JN^2 equations)

$$\pi_{ni}^{j'} = \pi_{ni}^j \left(\frac{\widehat{x}_i^j}{\widehat{P}_n^j} \widehat{\kappa}_{ni}^j \right)^{-\theta^j} \hat{T}_i^{j\ \theta^j \gamma_i^j}. \tag{A. 3}$$

Labor mobility condition (N equations):

$$\hat{L}_n = \frac{\left(\frac{\hat{\omega}_n}{\varphi_n \hat{P}_n \hat{U} + (1-\varphi_n)\hat{b}_n} \right)^{1/\beta_n}}{\sum_i L_i \left(\frac{\hat{\omega}_i}{\varphi_i \hat{P}_i \hat{U} + (1-\varphi_i)\hat{b}_i} \right)^{1/\beta_i}} L. \tag{A. 4}$$

Regional market clearing in final goods (JN equations):

$$X_n^{j\prime} = \sum\nolimits_{k=1}^{J} \gamma_n^{k,j} \left(\sum\nolimits_{i=1}^{N} \pi_{in}^{k\prime} X_i^{k\prime} \right) + \alpha^j \left(\hat{\omega}_n \left(\hat{L}_n \right)^{1-\beta_n} (I_n L_n + \Upsilon_n + S_n) - S_n' - \Upsilon_n' \right). \tag{A. 5}$$

Labor market clearing (N equations)

$$\hat{\omega}_n \left(\hat{L}_n \right)^{1-\beta_n} (L_n I_n + \Upsilon_n + S_n) = \sum\nolimits_j \gamma_n^j \sum\nolimits_i \pi_{in}^{\prime j} X_i^{\prime j},$$

where $\hat{b}_n = \frac{u_n' + s_n'}{u_n + s_n}$, $\varphi_n = \frac{1}{1 + \frac{\Upsilon_n + S_n}{L_n I_n}}$, $\hat{U} = \frac{1}{L} \sum_n L_n \left(\frac{1}{\varphi_n} \frac{\hat{\omega}_n}{\hat{P}_n} \left(\hat{L}_n \right)^{1-\beta_n} - \frac{1-\varphi_n}{\varphi_n} \frac{\hat{L}_n \hat{b}_n}{\hat{P}_n} \right)$, and $\widehat{P}_n = \prod_{j=1}^{J} \left(\hat{P}_n^j \right)^{\alpha^j}$.

The total number of unknowns is: $\hat{\omega}_n$ (N), $\hat{L}_n$ (N), $X_n^{j\prime}$ (JN), $\hat{P}_n^j$ (JN), $\pi_{ni}^{j\prime}$ $(J \times N \times N)$, $\hat{x}_n^j$ (JN). For a total of $2N + 3JN + JN^2$ equations and unknowns.

A.2.1 Allowing for Changes in Structures.—
Equilibrium conditions with changes in structures $\hat{H}_n$.
The labor mobility condition now becomes:

$$\hat{L}_n = \frac{\hat{H}_n \left(\frac{\hat{\omega}_n}{\varphi_n \hat{P}_n \hat{U} + (1-\varphi_n)\hat{b}_n} \right)^{1/\beta_n}}{\sum_i L_i \hat{H}_i \left(\frac{\hat{\omega}_i}{\varphi_i \hat{P}_i \hat{U} + (1-\varphi_i)\hat{b}_i} \right)^{1/\beta_i}} L$$

with $\hat{U} = \frac{1}{L} \sum_n L_n \left(\frac{1}{\varphi_n} \frac{\hat{\omega}_n}{\hat{P}_n} \left(\hat{H}_n \right)^{\beta_n} \left(\hat{L}_n \right)^{1-\beta_n} - \frac{1-\varphi_n}{\varphi_n} \frac{\hat{L}_n \hat{b}_n}{\hat{P}_n} \right)$. From the labor market clearing one obtains:

$$\hat{\omega}_n \left(\hat{H}_n \right)^{\beta_n} \left(\hat{L}_n \right)^{1-\beta_n} (L_n I_n + \Upsilon_n + S_n) = \sum\nolimits_j \gamma_n^j \sum\nolimits_i \pi_{in}^{\prime j} X_i^{\prime j}$$

and in the same way, the regional market clearing in final goods condition becomes

$$X_n^{j'} = \sum\nolimits_{k=1}^{J} \gamma_n^{k,j} + \alpha^j \left(\hat{\omega}_n \left(\hat{H}_n \right)^{\beta_n} \left(\hat{L}_n \right)^{1-\beta_n} (L_n I_n + \Upsilon_n + S_n) - S_n' - \Upsilon_n' \right)$$

where $\Upsilon'_n = \left(\iota_n \hat{\omega}_n \left(\hat{H}_n\right)^{\beta_n} \left(\hat{L}_n\right)^{1-\beta_n} r_n H_n - \varkappa' \hat{L}_n L_n\right) / \hat{L}_n L_n$, and with $\varkappa' = \frac{\sum_i \iota_i \hat{\omega}_n \left(\hat{H}_n\right)^{\beta_n} \left(\hat{L}_n\right)^{1-\beta_n} r_i H_i}{L}$.

A.3 Computation: Solving for Counterfactuals

Consider an exogenous change in S'_n, $\widehat{\kappa}^j_{ni}$, $\widehat{H}_n$, and/or $\widehat{T}^j_{ni}$. To solve for the counterfactual equilibrium in relative changes, we proceed as follows: Guess the relative change in regional factor prices $\hat{\boldsymbol{\omega}}$.

Step 1. Obtain $\hat{P}^j_n$ and $\widehat{x}^j_n$ consistent with $\hat{\boldsymbol{\omega}}$ using $(A.1)$ and $(A.2)$.

Step 2. Solve for trade shares, $\pi^{j'}_{ni}(\hat{\boldsymbol{\omega}})$, consistent with the change in factor prices using $\hat{P}^j_n(\hat{\boldsymbol{\omega}})$ and $\widehat{x}^j_n(\hat{\boldsymbol{\omega}})$ as well as the definition of trade shares given by $(A.3)$.

Step 3. Solve for the change in labor across regions consistent with the change in factor prices $\hat{L}_n(\hat{\boldsymbol{\omega}})$, given $\hat{P}^j_n(\hat{\boldsymbol{\omega}})$, and $\hat{x}^j_n(\hat{\boldsymbol{\omega}})$, using $(A.4)$.

Step 4. Solve for expenditures consistent with the change in factor prices $X^{j'}_n(\hat{\boldsymbol{\omega}})$, using $(A.5)$, which constitutes $N \times J$ linear equations in $N \times J$ unknown, $\{X^{j'}_n(\hat{\boldsymbol{\omega}})\}_{N\times J}$. This can be solved through matrix inversion. Observe that carrying out this step first requires having solved for $\hat{L}_n(\hat{\boldsymbol{\omega}})$.

Step 5. Obtain a new guess for the change in factor prices, $\hat{\omega}^*_n$, using

$$\hat{\omega}^*_n = \frac{\sum_j \gamma^j_n \sum_i \pi'^j_{in}(\hat{\boldsymbol{\omega}}) X'^j_i(\hat{\boldsymbol{\omega}})}{\hat{L}_n(\hat{\boldsymbol{\omega}})^{1-\beta_n}(L_n I_n + \Upsilon_n + S_n)}.$$

Repeat Steps 1 through 5 until $||\hat{\boldsymbol{\omega}}^* - \hat{\boldsymbol{\omega}}|| < \varepsilon$.

A.4 Data and Calibration

We calibrate the model to the 50 U.S. states and a total of 26 sectors classified according to the North American Industry Classification System (NAICS), 15 of which are tradable goods, 10 service sectors, and construction. We assume that all service sectors and construction are non-tradable. We present below a list of the sectors that we use, and describe how we combine a subset of these sectors to ease computations. As stated in the main text, carrying out structural quantitative exercises on the effects of disaggregated fundamental changes requires data on $\left\{I_n, L_n, \Upsilon_n, \pi^j_{ni}\right\}^{N,N,J}_{n=1,i=1,j=1}$, as well as values for the parameters $\left\{\theta^j, \alpha^j, \beta_n, \gamma^j_n, \gamma^{jk}_n\right\}^{N,J,J}_{n=1,j=1,k=1}$. We now describe the main aspects of the data.

A.4.1 Regional Employment and Income.—

We set $L = 1$ so that, for each $n \in \{1, ..., N\}$, L_n is interpreted as the share of state n's employment in total employment. Regional employment data is obtained from the Bureau of Economic Analysis (BEA), with aggregate employment across all states summing to 137.3 million in 2007.

A.4.2 Interregional Trade Flows and Surpluses.—

To measure the shares of expenditures in intermediates from region-sector (i, j) for each state n, π^j_{ni}, we use data from the Commodity Flow Survey (CFS). The dataset tracks pairwise trade flows across all 50 states for 18 sectors of the U.S. economy (three of these are aggregated for a total of 15 tradable goods sectors as described in A.4.5). The CFS contains data on the total value of trade across all states which amounts to 5.2 trillion in 2007 dollars. The most recent CFS data covers the year 2007 and was released in 2012. This explains our choice of 2007 as the baseline year of our analysis.

Even though the CFS aims to quantify only domestic trade, and leaves out all international transactions, some imports to a local destination that are then traded in another domestic transaction are potentially included. To exclude this imported part of gross output, we calculate U.S. domestic consumption of domestic goods by subtracting exports from gross production for each NAICS sector using sectoral measures of gross output from the BEA and exports from the U.S. Census. We then compare the sectoral domestic shipment of goods implied by the CFS for each sector to the aggregate measure of domestic consumption. As expected, the CFS domestic shipment of goods is larger than the domestic consumption measure for all sectors, by a

factor ranging from 1 to 1.4. We thus adjust the CFS tables proportionally so that they represent the total amount of domestic consumption of domestic goods.

A row sum in a CFS trade table associated with a given sector j represents total exports of sector j goods from that state to all other states. Conversely, a column sum in that trade table gives total imports of sector j goods to a given state from all other states. The difference between exports and imports allows us to directly compute domestic regional trade surpluses in all U.S. states. We obtain I_n by calculating total value added in each state using BEA data and adding interregional trade deficits from the CFS data and dividing the result by total population for that state in 2007.

Given $\{\iota_n\}_{N\times 1}$, we use information on value added by regions to calculate regional national portfolio balances, $\Upsilon_n = \iota_n r_n H_n - \chi L_n$, where $\chi = \sum_i \iota_i r_i H_i / \sum_i L_i$. We then solve for $\{S_n\}_{N\times 1}$ as the difference between observed trade surplus in the data and the one implied by regional national portfolio balances. We then solve for $\{\iota_n\}_{N\times 1}$ by minimizing the sum square of $\{S_n\}_{N\times 1}$.

A.4.3 Value Added Shares and Shares of Material Use.—

In order to obtain value added shares observe that, for a particular sector j, each row-sum of the corresponding adjusted CFS trade table equals gross output for that sector in each region, $\left\{\sum_{i=1}^{N} \pi_{in}^{j} X_i^j\right\}_{n=1}^{N}$. Hence, we divide value added from the BEA in region-sector pair (n, j) by its corresponding measure of gross output from the trade table to obtain the share of value added in gross output by region and sector for all tradeable goods, $\{\gamma_n^j\}_{n=1,j=1}^{N,15}$. For the 11 non-tradeable sectors, gross output is not available at the sectoral level by state. In those sectors, we assume that the value added shares are constant across states and equal to the national share of value added in gross output , $\gamma_n^j = \gamma^j \ \forall n \in \{1, ..., N\}$ and $j > 15$. Aggregate measures of gross output and value added in non-tradeable sectors are obtained from the BEA.

While material input shares are available from the BEA by sector, they are not disaggregated by state. Given the structure of our model, it is nevertheless possible to infer region-specific material input shares from a national input-output (IO) table and other available data. The BEA Use table gives the value of inputs from each industry used by every other industry at the aggregate level. This use table is available at 5 year intervals, the most recent of which was released for 2002 data. A column sum of the BEA Use table gives total dollar payments from a given sector to all other sectors. Therefore, at the national level, we can compute $\tilde{\gamma}^{jk}$, the share of material inputs from sector k in total payments to materials by sector j. Since $\sum_{k=1}^{N} \tilde{\gamma}^{jk} = 1$, one may then construct the share of payments from sector j to material inputs from sector k, for each state n, as $\gamma_n^{jk} = (1 - \gamma_n^j)\tilde{\gamma}^{jk}$ where recall that γ_n^j's are region-sector specific value added shares.

A.4.4 Share of Final Good Expenditure.—

The share of income spent on goods from different sectors is calculated as follows,

$$\alpha^j = \frac{Y^j + M^j - E^j - \sum_k \gamma^{k,j}\left(1 - \gamma^k\right) Y^k}{\sum_j \left(Y^j + M^j - E^j - \sum_k \gamma^{k,j}\left(1 - \gamma^k\right) Y^k\right)},$$

where E^j denotes total exports from the U.S. to the rest of the world, M^j represents total imports to the U.S., and all intermediate input shares are national averages.

A.4.5 Payments to Labor and Structure Shares.—

As noted in the previous section, we assume that the share of payments to labor in value added, $\{1-\beta_n\}_{n=1}^{N}$, is constant across sectors. Disaggregated data on compensation of employees from the BEA is not available by individual sector in every state. To calculate $1-\beta_n$ in a given region, we first sum data on compensation of employees across all available sectors in that region, and divide this sum by value added in the corresponding region. The resulting measure, denoted by $1 - \bar{\beta}_n$, overestimates the value added share of the remaining factor in our model, $\overline{\beta}_n$, associated with land and structures. That is, part of the remaining factor used in production involves equipment in addition to fixed structures. Accordingly, to adjust these shares, we rely on estimates from Greenwood, Hercowitz, and Krusell (1997) who measure separately the share of labor, structures, and equipment, in value added for the U.S. economy. These shares amount to 70 percent, 13 percent, and 17 percent respectively. We thus use these estimates to infer the share of structures in value

added across regions by taking the share of non-labor value added by region, $\bar{\beta}_n$, subtracting the share of equipment, and renormalizing so that the new shares add to one. Specifically, we calculate the share of land and structures as $\beta_n = (\bar{\beta}_n - 0.17)/0.83$. Since our model explicitly takes materials into account, we assign the share of equipment to that of materials. In other words, we adjust the share of value added to $0.83\gamma_n^j$, and adjust all calculations above accordingly. In this way, our quantitative exercise uses shares for labor as well as for land and structures at the regional level that are consistent with aggregate value added shares in the U.S.

A.4.6 List of Sectors.—

The paper uses data from the Commodity Flow Survey (CFS), jointly produced by the Census and the Bureau of Transportation. The trade tables resulting from the CFS was released for the first time in December 2010 and last revised in 2012 for data pertaining to 2007. Each trade table corresponds to a particular sector and is a 50×50 matrix whose entries represent pairwise trade flows for that sector among all U.S. states. The CFS contains comprehensive data for 18 manufacturing sectors with a total value of trade across all states amounting to 5.2 trillion in 2007 dollars. These sectors are Food Product & Beverage and Tobacco Product, (NAICS 311 & 312), Textile and Textile Product Mills, (NAICS 313 & 314), Apparel & Leather and Allied Product, (NAICS 315 & 316), Wood Product, (NAICS 321), Paper, (NAICS 322), Printing and Related support activities, (NAICS 323), Petroleum & Coal Products, (NAICS 324)[44], Chemical, (NAICS 325), Plastics & Rubber Products, (NAICS 326), Nonmetallic Mineral Product, (NAICS 327), Primary Metal, (NAICS 331), Fabricated Metal Product, (NAICS 332), Machinery, (NAICS 333), Computer and Electronic Product, (NAICS 334), Electrical Equipment and Appliance, (NAICS 335), Transportation Equipment, (NAICS 336), Furniture & Related Product, (NAICS 337), Miscellaneous, (NAICS 339). We aggregate 3 subsectors. Sectors Textile and Textile Product Mills (NAICS 313 & 314) together with Apparel & Leather and Allied Product (NAICS 315 & 316), Wood Product (NAICS 321) with Paper (NAICS 322) and sectors Primary Metal (NAICS 331) with Fabricated Metal Product (NAICS 332). We end up with a total of 15 manufacturing tradable sectors.

The list of non-tradable sectors are: Construction, Wholesale and Retail Trade, (NAICS 42 - 45), Transport Services, (NAICS 481 - 488), Information Services, (NAICS 511 - 518), Finance and Insurance, (NAICS 521 - 525), Real Estate, (NAICS 531 - 533), Education, (NAICS 61), Health Care, (NAICS 621 - 624), Arts and Recreation, (NAICS 711 - 713), Accom. and Food Services, (NAICS 721 - 722), Other Services, (NAICS 493 & 541 & 55 & 561 & 562 & 811 - 814)

A.4.7 Sectoral Distribution of Productivities.—

We obtain the dispersion of productivities from Caliendo and Parro (2015). They compute this parameter for 20 tradable sectors, using data at two-digit level of the third revision of the International Standard Industrial Classification (ISIC Rev. 3). We match their sectors to our NAICS 2007 sectors using the information available in concordance tables. In five of our sectors Caliendo and Parro present estimates at an either more aggregated or disaggregated level. When Caliendo and Parro report separates estimates for sub-sectors which we aggregate into a single sector, we use their data to compute the dispersion of productivity in our aggregate sector. In cases where a sector in our data is integrated to another sector in Caliendo and Parro, we input that elasticity.

The dispersion of productivity for our sector "Wood and Paper" (NAICS 321-322) is estimated separately for wood products and paper products in Caliendo and Parro. In this case, using their data we proceed to estimate the aggregate dispersion of productivity for these two sub-sectors. Similarly, they present separate estimates for primary metals and fabricated metals (NAICS 331-332), thus we use their data to estimate the aggregate elasticity of these two sectors. We also estimate the dispersion of productivity for Transport Equipment (NAICS 336), which is divided into motor vehicles, trailers and semi-trailers, and other transport equipment in Caliendo and Parro. Our sector "Printing and Related Support Activities" (NAICS 323) is estimated together with pulp and paper products (ISIC3 21-22) in Caliendo and Parro, thus we input that estimate. Similarly, Furniture (NAICS 337) is estimated together with other manufacturing (ISIC 3 36-37)

[44] The Petroleum and Coal Products Manufacturing sector is based on the transformation of crude petroleum and coal into usable products. The dominant process is petroleum refining, but it also includes further refined petroleum and coal products and produce products, such as asphalt coatings and petroleum lubricating oils.

in Caliendo and Parro, and therefore we input that estimated elasticity in the Furniture sector.

Table A4.1. Sectoral Dispersion of Productivities

Sector	Elasticities θ^j
Food, Beverage, Tobacco	2.55
Textile, Apparel, Leather	5.56
Wood and Paper	9.46
Printing	9.07
Petroleum and Coal	51.08
Chemical	4.75
Plastics and Rubber	1.66
Nonmetallic Mineral	2.76
Primary and Fabricated Metal	6.78
Machinery	1.52
Computer and Electronic	12.79
Electrical Equipment	10.6
Transportation Equipment	1.01
Furniture	5.0
Miscellaneous	5.0

A.4.8 Average Miles per Shipment by Sector.—
The data on average mileage of all shipments from one state to another by NAICS manufacturing industries comes from the special release of the Commodity Flow Survey.

A.5 Computing the importance of regional and sectoral shocks

In Section 1 of the paper, we present the results of a decomposition of the changes in TFP into a regional, a sectoral, a regional-sectoral component. This section of the Appendix explains how this decomposition is performed for the case of measured and fundamental TFP.

We calculate the changes in measured TFP, $\hat{A}_n^j$, using equation (18), that is:

$$\ln \hat{A}_n^j = \ln \widehat{GDP}_n^j - \ln \hat{L}_n^j - \ln \left(\frac{\hat{w}_n}{\hat{x}_n^j} \right)$$

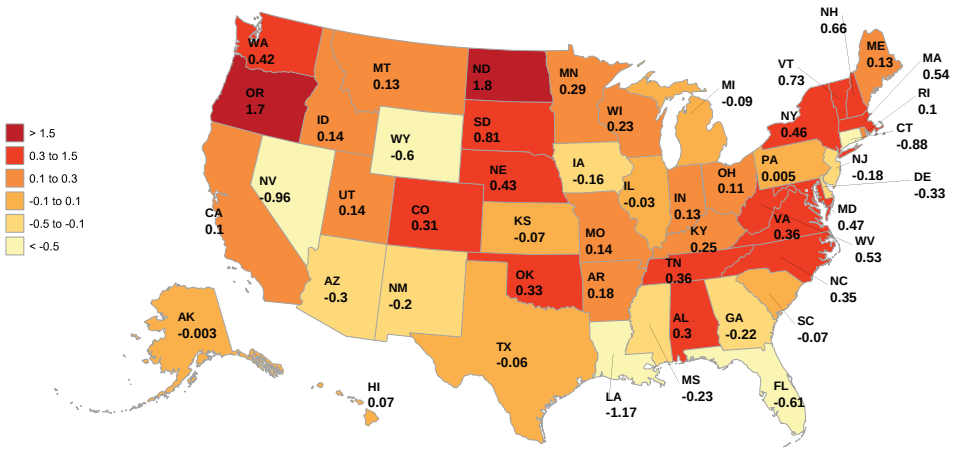
As this equation shows, to compute changes in measured TFP, we need data on real GDP, employment, nominal wages, and regional-sectoral price indices. We obtain the change in real GDP by sector and region, $\widehat{GDP}_n^j$, and the change in employment by sector and region, $\hat{L}_n^j$, from the BEA, as described in Appendix A.4. The change in nominal wages, $\hat{w}_n$, is computed as the ratio between the change in total labor compensation in region n, and the change in total employment in region n. To compute $\hat{x}_n^j$, we first construct the changes in the sectoral-regional prices indices, $\hat{P}_n^j$, as the ratio between the change in nominal and real GDP. With wage and price data, we use equation (3) expressed in relative changes to obtain $\hat{x}_n^j$.

To compute the change in fundamental TFP $\hat{T}_n^j$, and as explained in Footnote 19, we use the fact that producer prices indices computed by the BLS adjust for selection effects only sporadically, and therefore we obtain the changes in fundamental TFP as $\hat{T}_n^j = \left(\hat{A}_n^j \right)^{1/\gamma_n^j}$.

We compute the relative changes in TFP over the period 2002-2007, and over the period 2007-2012. Figure 5 in the main text presents the change in measured TFP for the period 2002 to 2007, while Figure A5.1 presents the computed measured TFP for the period 2007 to 2012.

After computing TFP, we study the relative contribution of sectoral and regional factors in explaining the variation in aggregate change in TFP. Specifically, we follow Koren and Tenreyro (2007) and decompose

Fig. A5.1. Regional measured TFP of the U.S. economy from 2007 to 2012
Change in TFP by regions (%)



measured, and fundamental, TFP in the following way

$$\hat{y}_n^j = \widetilde{\lambda}^j + \widetilde{\mu}_n + \widetilde{\varepsilon}_n^j,$$

where $\hat{y}_n^j$ is the weighted change in TFP where we weight each observation by its importance in aggregate TFP, that is, $\hat{y}_n^j = \omega_n^j \hat{A}_n^j$ (and $\hat{y}_n^j = \omega_n^j \hat{T}_n^j$, when using fundamental TFP), with $\omega_n^j = \frac{Y_n^j}{\sum_n \sum_j Y_n^j}$ (where Y_n^j is gross output). We also have that $\widetilde{\lambda}^j = \frac{1}{N}\sum_n \hat{y}_n^j$, $\widetilde{\mu}_n = \frac{1}{J}\sum_j \left(\hat{y}_n^j - \widetilde{\lambda}^j\right)$, and finally $\widetilde{\varepsilon}_n^j = \hat{y}_n^j - \widetilde{\lambda}^j - \widetilde{\mu}_n$. Note that we use the normalization $\sum_n \widetilde{\mu}_n = 0$, that is, regional and sectoral shocks are expressed relative to aggregate shocks.

With this decomposition we can now evaluate how sensible the total variation of TFP changes is to regional and sectoral changes. We do so by using Sobol's sensitivity index (Sobol, 1993). In particular, let the variable Y be divided into different groups X_i. Then the Sobol's sensitivity index is defined as S_i where

$$S_i = \frac{VAR(X_i)}{VAR(Y)}.$$

The results are presented in Table 2 in the main text and in Table A5.1 below.

Table A5.1. Importance of Regional and Sectoral TFP Changes

Variation in aggregate TFP changes explained by				
	Measured TFP		Fundamental TFP	
	2002-2007	2007-2012	2002-2007	2007-2012
Regional component	28.9%	28.6%	23.1%	27.8%
Sectoral component	21.1%	21.8%	18.3%	22.1%
Residual	50.0%	49.6%	58.6%	50.1%

Table shows Sobol's Sensitivity index.

A.6 Hurricane Katrina and its estimated costs

On August 29, 2005, Hurricane Katrina hit land where the Mississippi River enters the Gulf of Mexico as a category 4 hurricane. Six hours later, it entered the continental mainland at the border of Louisiana and Mississippi as a category 3 hurricane. It diminished to a major tropical storm in Columbus, Mississippi, turning into just a major storm by the time it hit Tennessee, just west of Nashville. Along the Mississippi coast, the storm surge erased small towns and cities, and uprooted and damaged oil platforms, harbors, and bridges. Hurricane Katrina hit New Orleans as a category 3 storm and although wind and rain damage in New Orleans were substantial, the direct effects of wind and rain were much more intense in Mississippi. However, within a few hours of the hurricane leaving New Orleans, major breaches in the levee system placed 80 percent of the city entirely under water. Residents of the lowest portions of the city found their homes under 20 feet of water.

Estimates of the cost of Katrina to the affected states (primarily Louisiana and Mississippi) are both plentiful and varied. Congleton (2006) put the total economic losses at over $200 billion. The Federal Emergency Management Agency (2006) estimated total economic losses of $125 billion and insured losses of $35 billion. Meanwhile, the National Institute of Standards and Technology (2006) estimated economic losses from Hurricane Katrina and Hurricane Rita (that followed less than a month after Katrina) at about $100 billion and insured losses at $45-65 billion. Damages from Katrina estimated by National Oceanic and Atmospheric Administration are $108 billion. Several private sector estimates also estimate losses in the range of $100-200 billion. There are also estimates of losses specific to certain sectors; e.g., the Department of Housing and Urban Development (2006) put out estimates of the extent of damage specifically to housing units. Burton and Hicks (2005) estimated total damages of $156 billion, which they broke down into commercial structure damages($21 billion), commercial equipment damages ($36 billion), residential structure damages ($50 billion), residential contents damages ($24 billion), commercial revenues damages ($5 billion), electric utility damages ($231 million), highway damages ($3 billion), and sewer system damages ($1.2 billion). Then, as of June 2006, the Insurance Information Institute estimated that there were $41.1 billion of insured losses from Hurricane Katrina, with the breakdown as follows: Louisiana (63%), Mississippi (34.2%), Alabama (2.7%), and minimal shares (basically 0) in Florida, Tennessee, and Georgia. Assuming that the share of uninsured losses from Hurricane Katrina was similar by state, we use the Burton and Hicks estimates combined with the Insurance Information Institute shares to calculate the estimates of structural damage to states that are in the table below.

Table A6.1. Hurricane Katrina's structural damage estimates

Damage to structures imputed by state using the estimated costs by Burton and Hicks (2005) and state shares from the Insurance Information Institute (thousands of dollars)				
	Alabama	Louisiana	Mississippi	Total
Commercial structure damages	569,943	13,298,674	7,219,280	21,109,006
Commercial equipment damages	982,835	22,932,825	12,449,248	36,401,310
Residential structure damages	1,342,560	31,326,404	17,005,762	49,724,451
Residential contents damages	659,800	15,395,328	8,357,464	24,437,028
Commercial revenues damages	125,132	2,919,756	1,585,010	4,634,533
Electric utility damages	6,247	145,764	79,129	231,371
Highway damages	82,343	1,921,348	1,043,017	3,049,758
Sewer system damages	34,088	795,383	431,779	1,262,512
Total structural damages	*2,035,182*	*47,487,572*	*25,778,968*	*75,377,098*
Total damages	*3,802,949*	*88,735,480*	*48,170,689*	*140,849,969*
Structural damages as a share of each state's GDP	*1.37%*	*25.25%*	*34.02%*	*18.28%*
Total damages as a share of each state's GDP	*2.56%*	*47.18%*	*63.57%*	*34.15%*

A.7 The Importance of Geographic Distance as a Trade Barrier

Once regional trade is taken into account, selection plays an essential role in understanding the impact of regional and sectoral productivity changes on aggregate measured TFP, GDP, and welfare. The two fundamental determinants of intermediate-goods-firm selection in a given region-sector pair (n, j) are i) its fundamental productivity, and ii) the bilateral regional trade barriers it faces. Furthermore, the international trade literature has identified geographic distance as the most important barrier to international trade flows (see e.g. Disdier and Head 2008). The importance of the selection mechanism emphasized by trade considerations, therefore, is closely related to the role of distance as a deterrent to regional trade. In this section, we evaluate the importance of geographic distance for aggregate TFP and GDP in the U.S. We do so by first separating the trade costs of moving goods across U.S. states into a geographic distance component and other regional trade barriers. We then quantify the aggregate effects arising from a reduction in each of these components of trade costs.

A.7.1 Gains from Reductions in Trade Barriers.—
To construct our measure of geographic distance, we use data on average miles per shipments between any two states for all 50 states and for the 15 tradable sectors considered in this paper. The data is available from the CFS which tracks ton-miles and tons shipped (in thousands) between states by NAICS manufacturing industries. We compute average miles per shipment by dividing ton-miles by tons shipped between states in each of our sectors. Average miles per shipment for goods shipped from each region of the U.S. range from 996 miles for goods shipped from Indiana to 4,154 miles for goods shipped from Hawaii.

To identify bilateral trade costs, we rely on the gravity equation implied by the model.[45] Using Equation (8), and taking the product of sector j goods shipped between two regions in one direction, and sector j goods shipped in the opposite direction, and dividing this product by the domestic expenditure shares in each region, we obtain that

$$\frac{\pi^j_{ni}\pi^j_{in}}{\pi^j_{nn}\pi^j_{ii}} = \left(\kappa^j_{ni}\kappa^j_{in}\right)^{-\theta^j}.$$

Notice that the ratio $\pi^j_{ni}\pi^j_{in}\Big/\pi^j_{nn}\pi^j_{ii}$ is invariant to all the determinants of bilateral trade flows including prices and technology, except for trade frictions κ. In other words, κ^j_{ni} identifies pure trade frictions and therefore, we do not need to regress them on fixed effects that proxy for prices, technologies, etc. Assuming that the cost of trading across regions is symmetric,[46] we can then infer bilateral trade costs for each sector j as

$$\kappa^j_{ni} = \left(\frac{\pi^j_{ni}\pi^j_{in}}{\pi^j_{nn}\pi^j_{ii}}\right)^{-1/2\theta^j}.$$

Following Anderson and Van Wincoop (2003) and others, we explore how domestic bilateral trade costs vary with geographic distance using a log-linear relationship. Thus, we estimate the following trade-cost equation

$$\log \kappa^j_{ni} = \delta^j \log d^j_{ni}/d^j_{\min} + \eta_n + \varepsilon^j_{ni}, \tag{A. 6}$$

where d^j_{ni} denotes average miles per shipment from region i to region n in sector j, which we normalize by the minimum bilateral distance in that sector, $d^j_{\min}$.[47] ε^j_{ni} is an error assumed to be orthogonal to our distance measure. OLS estimates from this regression may be used to decompose domestic bilateral trade costs, κ^j_{ni}, into a distance component, $(\delta^j \log d^j_{ni}/d^{j,\min}_{ni})$, and other trade barriers $(\eta_n + \varepsilon^j_{ni})$.

Specification (A. 6) is our preferred specification. Note that it decomposes trade frictions into distance

[45] This approach is commonly used in the international trade literature. See, for example, Head and Ries (2001), or Eaton and Kortum (2002).

[46] Here, we follow the literature that infers trade costs from observable trade flows, as in Head and Ries (2001), Anderson and van Wincoop (2003) and Waugh (2010).

[47] The minimum, $d^j_{\min}$, is computed for each sector j across all n and i. This normalization allows us to estimate a sectoral distance coefficient that is comparable across sectors. Note that this is equivalent to adding a distance-sectoral fixed effect to the specification.

and other trade frictions. In this regards, the fixed effects η_n capture trade barriers other than distance and that are common to exporting regions. One example is trade regulations at the regional level that affect all destinations.[48] Yet, we also consider an alternative specification where we regress trade costs on distance with no fixed effects. The results from both specifications are presented in Table A7.1.

Table A7.1 presents six columns. In column one and two we present the elasticity of trade costs with respect to distance and the corresponding standard errors after our preferred specification, (A. 6). Column three and four present the results when we exclude the fixed effects. Columns five and six present the implied distance elasticity conditional on the trade elasticities that we estimated before. Our estimated elasticities from our preferred specification are in the range of those estimated in the literature. Disdier and Head (2008) examine 1467 distance effects estimated in 103 papers and find that 90% of the estimates lie between -0.28 and -1.55 (with the range of all estimates between 0.03 and -2.33). Feyrer (2009) exploits a temporary shock to distance, the closing of the Suez Canal in 1967 and it's reopening in 1975, to examine the effect of distance on trade and the effect of trade on income and find elasticities between -0.15 and -0.46. These ranges of estimates in the literature corresponds to aggregate elasticities, not sector specific and not across regions inside a country. Still, our sectoral estimates also lie in the range of the most frequent estimates in the literature, except for Electrical Equipment where our estimate is below most of the estimates, and Petroleum and Coal where we estimate a positive effect of distance on trade flows. In addition, our median sectoral elasticity is -0.72, close to the -0.85 median point of these literature' estimates.

Table A7.1. Elasticities of inter-regional trade costs and flows with respect to distance

	Distance elasticity					
	Ttrade costs				Trade flows	
	δ^j	s.d.	δ^j	s.d.	$-\delta^j\theta^j$	$-\delta^j\theta^j$
Food, Beverage, Tobacco	0.394	0.011	0.460	0.003	-1.006	-1.172
Textile, Apparel, Leather	0.126	0.014	0.203	0.005	-0.703	-1.127
Wood and Paper	0.080	0.012	0.148	0.003	-0.753	-1.400
Printing	0.079	0.012	0.143	0.004	-0.718	-1.296
Petroleum and Coal	-0.018	0.007	0.022	0.004	0.932	-1.135
Chemical	0.190	0.013	0.264	0.003	-0.903	-1.253
Plastics and Rubber	0.667	0.013	0.738	0.003	-1.108	-1.225
Nonmetallic Mineral	0.421	0.011	0.482	0.003	-1.163	-1.331
Primary and Fabricated Metal	0.128	0.014	0.207	0.003	-0.865	-1.401
Machinery	0.452	0.012	0.518	0.003	-0.686	-0.787
Computer and Electronic	0.021	0.015	0.102	0.006	-0.270	-1.310
Electrical Equipment	0.003	0.011	0.065	0.004	-0.035	-0.686
Transportation Equipment	0.701	0.009	0.754	0.003	-0.708	-0.761
Furniture	0.181	0.014	0.260	0.005	-0.904	-1.300
Miscellaneous	0.102	0.014	0.180	0.004	-0.512	-0.901
Fixed effects, η_n	Yes		No		Yes	No
Observations	20,546		20,546			
Adjusted R^2	0.924		0.917			

We then use this decomposition to calculate the effects of a reduction in distance and other trade barriers on measured TFP, GDP, and welfare.

Table A7.2 presents our findings using our preferred specification. First, the table shows that the aggregate economic cost of domestic trade barriers is large. This finding is at the basis of our emphasis on the geography of economic activity. Furthermore, the table shows that the effect of eliminating barriers related to distance is almost an order of magnitude larger than that of eliminating other trade barriers. Therefore, focusing

[48] Note that adding the fixed effect does not violate our symmetry assumption since the decomposition on the right hand side will always add up to the symmetric trade cost on the left hand side. In other words, our symmetry assumption imposes that $\eta_n + \varepsilon^j_{ni} = \eta_i + \varepsilon^j_{in}$, and we impose so by using both κ^j_{ni} and κ^j_{in} as dependent variables.

Table A7.2. Reduction of trade cost across U.S. states

	Geographic distance	Other barriers
Aggregate TFP gains	50.98%	3.62%
Aggregate GDP gains	125.88%	10.54%
Welfare gains	58.83%	10.10%

on distance as the main obstacle to the flow of goods across states is a good approximation.[49] The latter observation is reminiscent of similar findings in the international trade literature, and it is noteworthy that distance plays such as a large role even domestically. In addition, changes in TFP and welfare in Table A7.2 are noticeably smaller than changes in GDP. As emphasized throughout the analysis, this finding reflects the effects of migration in the presence of local fixed factors. In the longer run, to the extent that some of these local factors are accumulated, such as structures, differences between TFP or welfare and GDP changes may be attenuated.

It is important to keep in mind that our counterfactual experiment in this section has no bearing on policy since reducing distance to zero is infeasible. Reductions in the importance of distance as a trade barrier may arise, however, with technological improvements related to the shipping of goods. Still, the exercise emphasizes the current importance of regional trade costs and geography in understanding changes in output and productivity. Put another way, the geography of economic activity in 2007 was, and likely still is, an essential determinant of the behavior of TFP, GDP, and welfare, in response to fundamental changes in productivity.

A.8. Regional and Sectoral TFP/GDP Aggregation

This Appendix describes how we aggregate TFP and GDP measures into regional, sectoral, and national aggregates.

A.8.1 Computing Aggregate, Regional, and Sectoral Measured TFP.—
Since measured TFP at the level of a sector in a region is calculated based on gross output in Equation (15), we use gross output revenue shares to aggregate these TFP measures into regional, sectoral, or national measures. Changes in regional and sectoral measured TFP are then simply weighted averages of changes in measured TFP in each region-sector pair (n, j), where the weights are the corresponding (n, j) gross output revenue shares. Thus, since gross output revenue, Y_n^j, is given by Equation (16), regional changes in measured TFP are given by

$$\hat{A}_n = \sum_{j=1}^{J} \frac{Y_n^j}{\sum_{j=1}^{J} Y_n^j} \hat{A}_n^j = \sum_{j=1}^{J} \frac{\frac{w_n L_n^j}{\gamma_n^j (1-\beta_n)}}{\sum_{j=1}^{J} \frac{w_n L_n^j}{\gamma_n^j (1-\beta_n)}} \hat{A}_n^j, \tag{A. 7}$$

while sectoral changes in measured TFP can be expressed as

$$\hat{A}^j = \sum_{n=1}^{N} \frac{Y_n^j}{\sum_{n=1}^{N} Y_n^j} \hat{A}_n^j = \sum_{n=1}^{N} \frac{\frac{w_n L_n^j}{\gamma_n^j (1-\beta_n)}}{\sum_{n=1}^{N} \frac{w_n L_n^j}{\gamma_n^j (1-\beta_n)}} \hat{A}_n^j. \tag{A. 8}$$

Similarly, changes in aggregate TFP are then given by

$$\hat{A} = \sum_{j=1}^{J} \sum_{n=1}^{N} \frac{Y_n^j}{\sum_{j=1}^{J} \sum_{n=1}^{N} Y_n^j} \hat{A}_n^j = \sum_{j=1}^{J} \sum_{n=1}^{N} \frac{\frac{w_n L_n^j}{\gamma_n^j (1-\beta_n)}}{\sum_{j=1}^{J} \sum_{n=1}^{N} \frac{w_n L_n^j}{\gamma_n^j (1-\beta_n)}} \hat{A}_n^j. \tag{A. 9}$$

[49] The results without fixed effects reinforce our findings that geographical distance matters. In particular, we find that the aggregate TFP, GDP, and welfare effects from reducing distance are 69%, 203%, and 81% respectively.

A.8.2 Computing Aggregate, Regional, and Sectoral real GDP.—

Given that real GDP is a value added measure, we use value added shares in constant prices for aggregation purposes. Denote sectoral and regional value added (n, j) shares in a given benchmark year by

$$\upsilon_n^j = \frac{w_n L_n^j + r_n H_n^j}{\sum_{j=1}^{J} \left(w_n L_n^j + r_n H_n^j \right)},$$

and

$$\xi_n^j = \frac{w_n L_n^j + r_n H_n^j}{\sum_{n=1}^{N} \left(w_n H_n^j + r_n H_n^j \right)}$$

respectively. Then, the change in regional real GDP arising from a change in fundamentals is given by

$$\widehat{GDP}_n = \sum_{j=1}^{J} \upsilon_n^j \widehat{GDP}_n^j. \tag{A. 10}$$

Similarly, the change in sectoral real GDP may be expressed as

$$\widehat{GDP}^j = \sum_{n=1}^{N} \xi_n^j \widehat{GDP}_n^j. \tag{A. 11}$$

Finally, aggregate change in GDP is given by

$$\widehat{GDP} = \sum_{j=1}^{J} \sum_{n=1}^{N} \phi_n^j \widehat{GDP}_n^j, \tag{A. 12}$$

where

$$\phi_n^j = \frac{w_n L_n^j + r_n H_n^j}{\sum_{j=1}^{J} \sum_{n=1}^{N} \left(w_n L_n^j + r_n H_n^j \right)}$$

is the share of region-sector pair (n, j) in value added in the base year.

A.9 Additional Results

In this section of the appendix we present additional results. In Figures A9.1 and A9.2 we present the aggregate TFP and GDP elasticities, respectively, of a change in a state's fundamental productivity. In contrast to the results in Section 5, here we compute the elasticity without normalizing by the size of the region. Namely these figures are computed by taking the product between the elasticities in Figures 8e and 8f and the appropriate regional shares from the data (for the case of GDP Figure 1a).

Fig. A9.1. Aggregate TFP elasticity from a 10 percentage change in regional TFP (hundreds)

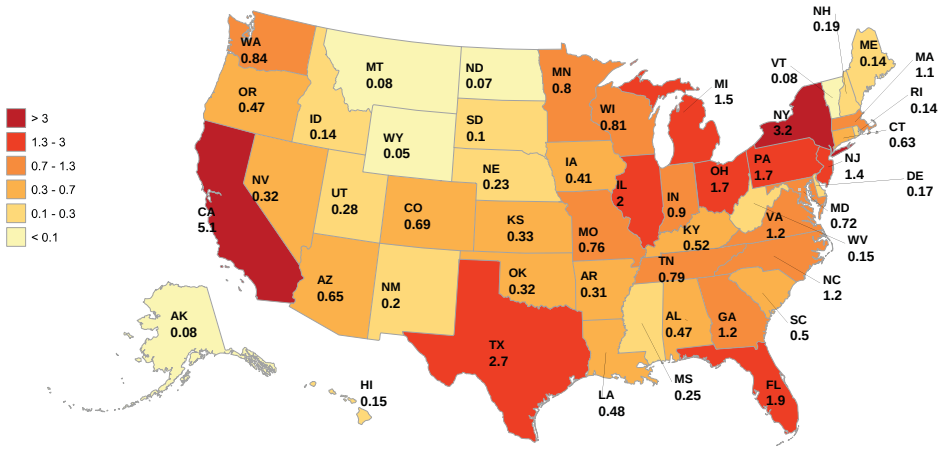
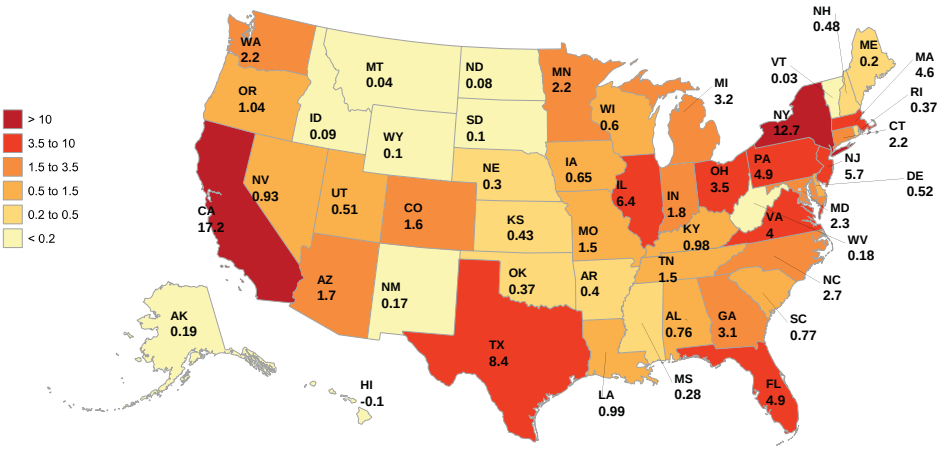



Fig. A9.2. Aggregate GDP elasticity from a 10 percentage change in regional TFP (hundreds)